05 Amazon Fine Food Reviews Analysis_Logistic Regression

January 11, 2019

1 Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

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

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

2 [1]. Reading Data

2.1 [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 [65]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

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

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

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

from tqdm import tqdm
import os
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data point
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5
```

```
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5000

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negativ
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 (5000, 10)
```

```
Out[2]:    Id   ProductId          UserId                      ProfileName  \
        0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
        1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
        2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

           HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
        0                     1                       1      1  1303862400
        1                     0                       0      0  1346976000
        2                     1                       1      1  1219017600

                         Summary                                              Text
        0  Good Quality Dog Food  I have bought several of the Vitality canned d...
        1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
        2  "Delight" says it all  This is a confection that has been around a fe...
```

```
In [3]: display = pd.read_sql_query("""
        SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
        FROM Reviews
        GROUP BY UserId
        HAVING COUNT(*)>1
        """, con)
```

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

```
(80668, 7)
```

```
Out[4]:                UserId   ProductId             ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
```

```
1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
3  #oc-R11O5J5ZVQE25C  B005HG9ET0           Penguin Chick  1346889600      5
4  #oc-R12KPBODL2B5ZD  B007OSBE1U   Christopher P. Presta  1348617600      1

                                                Text  COUNT(*)
0  Overall its just OK when considering the price...         2
1  My wife has recurring extreme muscle spasms, u...         3
2  This coffee is horrible and unfortunately not ...         2
3  This will be the bottle that you grab from the...         3
4  I didnt like this coffee. Instead of telling y...         2
```

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

```
Out[5]:               UserId   ProductId                     ProfileName        Time  \
        80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

               Score                                               Text  COUNT(*)
        80638      5  I was recommended to try green tea extract to ...         5
```

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

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

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

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

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

```
Out[7]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        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

           HelpfulnessDenominator  Score        Time  \
        0                       2      5  1199577600
```

```
1                              2       5   1199577600
2                              2       5   1199577600
3                              2       5   1199577600
4                              2       5   1199577600

                                     Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  LOACKER QUADRATINI VANILLA WAFERS
3  LOACKER QUADRATINI VANILLA WAFERS
4  LOACKER QUADRATINI VANILLA WAFERS

                                                 Text
0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

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

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

In [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

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

Out[9]: (4986, 10)

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

Out[10]: 99.72

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

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

         display.head()
```

```
Out[11]:       Id   ProductId          UserId              ProfileName  \
         0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
         1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

            HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         0                     3                       1      5  1224892800
         1                     3                       2      4  1212883200

                                                  Summary  \
         0              Bought This for My Son at College
         1  Pure cocoa taste with crunchy almonds inside

                                                         Text
         0  My son loves spaghetti so I didn't hesitate or...
         1  It was almost a 'love at first bite' - the per...
```

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

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

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

```
(4986, 10)
```

```
Out[13]: 1    4178
         0     808
         Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

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

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

1. Begin by removing the html tags

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

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

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

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

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

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

```
Why is this $[...] when the same product is available for $[...] here?<br />http://www.amazon.c
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The bes
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the oth
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />This k cup is great coffee
==================================================
```

In [15]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor
```

In [16]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-
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)
```

```
Why is this $[...] when the same product is available for $[...] here? />The Victor M380 and M5
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The bes
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the oth
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cup is great coffee.  dcaf
```

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

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

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

In [18]:
```
sent_1500 = decontracted(sent_1500)
```

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

```
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the ot
==================================================
```

```
In [19]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
         sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
         print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victo
```

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

```
Wow So far two two star reviews One obviously had no idea what they were ordering the other wa
```

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

         stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselv
                     "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
                     'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
                     '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', 'a
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
                     's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
                     've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
                     "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                     "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                     'won', "won't", 'wouldn', "wouldn't"])
```

```
In [22]: # Combining all the above stundents
         from tqdm import tqdm
         preprocessed_reviews = []
         # tqdm is for printing the status bar
         for sentance in tqdm(final['Text'].values):
             sentance = re.sub(r"http\S+", "", sentance)
```

```
            sentance = BeautifulSoup(sentance, 'lxml').get_text()
            sentance = decontracted(sentance)
            sentance = re.sub("\S*\d\S*", "", sentance).strip()
            sentance = re.sub('[^A-Za-z]+', ' ', sentance)
            # https://gist.github.com/sebleier/554280
            sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwo
            preprocessed_reviews.append(sentance.strip())
```

```
100%|| 4986/4986 [00:01<00:00, 3137.37it/s]
```

In [23]:
```
preprocessed_reviews[1500]
```

Out[23]:
```
'wow far two two star reviews one obviously no idea ordering wants crispy cookies hey
```

[3.2] Preprocessing Review Summary

In [6]:
```
## Similartly you can do preprocessing for review summary also.
```

5 [4] Featurization

I am used to select 100k data points randaand sord them using time based splitting

In [5]:
```
# Split the data into train , test and crossvalidation datasets
# load "preprocessed.pkl" data frame
df = pd.read_pickle("files/preprocessed.pkl")
df.head(1)
```

Out[5]:
```
            Id   ProductId         UserId      ProfileName  \
138706  150524  0006641040  ACITT7DI6IDDL  shari zychinski

        HelpfulnessNumerator  HelpfulnessDenominator  Score       Time  \
138706                     0                       0      1  939340800

                          Summary  \
138706  EVERY book is educational

                                                     Text  \
138706  this witty little book makes my son laugh at l...

                                              CleanedText  \
138706  witty little book makes son laugh loud recite ...

                  CleanedSummary
138706  every book educational
```

In [6]:
```
df.shape
```

Out[6]:
```
(364171, 12)
```

In [7]:
```
# take 50k sample data randomly
sample_data = df.sample(100000)
sample_data.shape
```

Out[7]: (100000, 12)

In [8]:
```
# sorted the data using time based
sorted_data = sample_data.sort_values('Time', axis=0, inplace=False)
sorted_data.shape
```

Out[8]: (100000, 12)

In [9]:
```
sorted_data['Score'].value_counts()
```

Out[9]:
```
1    84283
0    15717
Name: Score, dtype: int64
```

In [10]:
```
from sklearn.model_selection import train_test_split
```

In [11]:
```
X = np.array(sorted_data['CleanedText'])
y = np.array(sorted_data['Score'])
print(X.shape)
print(y.shape)
```

```
(100000,)
(100000,)
```

In [12]:
```
# Simple cross validation
# split the data sent into train and test
train , test , train_y , test_y = train_test_split(X, y, test_size = 0.3, random_state

# split the train data set into cross validation train and cross validation test
train, cv , train_y, cv_y = train_test_split(train, train_y, test_size=0.3, random_sta

print("train data = ", train.shape)
print("cros validation = ", cv.shape)
print("test data = ", test.shape)
```

```
train data =  (49000,)
cros validation =  (21000,)
test data =  (30000,)
```

5.1 [4.1] BAG OF WORDS

In [15]:
```
#BoW
count_vect = CountVectorizer(min_df=10 ,) #in scikit-learn
count_vect.fit(train)
```

```
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts_train = count_vect.fit_transform(train)
final_counts_cv = count_vect.transform(cv)
final_counts_test = count_vect.transform(test)
print("============Train Data=========")
print("the type of count vectorizer ",type(final_counts_train))
print("the shape of out text BOW vectorizer ",final_counts_train.get_shape())
print("the number of unique words ", final_counts_train.get_shape()[1])
print("============Cross validation Data=========")
print("the type of count vectorizer ",type(final_counts_cv))
print("the shape of out text BOW vectorizer ",final_counts_cv.get_shape())
print("the number of unique words ", final_counts_cv.get_shape()[1])
print("============Test Data=========")
print("the type of count vectorizer ",type(final_counts_test))
print("the shape of out text BOW vectorizer ",final_counts_test.get_shape())
print("the number of unique words ", final_counts_test.get_shape()[1])
```

```
some feature names  ['ability', 'able', 'able buy', 'able drink', 'able eat', 'able enjoy', 'al
==================================================
============Train Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 18540)
the number of unique words  18540
============Cross validation Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (21000, 18540)
the number of unique words  18540
============Test Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 18540)
the number of unique words  18540
```

5.2 [4.2] Bi-Grams and n-Grams.

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

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

# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
```

```
print("the number of unique words including both unigrams and bigrams ", final_bigram_
```

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

5.3 [4.3] TF-IDF

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

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

```
some sample features(unique words in the corpus) ['ability', 'able', 'able find', 'able get',
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

5.4 [4.4] Word2Vec

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

In [42]:
```
# Using Google News Word2Vectors

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


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

```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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

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

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wonderful', 0.994603216648
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('popcorn', 0.999275088310
```

In [36]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'stinky', 'right', 'nearby
```

5.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [38]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
```

```
            sent_vec /= cnt_words
        sent_vectors.append(sent_vec)
    print(len(sent_vectors))
    print(len(sent_vectors[0]))
```

100%|| 4986/4986 [00:03<00:00, 1330.47it/s]

4986
50

[4.4.1.2] TFIDF weighted W2v

```
In [39]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
         model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(preprocessed_reviews)
         # we are converting a dictionary with word as a key, and the idf as a value
         dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
In [41]: # TF-IDF weighted Word2Vec
         tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

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

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

6 [5] Assignment 5: Apply Logistic Regression

Apply Logistic Regression on these feature sets
SET 1:Review text, preprocessed one converted into vectors using (BOW)
SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)
Hyper paramter tuning (find best hyper parameters corresponding the algorithm that you choose)
Find the best hyper parameter which will give the maximum AUC value
Find the best hyper paramter using k-fold cross validation or simple cross validation data
Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

```
</ul>
</li>
<br>
<li><strong>Pertubation Test</strong>
    <ul>
<li>Get the weights W after fit your model with the data X.</li>
<li>Add a noise to the X (X' = X + e) and get the new data set X' (if X is a sparse
```

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

```
    <li> Print the feature names whose % change is more than a threshold x(in our example it's
    </ul>
</li>
<br>
<li><strong>Sparsity</strong>
    <ul>
<li>Calculate sparsity on weight vector obtained after using L1 regularization</li>
    </ul>
</li>
<br><font color='red'>NOTE: Do sparsity and multicollinearity for any one of the vectorizers. I
<br>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Get top 10 important features for both positive and negative classes separately.</li>
```

```
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature engine
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

Note: Data Leakage

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

7 Applying Logistic Regression

In [2]:
```
# after preprocessing
df = pd.read_pickle("files/preprocessed.pkl")
df.shape
```

Out[2]:
```
(364171, 12)
```

In [3]: df.head()

```
Out[3]:             Id   ProductId          UserId                   ProfileName  \
        138706  150524  0006641040   ACITT7DI6IDDL               shari zychinski
        138688  150506  0006641040  A2IW4PEEKO2R0U                         Tracy
        138689  150507  0006641040  A1S4A3IQ2MU7V4         sally sue "sally sue"
        138690  150508  0006641040     AZGXZ2UUK6X  Catherine Hallberg "(Kate)"
        138691  150509  0006641040  A3CMRKGE0P909G                        Teresa

                HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
        138706                     0                       0      1   939340800
        138688                     1                       1      1  1194739200
        138689                     1                       1      1  1191456000
        138690                     1                       1      1  1076025600
        138691                     3                       4      1  1018396800

                                                   Summary  \
        138706                   EVERY book is educational
        138688  Love the book, miss the hard cover version
        138689               chicken soup with rice months
        138690      a good swingy rhythm for reading aloud
        138691             A great way to learn the months

                                                              Text  \
        138706  this witty little book makes my son laugh at l...
        138688  I grew up reading these Sendak books, and watc...
        138689  This is a fun way for children to learn their ...
        138690  This is a great little book to read aloud- it ...
        138691  This is a book of poetry about the months of t...

                                                       CleanedText  \
        138706  witty little book makes son laugh loud recite ...
        138688  grew reading sendak books watching really rosi...
        138689  fun way children learn months year learn poems...
        138690  great little book read aloud nice rhythm well ...
        138691  book poetry months year goes month cute little...

                                  CleanedSummary
        138706             every book educational
        138688  love book miss hard cover version
        138689            chicken soup rice months
        138690   good swingy rhythm reading aloud
        138691             great way learn months
```

In [ ]:

In [ ]:

In [4]:
```
#code source: http://occam.olin.edu/sites/default/files/DataScienceMaterials/machine_l
from sklearn.model_selection import train_test_split
```

```
from sklearn.grid_search import GridSearchCV
from sklearn.datasets import *
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score , f1_score , confusion_matrix
from collections import Counter
from sklearn.metrics import accuracy_score, roc_auc_score , roc_curve
from sklearn.model_selection import train_test_split
```

```
/home/prasad/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: Deprecation
  "This module will be removed in 0.20.", DeprecationWarning)
/home/prasad/anaconda3/lib/python3.6/site-packages/sklearn/grid_search.py:42: DeprecationWarni
  DeprecationWarning)
```

7.1 [5.1] Logistic Regression on BOW, SET 1

In [99]:
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
#BoW
count_vect = CountVectorizer(min_df=5, ngram_range=(1,2)) #in scikit-learn
count_vect.fit(train)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

bow_train = count_vect.fit_transform(train)
bow_cv = count_vect.transform(cv)
bow_test = count_vect.transform(test)
print("============Train Data=========")
print("the type of count vectorizer ",type(bow_train))
print("the shape of out text BOW vectorizer ",bow_train.get_shape())
print("the number of unique words ", bow_train.get_shape()[1])
print("============Cross validation Data=========")
print("the type of count vectorizer ",type(bow_cv))
print("the shape of out text BOW vectorizer ",bow_cv.get_shape())
print("the number of unique words ", bow_cv.get_shape()[1])
print("============Test Data=========")
print("the type of count vectorizer ",type(bow_test))
print("the shape of out text BOW vectorizer ",bow_test.get_shape())
print("the number of unique words ", bow_test.get_shape()[1])
```

```
some feature names  ['aa', 'aback', 'abandon', 'abandoned', 'abdominal', 'ability', 'ability ma
==================================================
============Train Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 64147)
the number of unique words  64147
============Cross validation Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

```
the shape of out text BOW vectorizer  (21000, 64147)
the number of unique words  64147
============Test Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 64147)
the number of unique words  64147
```

In [100]:
```
C = [pow(10,j) for j in range(-4,4,1)]
```

In [101]:
```
bow_train_auc = []
bow_cv_auc = []
for i in C:
    LR = LogisticRegression(C=i)
    LR.fit(bow_train, train_y)
    # train data
    y_prob_train = LR.predict_proba(bow_train)[:,1]
    y_pred = np.where(y_prob_train > 0.5, 1, 0)
    auc_roc_train = roc_auc_score(train_y , y_prob_train)
    print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float
    bow_train_auc.append(auc_roc_train)
    # CV
    y_prob_cv = LR.predict_proba(bow_cv)[:,1]
    y_pred = np.where(y_prob_cv > 0.5, 1, 0)
    auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
    print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))
    bow_cv_auc.append(auc_roc_cv)
    print("="*50)
```

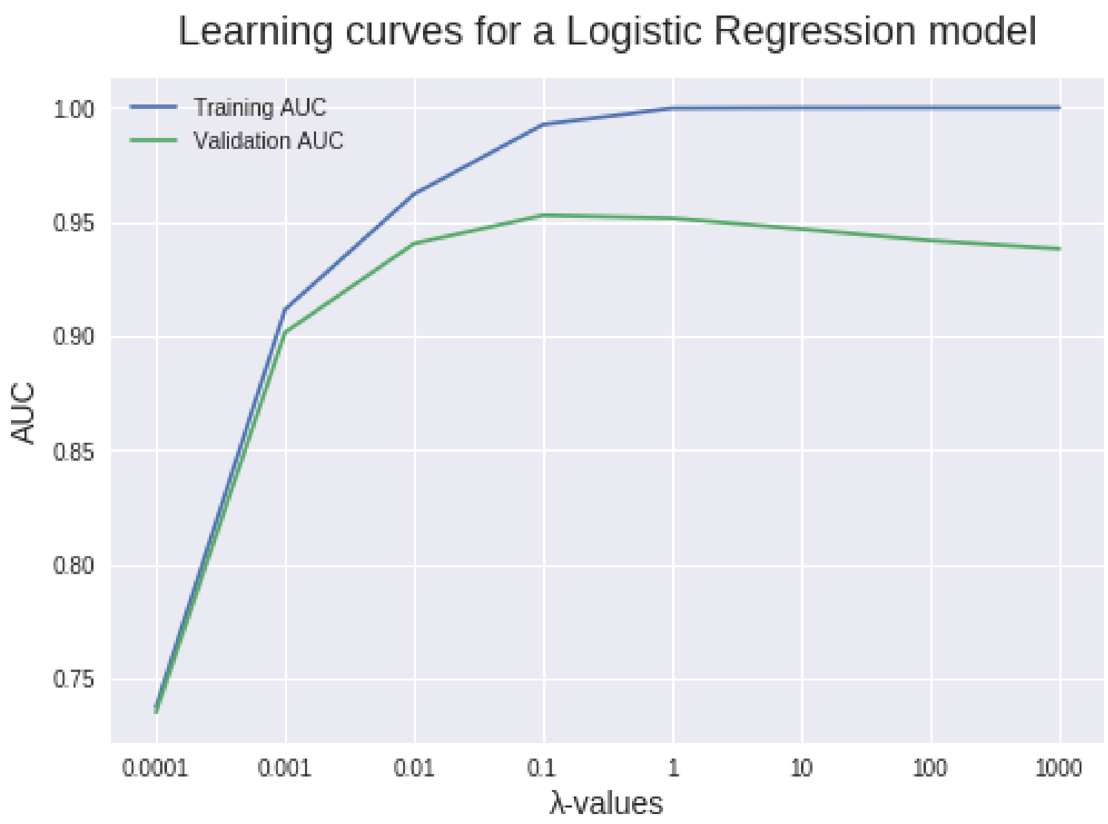
```
Train AUC for  = 0.0001 is 73.77%

CV AUC for  = 0.0001 is 73.53%
==================================================

Train AUC for  = 0.001 is 91.16%

CV AUC for  = 0.001 is 90.16%
==================================================

Train AUC for  = 0.01 is 96.22%

CV AUC for  = 0.01 is 94.05%
==================================================

Train AUC for  = 0.1 is 99.26%

CV AUC for  = 0.1 is 95.29%
```

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

Train AUC for  = 1 is 99.98%

CV AUC for  = 1 is 95.16%
==================================================

Train AUC for  = 10 is 100.00%

CV AUC for  = 10 is 94.69%
==================================================

Train AUC for  = 100 is 100.00%

CV AUC for  = 100 is 94.18%
==================================================

Train AUC for  = 1000 is 100.00%

CV AUC for  = 1000 is 93.82%
==================================================
```

In [102]:
```
hyper = [str(pow(10,j)) for j in range(-4,4)]
```

In [103]:
```
# https://www.dataquest.io/blog/learning-curves-machine-learning/

import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')

plt.plot(hyper,bow_train_auc,label = 'Training AUC')
plt.plot(hyper, bow_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC', fontsize = 14)
plt.xlabel('\u03BB-values', fontsize = 14)
plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03)
plt.legend()
```

Out[103]:
```
<matplotlib.legend.Legend at 0x7f39469e4908>
```



In [104]:
```
i = 0.1
LR = LogisticRegression(C=i)
LR.fit(bow_train, train_y)
# train data
y_prob_train = LR.predict_proba(bow_train)[:,1]
fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
# CV
y_prob_cv = LR.predict_proba(bow_cv)[:,1]
fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
# Test
y_prob_test = LR.predict_proba(bow_test)[:,1]
fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test)
print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

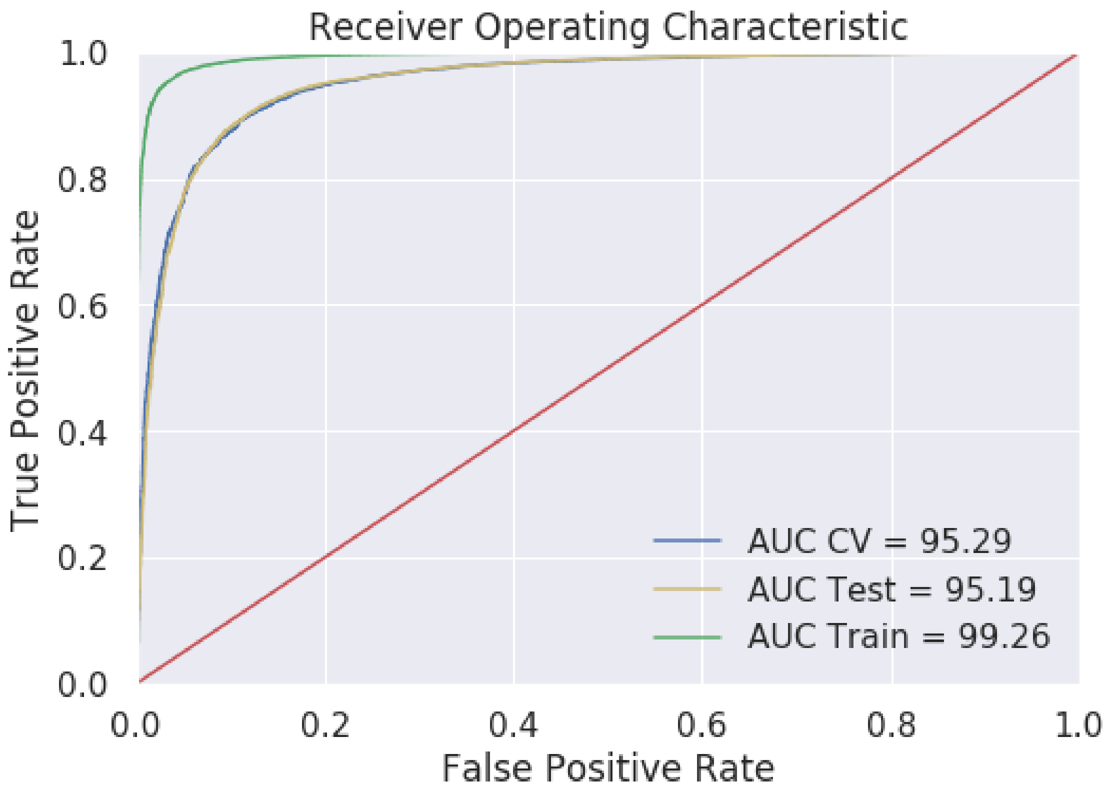
```
Train AUC for  = 0.1 is 99.26%

CV AUC for  = 0.1 is 95.29%

Test AUC for  = 0.1 is 95.19%
```

```
In [110]: # number of non-zero weights
          w = LR.coef_
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of non-zero weights :  64147
```

observation : The number of non-zero weights are same as the total weights . we can observe that there is no sparsity in this weights

```
In [111]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

          import matplotlib.pyplot as plt
          plt.title('Receiver Operating Characteristic')
          plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
          plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
          plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
          plt.legend(loc = 'lower right')
          plt.plot([0, 1], [0, 1],'r')
          plt.xlim([0, 1])
          plt.ylim([0, 1])
          plt.ylabel('True Positive Rate')
          plt.xlabel('False Positive Rate')
          plt.show()
```

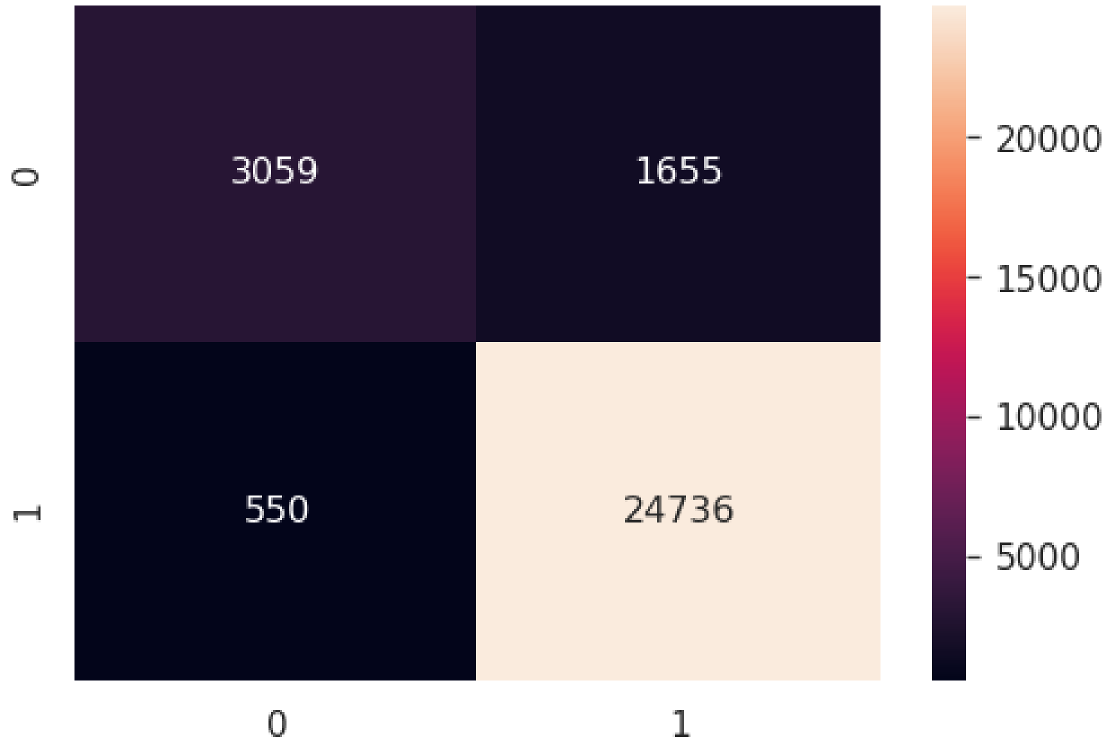


In [112]:
```
print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.96
```

In [113]:
```
df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

Out[113]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f394a1d2f28>
```



7.1.1 [5.1.1] Applying Logistic Regression with L1 regularization on BOW, SET 1

```
In [114]: C = [pow(10,j) for j in range(-4,4,1)]
```

```
In [116]: bow_train_auc = []
          bow_cv_auc = []
          for i in C:
              LR = LogisticRegression(C=i , penalty="l1")
              LR.fit(bow_train, train_y)
              # train data
              y_prob_train = LR.predict_proba(bow_train)[:,1]
              y_pred = np.where(y_prob_train > 0.5, 1, 0)
              auc_roc_train = roc_auc_score(train_y , y_prob_train)
              print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float
              bow_train_auc.append(auc_roc_train)
              # CV
              y_prob_cv = LR.predict_proba(bow_cv)[:,1]
              y_pred = np.where(y_prob_cv > 0.5, 1, 0)
              auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
              print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
              bow_cv_auc.append(auc_roc_cv)
              print("="*50)
```

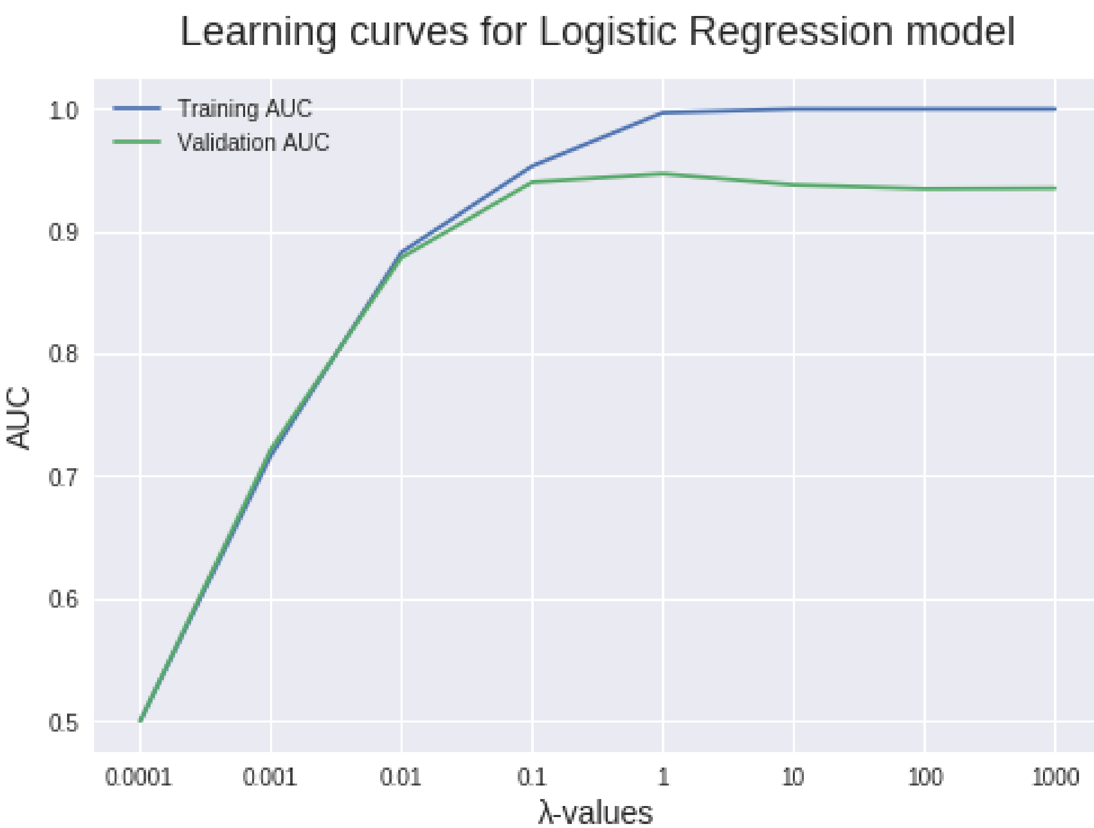
```
Train AUC for  = 0.0001 is 50.00%

CV AUC for  = 0.0001 is 50.00%
==================================================

Train AUC for  = 0.001 is 71.71%

CV AUC for  = 0.001 is 72.23%
==================================================

Train AUC for  = 0.01 is 88.30%

CV AUC for  = 0.01 is 87.87%
==================================================

Train AUC for  = 0.1 is 95.33%

CV AUC for  = 0.1 is 94.02%
==================================================

Train AUC for  = 1 is 99.70%

CV AUC for  = 1 is 94.70%
==================================================

Train AUC for  = 10 is 100.00%

CV AUC for  = 10 is 93.80%
==================================================

Train AUC for  = 100 is 100.00%

CV AUC for  = 100 is 93.47%
==================================================

Train AUC for  = 1000 is 100.00%

CV AUC for  = 1000 is 93.52%
==================================================
```

In [46]:
```
hyper = [str(pow(10,j)) for j in range(-4,4)]
```

In [117]:
```
# https://www.dataquest.io/blog/learning-curves-machine-learning/

import matplotlib.pyplot as plt
%matplotlib inline
```

```
plt.style.use('seaborn')

plt.plot(hyper,bow_train_auc,label = 'Training AUC')
plt.plot(hyper, bow_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC', fontsize = 14)
plt.xlabel('\u03BB-values', fontsize = 14)
plt.title('Learning curves for Logistic Regression model', fontsize = 18, y = 1.03)
plt.legend()
```

Out[117]: <matplotlib.legend.Legend at 0x7f39491b4908>



In [118]:
```
i = 1
LR = LogisticRegression(C=i)
LR.fit(bow_train, train_y)
# train data
y_prob_train = LR.predict_proba(bow_train)[:,1]
fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
```

```
        print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100
        # CV
        y_prob_cv = LR.predict_proba(bow_cv)[:,1]
        fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
        y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
        auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
        print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
        # Test
        y_prob_test = LR.predict_proba(bow_test)[:,1]
        fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
        y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
        auc_roc_test = roc_auc_score(test_y , y_prob_test)
        print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100))
```

```
Train AUC for  = 1 is 99.98%

CV AUC for  = 1 is 95.16%

Test AUC for  = 1 is 95.06%
```

In [122]:
```
# number of non-zero weights
w = LR.coef_
print("Number of non-zero weights : ",np.count_nonzero(w))
```

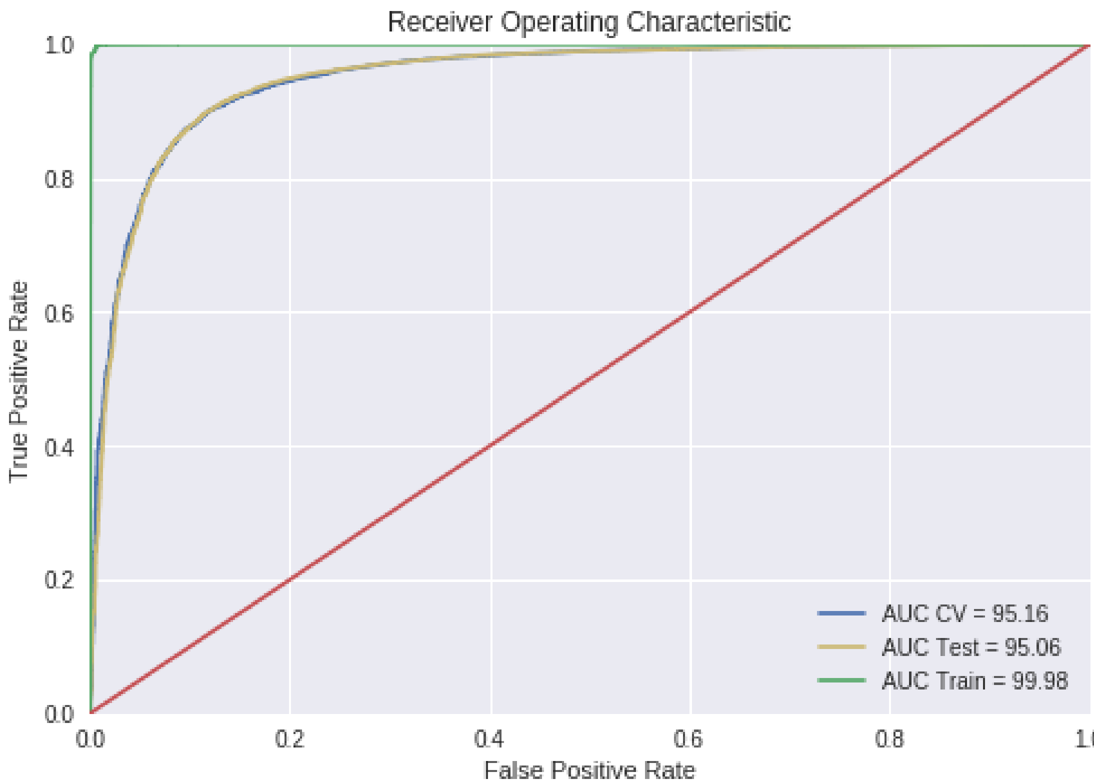
```
Number of non-zero weights :  64147
```

In [124]:
```
w.shape
```

Out[124]:
```
(1, 64147)
```

observation : The number of non-zero weights are same as the total weights . we can observe that there is no sparsity in this weights

In [119]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100))
plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

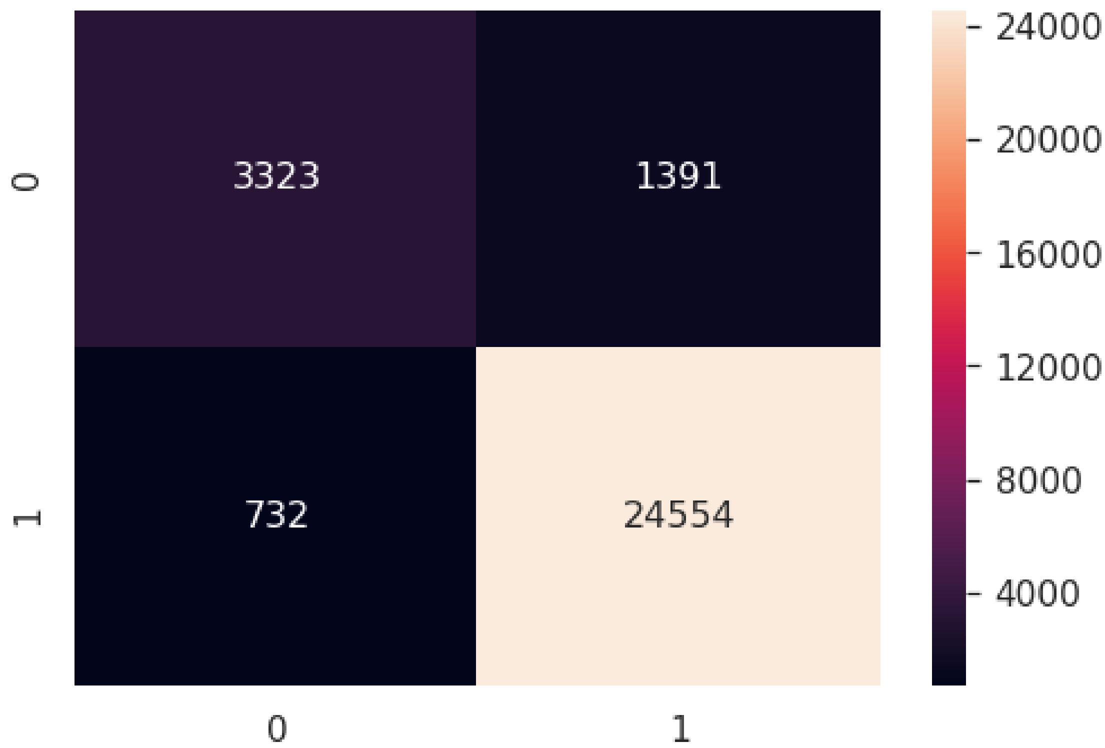


In [120]:
```
print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.96
```

In [121]:
```
df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

Out[121]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f394e034a90>
```



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

```
In [125]: # Please write all the code with proper documentation
          # number of non-zero weights
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64147
```

observation : The number of non-zero weights are same as the total weights . we can observe that there is no sparsity in this weights

```
In [126]: # we want to increase Lambda (decreasing C)
          i = 0.1
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64147
```

```
In [127]: # we want to increase Lambda (decreasing C)
          i = 0.01
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64147
```

```
In [128]: # we want to increase Lambda (decreasing C)
          i = 0.001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64147
```

```
In [129]: # we want to increase Lambda (decreasing C)
          i = 0.0001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64147
```

```
In [130]: # we want to increase Lambda (decreasing C)
          i = 0.00001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64147
```

```
In [141]: # we want to increase Lambda (decreasing C)
          i = 0.000000001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64138
```

Observation : hear it self stating sparcity

```
In [142]: # we want to increase Lambda (decreasing C)
          i = 0.00000000001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64139
```

```
In [143]: # we want to increase Lambda (decreasing C)
          i = 0.0000000000001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  64135
```

```
In [148]: # we want to increase Lambda (decreasing C)
          i = 0.0000000000000000001
          LR = LogisticRegression(C=i)
          LR.fit(bow_train, train_y)
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  64147
Number of non-zero weights :  0
```

Observation : we Observe More Sparsity (Fewer elements of W* being non-zero) by increasing Lambda (decreasing C)

7.1.2 [5.1.2] Applying Logistic Regression with L2 regularization on BOW, SET 1

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

In [282]:
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
# Please write all the code with proper documentation
#BoW
count_vect = CountVectorizer(min_df=15) #in scikit-learn
count_vect.fit(train)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

bow_train = count_vect.fit_transform(train)
bow_cv = count_vect.transform(cv)
bow_test = count_vect.transform(test)
print("============Train Data=========")
print("the type of count vectorizer ",type(bow_train))
print("the shape of out text BOW vectorizer ",bow_train.get_shape())
print("the number of unique words ", bow_train.get_shape()[1])
print("============Cross validation Data=========")
print("the type of count vectorizer ",type(bow_cv))
print("the shape of out text BOW vectorizer ",bow_cv.get_shape())
print("the number of unique words ", bow_cv.get_shape()[1])
print("============Test Data=========")
print("the type of count vectorizer ",type(bow_test))
print("the shape of out text BOW vectorizer ",bow_test.get_shape())
print("the number of unique words ", bow_test.get_shape()[1])
```

```
some feature names  ['ability', 'able', 'absence', 'absolute', 'absolutely', 'absolutly', 'abso
==================================================
============Train Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 7033)
the number of unique words  7033
============Cross validation Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (21000, 7033)
the number of unique words  7033
============Test Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 7033)
the number of unique words  7033
```

In [439]:
```
# createing a noise (epsilon)
epsilon = np.random.normal(loc=0.0, scale=0.0001)
```

In [440]:
```
from scipy.sparse import csr_matrix
```

In [441]:
```
# adding a noise to test data only
bow_train_noise = csr_matrix(bow_train)
bow_train_noise.data = bow_train_noise.data + epsilon
```

In [442]:
```
bow_train_noise.shape
```

Out[442]:
```
(49000, 7033)
```

In [443]:
```
# train a Logistic Regression model with noised data
i = 0.1
LR = LogisticRegression(C=i)
LR.fit(bow_train_noise, train_y)
noised_w = LR.coef_
```

In [560]:
```
# train a Logistic Regression model with un-noised data data
i = 0.1
LR = LogisticRegression(C=i)
LR.fit(bow_train, train_y)
w = LR.coef_
```

In [561]:
```
weights = w
```

In [468]:
```
# and adding a small eps value (to eliminate the divisible by zero error)
e = 10**-6
w = w + e
noised_w = noised_w + e
```

In [469]:
```
# claculate the % change between w and noised_w
percent_changed = abs((w - noised_w)/w)*100
```

In [470]:
```
a = np.sort(percent_changed, axis=None)
```

In [471]:
```
max(a)
```

Out[471]:
```
25.83058033878627
```

In [472]:
```
min(a)
```

Out[472]:
```
5.775007388487825e-07
```

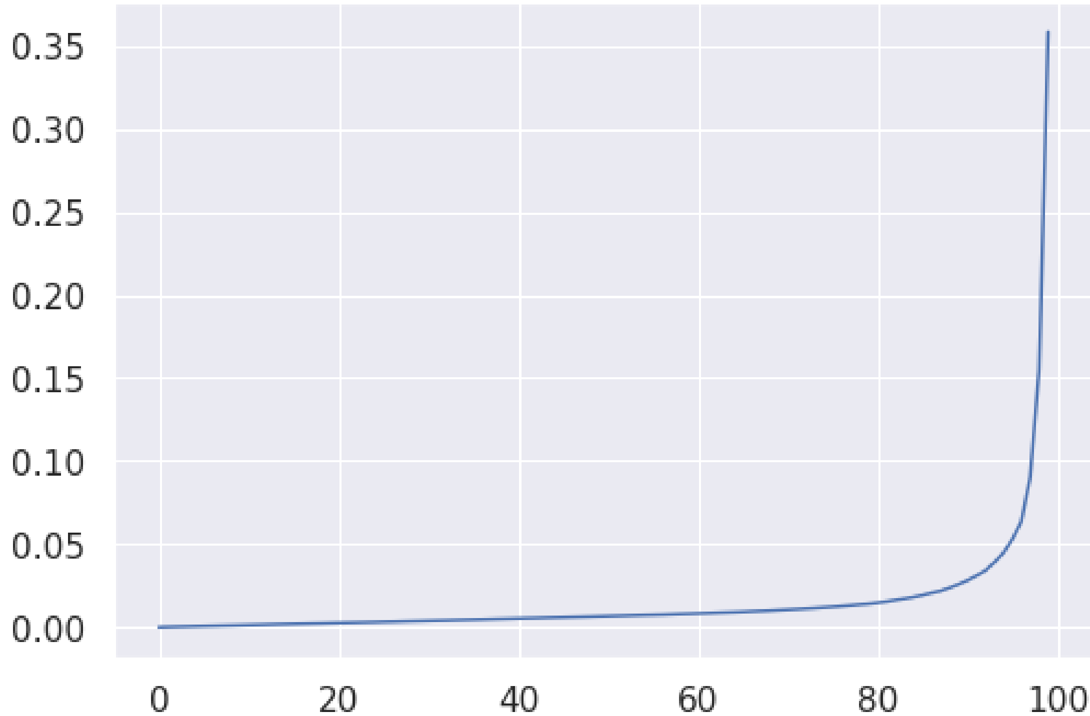
In [473]:
```
a.shape
```

Out[473]:
```
(7033,)
```

In [474]:
```
a_percentile = []
for i in range(0,100,1):
    p = np.percentile(a,i)
    a_percentile.append(p)
```

In [475]:
```
plt.plot(a_percentile)
```

Out[475]: [<matplotlib.lines.Line2D at 0x7f394e4cccc0>]



Observation : from above percentile plot we can observe there is sudden rise between 95th percentile and 100th percentile , now we want to find threshold

In [482]:
```
[np.percentile(a,i) for i in range(95,101,1)]
```

Out[482]:
```
[0.05281317830811581,
 0.06336159816657352,
 0.0903473829166577,
 0.15490152148891556,
 0.35853650608036164,
 25.83058033878627]
```

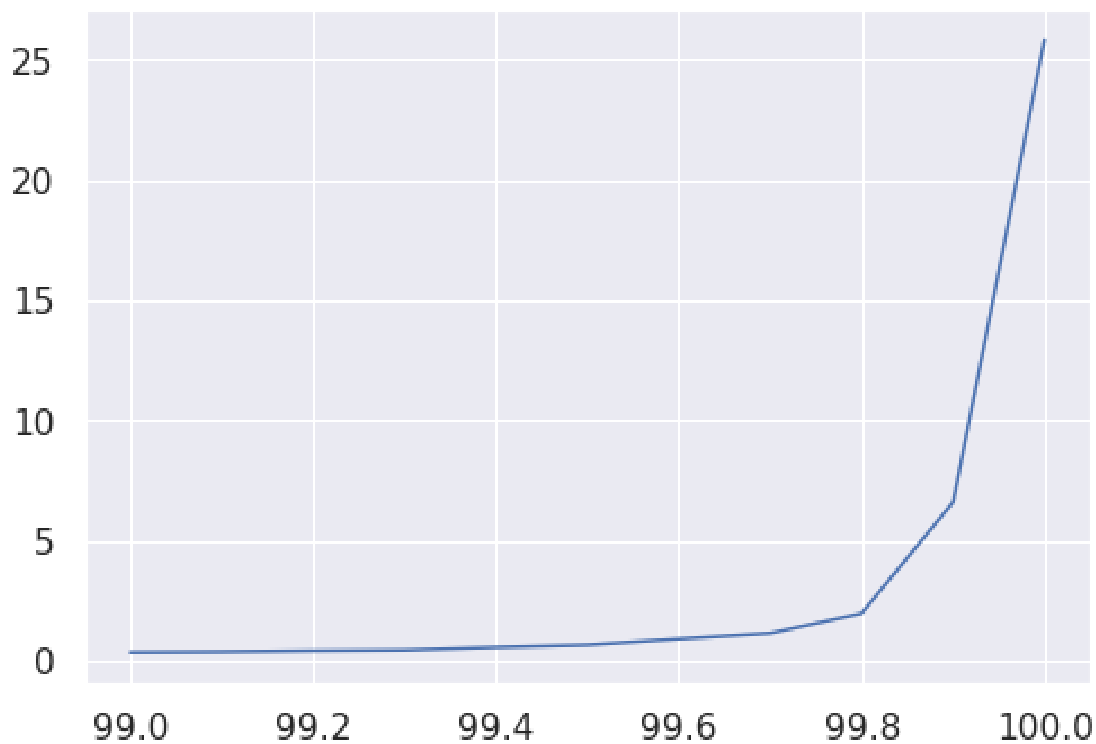
Observation : from the above loop we observed sudden rise b/w 99th and 100th percentiles

In [505]:
```
l = [99, 99.1, 99.2, 99.3, 99.4, 99.5, 99.6, 99.7, 99.8, 99.9, 100]
pl = []
for i in l:
    p = np.percentile(a,i)
    pl.append(p)
    print("%0.1f values = %f"%(i,p))
```

```
99.0 values = 0.358537
99.1 values = 0.378953
```

```
99.2 values = 0.423514
99.3 values = 0.448876
99.4 values = 0.567246
99.5 values = 0.662503
99.6 values = 0.916526
99.7 values = 1.152944
99.8 values = 1.975175
99.9 values = 6.604124
100.0 values = 25.830580
```

```
In [506]: plt.plot(l,pl)

Out[506]: [<matplotlib.lines.Line2D at 0x7f394dcb4518>]
```



Observe : we observe from the above plot there is a sudden rise from 1.9 to 6.6 . we can select the threshold as 1.9

Threshold = 1.9

```
In [531]: # now we want to print the feature names whose % change is more than a threshold 1.9
          weights = percent_changed.tolist()[0]
          feature_names = count_vect.get_feature_names()
          features = dict(zip(weights,feature_names))
```

```
In [559]: print("Feature names ==> Weights")
          print("="*50)
          for key,value in features.items():
              if key > 1.9:
                  print('%s ==> %s'%(str(value),str(round(key,3))))
```

```
Feature names ==> Weights
==================================================
causing ==> 9.43
containing ==> 4.927
crave ==> 23.433
crushed ==> 10.516
darjeeling ==> 1.944
draw ==> 3.847
gatorade ==> 3.399
growth ==> 2.69
making ==> 5.594
near ==> 8.749
oats ==> 5.465
painful ==> 1.977
region ==> 7.338
repeatedly ==> 6.638
spend ==> 9.14
spite ==> 1.947
wanting ==> 25.831
```

7.1.3 [5.1.3] Feature Importance on BOW, SET 1

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

```
In [579]: # Please write all the code with proper documentation
          feture_weights = weights.tolist()[0]
          feature_names = count_vect.get_feature_names()
          features = dict(zip(feture_weights,feature_names))
```

```
In [584]: features_df = pd.DataFrame.from_dict(features, orient='index')
```

```
In [587]: sorted_features = features_df.sort_index(axis=0,ascending=False )
```

```
In [590]: # top 10 important features of positive class
          sorted_features.head(10)
```

Out[590]:

	0
1.471624	delicious
1.373267	excellent
1.265165	perfect
1.211439	highly
1.207375	wonderful

```
1.206477      great
1.205229    amazing
1.194831       best
1.093144      yummy
1.069295    awesome
```

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

```
In [599]: # Please write all the code with proper documentation
          sorted_features = features_df.sort_index(axis=0,ascending=True )
          sorted_features.head(10)

Out[599]:                         0
          -1.946078   disappointing
          -1.669927           worst
          -1.538319  disappointment
          -1.498460        terrible
          -1.394829           awful
          -1.381296     disappointed
          -1.377574           threw
          -1.255345   unfortunately
          -1.168864        horrible
          -1.161546           stale
```

7.2 [5.2] Logistic Regression on TFIDF, SET 2

7.2.1 [5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

```
In [631]: # Please write all the code with proper documentation

          model = TfidfVectorizer(min_df=20, ngram_range=(1,2))
          #tf_idf_matrix = model.fit_transform(train)

          print("================Train Data===========")
          tf_idf_train = model.fit_transform(train)
          print("the type of count vectorizer ",type(tf_idf_train))
          print("the shape of out text TFIDF vectorizer ",tf_idf_train.get_shape())
          print("the number of unique words including both unigrams and bigrams ",tf_idf_train
          print("================CV Data===========")
          tf_idf_cv = model.transform(cv)
          print("the type of count vectorizer ",type(tf_idf_cv))
          print("the shape of out text TFIDF vectorizer ",tf_idf_cv.get_shape())
          print("the number of unique words including both unigrams and bigrams ",tf_idf_cv.get
          print("================Test Data===========")
          tf_idf_test = model.transform(test)
          print("the type of count vectorizer ",type(tf_idf_test))
          print("the shape of out text TFIDF vectorizer ",tf_idf_test.get_shape())
          print("the number of unique words including both unigrams and bigrams ", tf_idf_test
```

```
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
================Train Data===========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (49000, 13790)
the number of unique words including both unigrams and bigrams  13790
================CV Data===========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (21000, 13790)
the number of unique words including both unigrams and bigrams  13790
================Test Data===========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (30000, 13790)
the number of unique words including both unigrams and bigrams  13790
```

In [632]:
```
C = [pow(10,j) for j in range(-4,4,1)]
tfidf_train_auc = []
tfidf_cv_auc = []
for i in C:
    LR = LogisticRegression(C=i , penalty="l1")
    LR.fit(tf_idf_train, train_y)
    # train data
    y_prob_train = LR.predict_proba(tf_idf_train)[:,1]
    y_pred = np.where(y_prob_train > 0.5, 1, 0)
    auc_roc_train = roc_auc_score(train_y , y_prob_train)
    print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float
    tfidf_train_auc.append(auc_roc_train)
    # CV
    y_prob_cv = LR.predict_proba(tf_idf_cv)[:,1]
    y_pred = np.where(y_prob_cv > 0.5, 1, 0)
    auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
    print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))
    tfidf_cv_auc.append(auc_roc_cv)
    print("="*50)
```

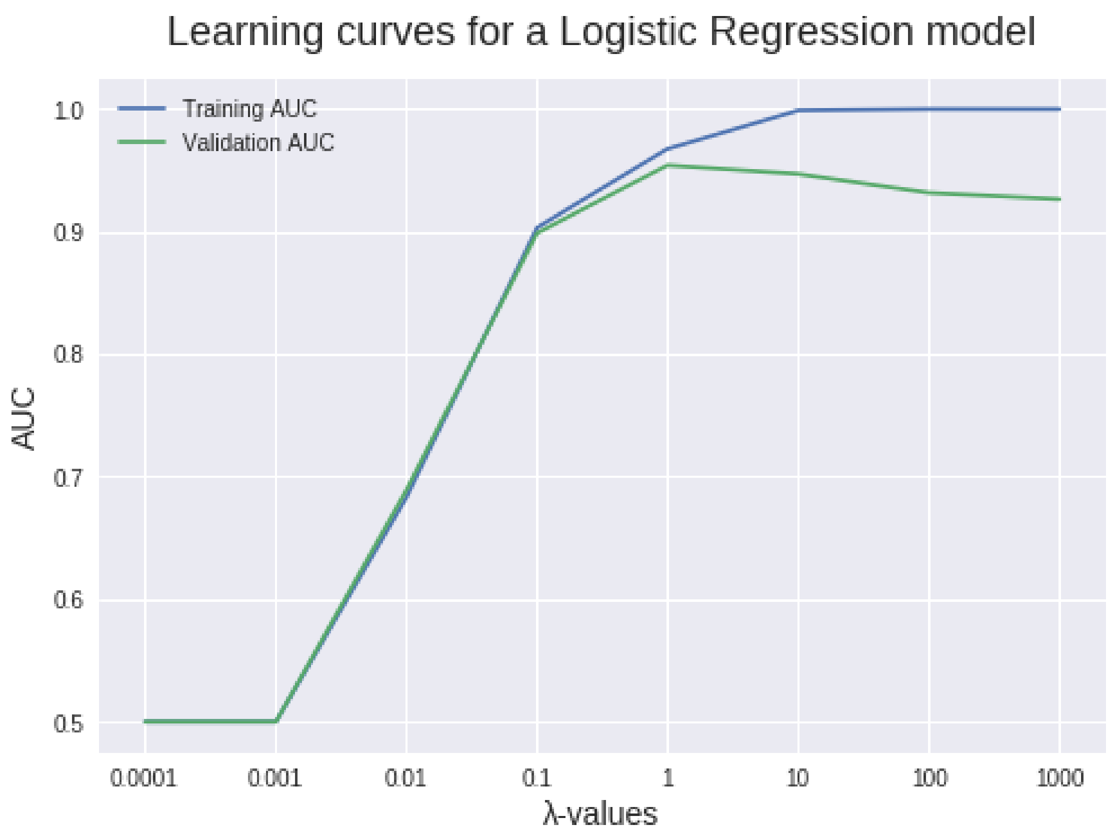
```
Train AUC for  = 0.0001 is 50.00%

CV AUC for  = 0.0001 is 50.00%
==================================================

Train AUC for  = 0.001 is 50.00%

CV AUC for  = 0.001 is 50.00%
==================================================
```

```
Train AUC for  = 0.01 is 68.31%

CV AUC for  = 0.01 is 68.91%
==================================================

Train AUC for  = 0.1 is 90.33%

CV AUC for  = 0.1 is 89.89%
==================================================

Train AUC for  = 1 is 96.76%

CV AUC for  = 1 is 95.41%
==================================================

Train AUC for  = 10 is 99.89%

CV AUC for  = 10 is 94.70%
==================================================

Train AUC for  = 100 is 100.00%

CV AUC for  = 100 is 93.16%
==================================================

Train AUC for  = 1000 is 100.00%

CV AUC for  = 1000 is 92.64%
==================================================
```

In [633]:
```
hyper = [str(pow(10,j)) for j in range(-4,4)]
```

In [634]:
```
# https://www.dataquest.io/blog/learning-curves-machine-learning/

import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')

plt.plot(hyper,tfidf_train_auc,label = 'Training AUC')
plt.plot(hyper, tfidf_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC', fontsize = 14)
plt.xlabel('\u03BB-values', fontsize = 14)
plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03
plt.legend()
```

Out[634]:
```
<matplotlib.legend.Legend at 0x7f394cefe908>
```

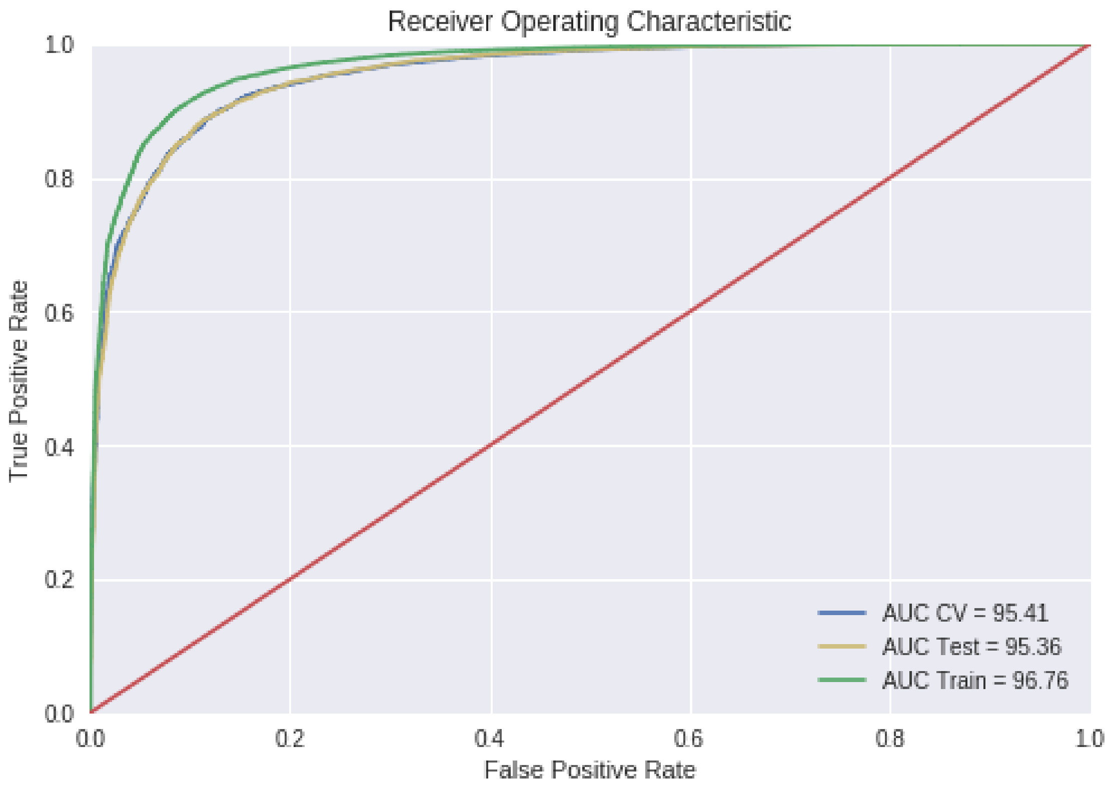


In [635]:
```
i = 1
LR = LogisticRegression(C=i , penalty="l1")
LR.fit(tf_idf_train, train_y)
# train data
y_prob_train = LR.predict_proba(tf_idf_train)[:,1]
fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100
# CV
y_prob_cv = LR.predict_proba(tf_idf_cv)[:,1]
fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
# Test
y_prob_test = LR.predict_proba(tf_idf_test)[:,1]
fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test)
```

```
print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100))
```

```
Train AUC for  = 1 is 96.76%

CV AUC for  = 1 is 95.41%

Test AUC for  = 1 is 95.36%
```

In [636]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

import matplotlib.pyplot as plt
plt.clf()
plt.title('Receiver Operating Characteristic')
plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100))
plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

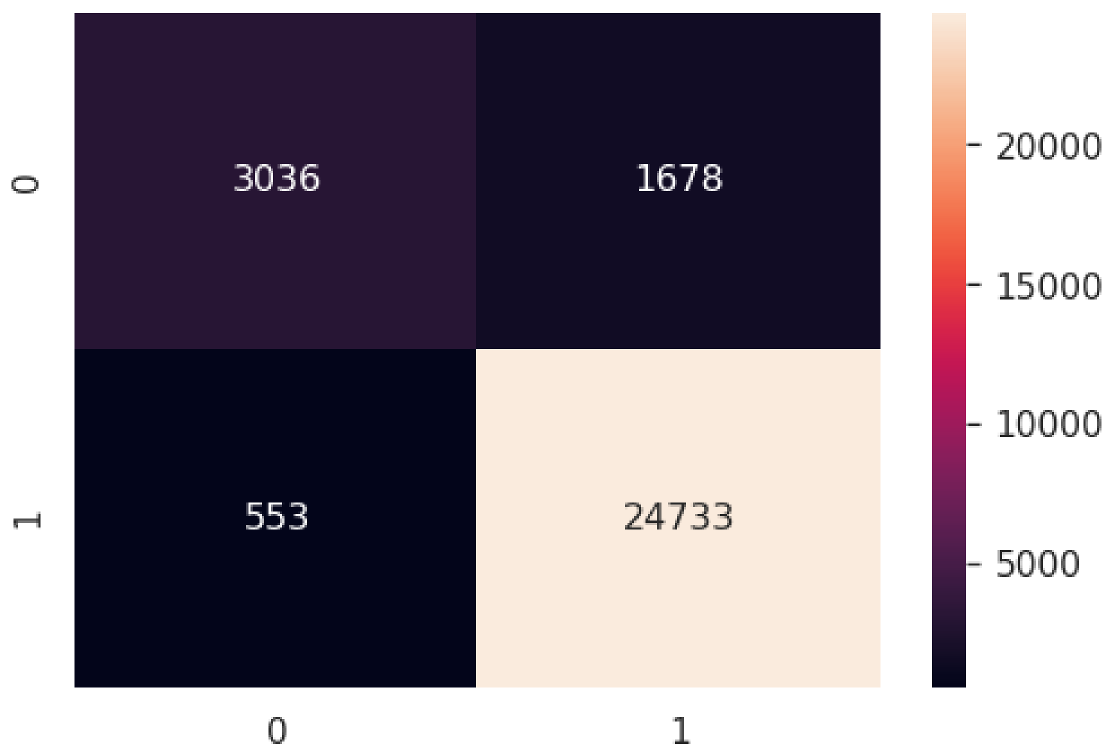


In [637]:
```
print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.96
```

In [638]:
```
df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

Out[638]: <matplotlib.axes._subplots.AxesSubplot at 0x7f394a50d630>



In [640]:
```
# number of non-zero weights
w = LR.coef_
print("Number of weights : ", w.shape[1])
print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  13790
Number of non-zero weights :  1190
```

7.2.2 [5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

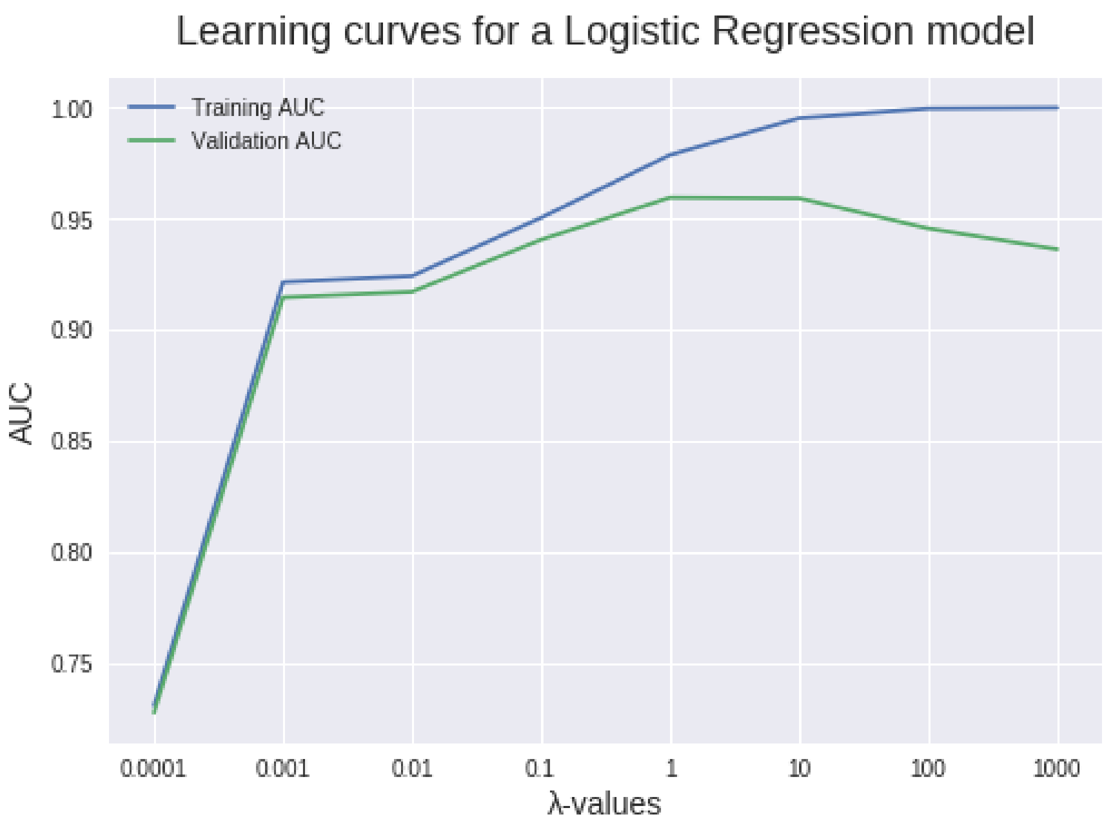
```
In [641]: # Please write all the code with proper documentation
          C = [pow(10,j) for j in range(-4,4,1)]
          tfidf_train_auc = []
          tfidf_cv_auc = []
          for i in C:
              LR = LogisticRegression(C=i , penalty="l2")
              LR.fit(tf_idf_train, train_y)
              # train data
              y_prob_train = LR.predict_proba(tf_idf_train)[:,1]
              y_pred = np.where(y_prob_train > 0.5, 1, 0)
              auc_roc_train = roc_auc_score(train_y , y_prob_train)
              print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float
              tfidf_train_auc.append(auc_roc_train)
              # CV
              y_prob_cv = LR.predict_proba(tf_idf_cv)[:,1]
              y_pred = np.where(y_prob_cv > 0.5, 1, 0)
              auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
              print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
              tfidf_cv_auc.append(auc_roc_cv)
              print("="*50)
```

```
Train AUC for  = 0.0001 is 73.06%

CV AUC for  = 0.0001 is 72.73%
==================================================

Train AUC for  = 0.001 is 92.14%

CV AUC for  = 0.001 is 91.45%
==================================================

Train AUC for  = 0.01 is 92.42%

CV AUC for  = 0.01 is 91.71%
==================================================

Train AUC for  = 0.1 is 95.04%

CV AUC for  = 0.1 is 94.05%
==================================================

Train AUC for  = 1 is 97.88%

CV AUC for  = 1 is 95.95%
==================================================
```

```
Train AUC for  = 10 is 99.53%

CV AUC for  = 10 is 95.92%
==================================================

Train AUC for  = 100 is 99.97%

CV AUC for  = 100 is 94.56%
==================================================

Train AUC for  = 1000 is 100.00%

CV AUC for  = 1000 is 93.62%
==================================================
```

In [642]:
```
# https://www.dataquest.io/blog/learning-curves-machine-learning/

import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')

plt.plot(hyper,tfidf_train_auc,label = 'Training AUC')
plt.plot(hyper, tfidf_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC', fontsize = 14)
plt.xlabel('\u03BB-values', fontsize = 14)
plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03)
plt.legend()
```

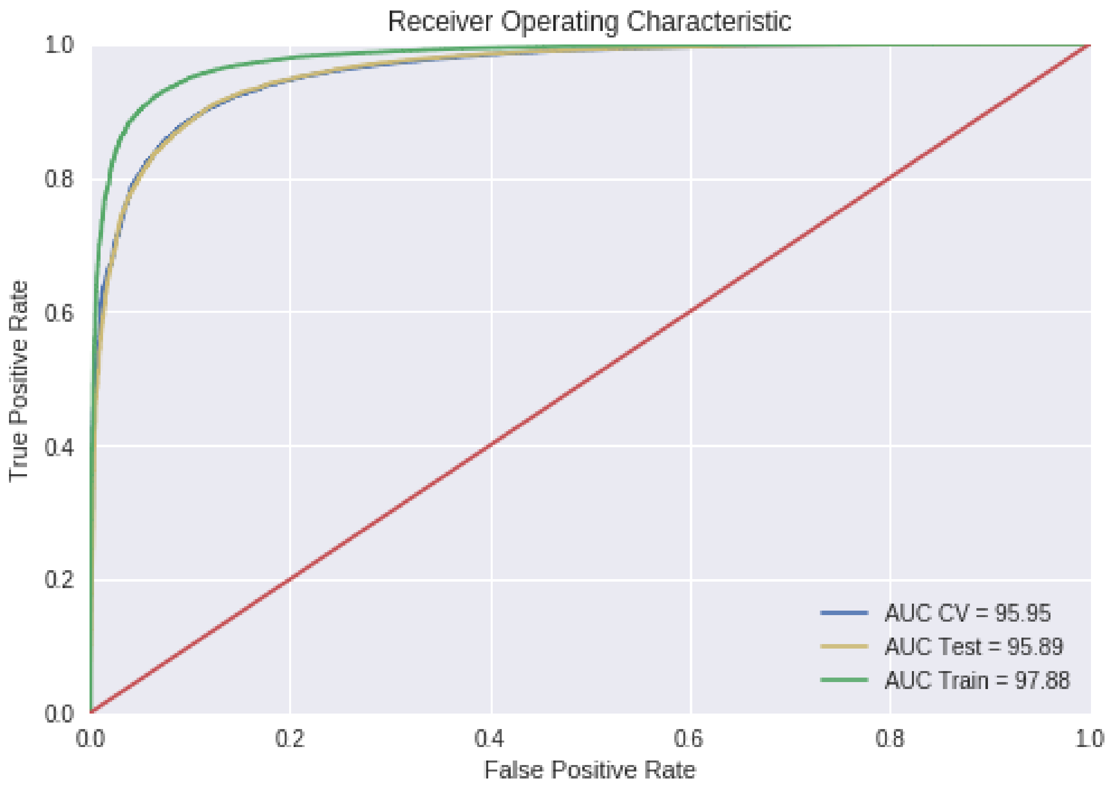
Out[642]:
```
<matplotlib.legend.Legend at 0x7f394c65ac18>
```



In [643]:
```
i = 1
LR = LogisticRegression(C=i , penalty="l2")
LR.fit(tf_idf_train, train_y)
# train data
y_prob_train = LR.predict_proba(tf_idf_train)[:,1]
fprt, tprt, thresholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
# CV
y_prob_cv = LR.predict_proba(tf_idf_cv)[:,1]
fprc, tprc, thresholdc = roc_curve(cv_y, y_prob_cv)
y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
# Test
y_prob_test = LR.predict_proba(tf_idf_test)[:,1]
fprts, tprts, thresholdts = roc_curve(test_y, y_prob_test)
y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test)
print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

```
Train AUC for  = 1 is 97.88%

CV AUC for  = 1 is 95.95%

Test AUC for  = 1 is 95.89%
```

```
In [644]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

          import matplotlib.pyplot as plt
          plt.clf()
          plt.title('Receiver Operating Characteristic')
          plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
          plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
          plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
          plt.legend(loc = 'lower right')
          plt.plot([0, 1], [0, 1],'r')
          plt.xlim([0, 1])
          plt.ylim([0, 1])
          plt.ylabel('True Positive Rate')
          plt.xlabel('False Positive Rate')
          plt.show()
```

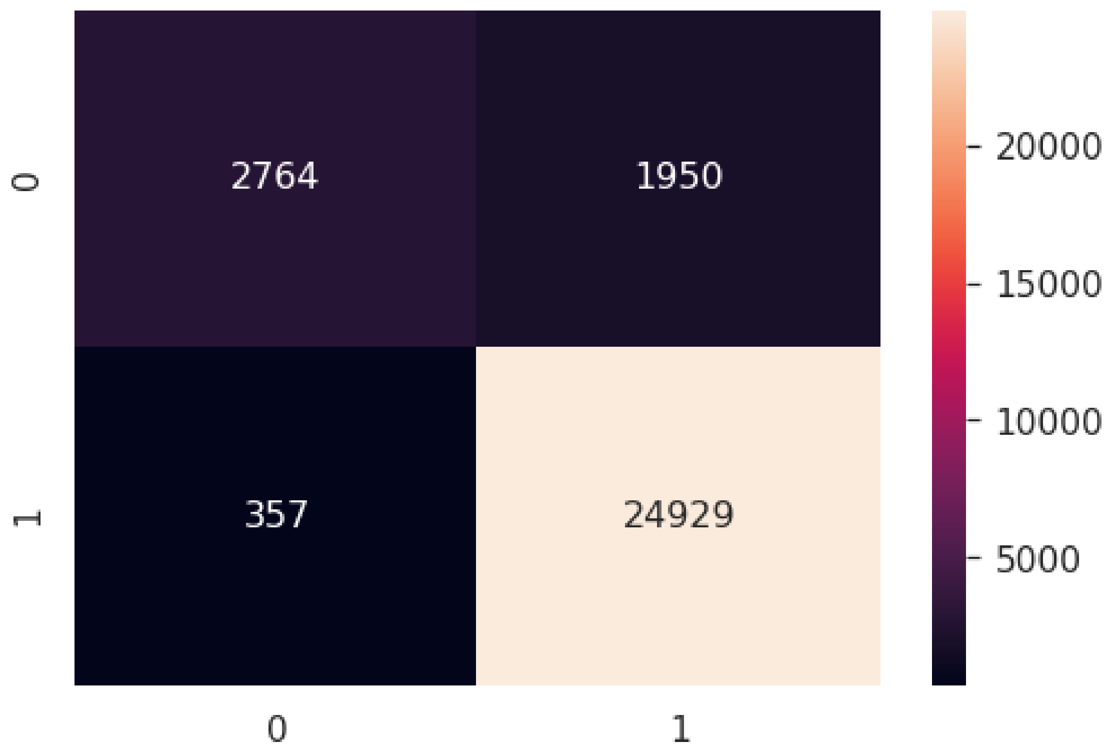


```
In [645]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.96
```

```
In [646]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
          sns.set(font_scale=1.4)
          sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

```
Out[646]: <matplotlib.axes._subplots.AxesSubplot at 0x7f394a329dd8>
```




```
In [647]: # number of non-zero weights
          w = LR.coef_
          print("Number of weights : ", w.shape[1])
          print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  13790
Number of non-zero weights :  13790
```

7.2.3 [5.2.3] Feature Importance on TFIDF, SET 2

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

In [648]:
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
feture_weights = w.tolist()[0]
feature_names = model.get_feature_names()
features = dict(zip(feture_weights,feature_names))
```

In [649]:
```
features_df = pd.DataFrame.from_dict(features, orient='index')
sorted_features = features_df.sort_index(axis=0,ascending=False )
```

In [650]:
```
sorted_features.head(10)
```

Out[650]:

	0
10.468457	great
7.847426	best
7.318638	delicious
6.693858	good
6.271667	love
5.871083	perfect
5.546432	excellent
5.454443	wonderful
4.946091	loves
4.931072	favorite

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

In [652]:
```
# Please write all the code with proper documentation
sorted_features = features_df.sort_index(axis=0,ascending=True)
sorted_features.head(20)
```

Out[652]:

	0
-7.670323	disappointed
-6.237773	worst
-6.167293	disappointing
-6.089685	not
-5.889116	terrible
-5.882416	not worth
-5.689663	not recommend
-5.607655	not good
-5.434806	awful
-4.931310	unfortunately
-4.911874	disappointment
-4.788995	horrible
-4.740220	stale
-4.574250	not buy
-4.518183	threw

```
-4.459906           weak
-4.413308          bland
-4.029540         return
-3.950828          waste
-3.884125            bad
```

7.3 [5.3] Logistic Regression on AVG W2V, SET 3

```
In [13]: # Train your own Word2Vec model using your own text corpus
         ######## Train Set #########
         i=0
         list_of_train_sentance=[]
         for sentance in train:
             list_of_train_sentance.append(sentance.split())
         ######## CV Set ###########
         i=0
         list_of_cv_sentance=[]
         for sentance in cv:
             list_of_cv_sentance.append(sentance.split())
         ######## Test Set #########
         i=0
         list_of_test_sentance=[]
         for sentance in test:
             list_of_test_sentance.append(sentance.split())
         print("Length of Train = ", len(list_of_train_sentance))
         print("Length of CV = ", len(list_of_cv_sentance))
         print("Length of Test = ", len(list_of_test_sentance))
```

```
Length of Train =  49000
Length of CV =  21000
Length of Test =  30000
```

```
In [15]: w2v_model=Word2Vec(list_of_train_sentance,min_count=15,size=100, workers=4)
         print(w2v_model.wv.most_similar('great'))
         print('='*50)
         print(w2v_model.wv.most_similar('worst'))
```

```
[('fantastic', 0.8073837161064148), ('awesome', 0.7942715883255005), ('excellent', 0.76791244
==================================================
[('greatest', 0.8097379207611084), ('best', 0.7145651578903198), ('freshest', 0.627055644989013
```

```
In [16]: w2v_words = list(w2v_model.wv.vocab)
         print("number of words that occured minimum 5 times ",len(w2v_words))
         print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  7530
sample words  ['lb', 'yorkie', 'loves', 'chews', 'give', 'one', 'night', 'chewing', 'actually'
```

In [17]:
```
######## Train data ########
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this lis
for sent in tqdm(list_of_train_sentance): # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length 50, you might need
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))
```

```
100%|| 49000/49000 [02:14<00:00, 363.37it/s]

49000
100
```

In [18]:
```
######## CV data ########
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_cv_sentance): # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length 50, you might need
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))
```

```
100%|| 21000/21000 [00:56<00:00, 369.85it/s]

21000
100
```

```
In [19]: ######## Test data ########
         # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(list_of_test_sentance): # for each review/sentence
             sent_vec = np.zeros(100) # as word vectors are of zero length 50, you might need
             cnt_words =0; # num of words with a valid vector in the sentence/review
             for word in sent: # for each word in a review/sentence
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
                 sent_vec /= cnt_words
             sent_vectors_test.append(sent_vec)
         print(len(sent_vectors_test))
         print(len(sent_vectors_test[0]))
```

```
100%|| 30000/30000 [01:21<00:00, 368.90it/s]

30000
100
```

```
In [20]: # save the datasets as numpy array
         w2v_train = np.array(sent_vectors_train)
         w2v_cv = np.array(sent_vectors_cv)
         w2v_test = np.array(sent_vectors_test)
```

7.3.1 [5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

```
In [21]: # Please write all the code with proper documentation
         # Please write all the code with proper documentation
         C = [pow(10,j) for j in range(-4,4,1)]
         w2v_train_auc = []
         w2v_cv_auc = []
         for i in C:
             LR = LogisticRegression(C=i , penalty="l1")
             LR.fit(w2v_train, train_y)
             # train data
             y_prob_train = LR.predict_proba(w2v_train)[:,1]
             y_pred = np.where(y_prob_train > 0.5, 1, 0)
             auc_roc_train = roc_auc_score(train_y , y_prob_train)
```

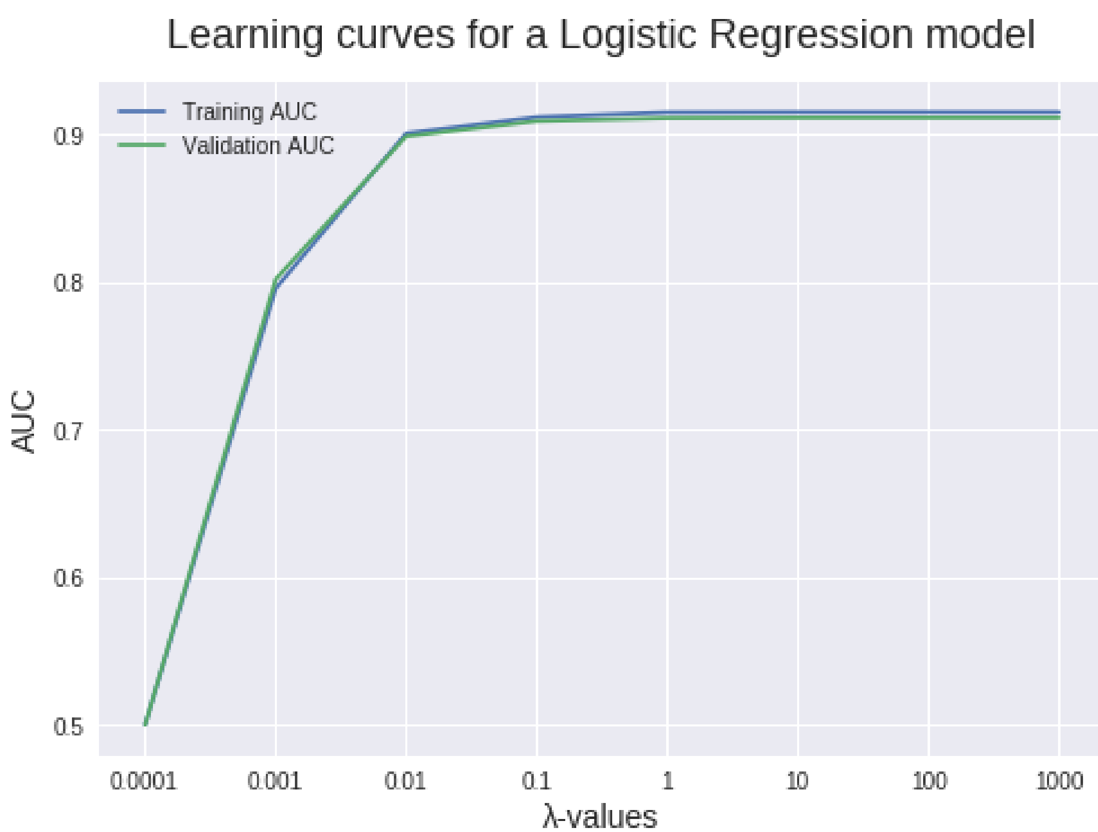
```python
            print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(
            w2v_train_auc.append(auc_roc_train)
            # CV
            y_prob_cv = LR.predict_proba(w2v_cv)[:,1]
            y_pred = np.where(y_prob_cv > 0.5, 1, 0)
            auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
            print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
            w2v_cv_auc.append(auc_roc_cv)
            print("="*50)
```

```
Train AUC for  = 0.0001 is 50.00%

CV AUC for  = 0.0001 is 50.00%
==================================================

Train AUC for  = 0.001 is 79.58%

CV AUC for  = 0.001 is 80.21%
==================================================

Train AUC for  = 0.01 is 90.08%

CV AUC for  = 0.01 is 89.88%
==================================================

Train AUC for  = 0.1 is 91.18%

CV AUC for  = 0.1 is 90.91%
==================================================

Train AUC for  = 1 is 91.50%

CV AUC for  = 1 is 91.11%
==================================================

Train AUC for  = 10 is 91.52%

CV AUC for  = 10 is 91.14%
==================================================

Train AUC for  = 100 is 91.52%

CV AUC for  = 100 is 91.14%
==================================================

Train AUC for  = 1000 is 91.52%
```

```
CV AUC for  = 1000 is 91.14%
==================================================
```

```
In [23]: hyper = [str(pow(10,j)) for j in range(-4,4)]
         # https://www.dataquest.io/blog/learning-curves-machine-learning/

         import matplotlib.pyplot as plt
         %matplotlib inline

         plt.style.use('seaborn')

         plt.plot(hyper,w2v_train_auc,label = 'Training AUC')
         plt.plot(hyper, w2v_cv_auc, label = 'Validation AUC')

         plt.ylabel('AUC', fontsize = 14)
         plt.xlabel('\u03BB-values', fontsize = 14)
         plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03)
         plt.legend()
```

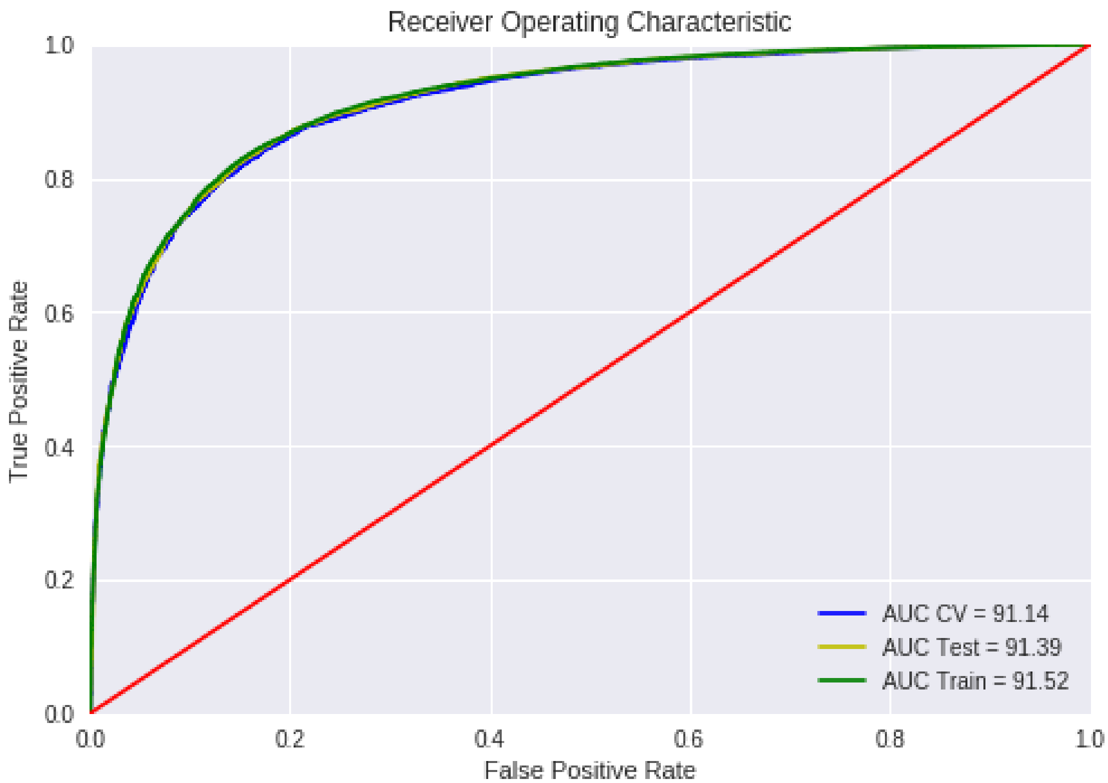
```
Out[23]: <matplotlib.legend.Legend at 0x7fe9c13bfd30>
```



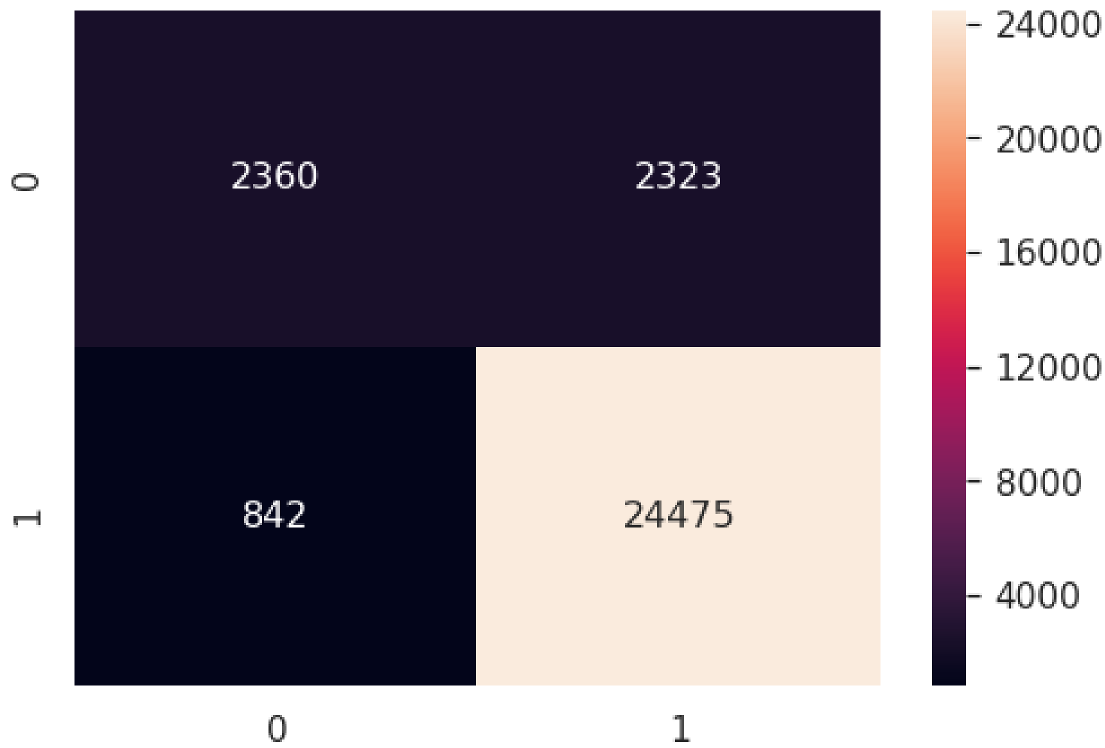
```
In [24]: i = 10
         LR = LogisticRegression(C=i , penalty="l1")
         LR.fit(w2v_train, train_y)
         # train data
         y_prob_train = LR.predict_proba(w2v_train)[:,1]
         fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
         y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
         auc_roc_train = roc_auc_score(train_y , y_prob_train)
         print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
         # CV
         y_prob_cv = LR.predict_proba(w2v_cv)[:,1]
         fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
         y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
         auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
         print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
         # Test
         y_prob_test = LR.predict_proba(w2v_test)[:,1]
         fprts, tprts, thrsholdts = roc_curve(test_y, y_prob_test)
         y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
         auc_roc_test = roc_auc_score(test_y , y_prob_test)
         print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

```
Train AUC for  = 10 is 91.52%

CV AUC for  = 10 is 91.14%

Test AUC for  = 10 is 91.39%
```

```
In [25]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

         import matplotlib.pyplot as plt
         plt.clf()
         plt.title('Receiver Operating Characteristic')
         plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
         plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
         plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
         plt.legend(loc = 'lower right')
         plt.plot([0, 1], [0, 1],'r')
         plt.xlim([0, 1])
         plt.ylim([0, 1])
         plt.ylabel('True Positive Rate')
         plt.xlabel('False Positive Rate')
         plt.show()
```




```
In [26]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))

F1-Score on test set: 0.94


In [27]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe9c12329b0>
```




```
In [28]: # number of non-zero weights
         w = LR.coef_
         print("Number of weights : ", w.shape[1])
         print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  100
Number of non-zero weights :  100
```

7.3.2 [5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

```
In [3]: # Please write all the code with proper documentation
```

```
In [29]: # Please write all the code with proper documentation
         # Please write all the code with proper documentation
         C = [pow(10,j) for j in range(-4,4,1)]
         w2v_train_auc = []
         w2v_cv_auc = []
         for i in C:
             LR = LogisticRegression(C=i , penalty="l2")
             LR.fit(w2v_train, train_y)
             # train data
             y_prob_train = LR.predict_proba(w2v_train)[:,1]
```

```
            y_pred = np.where(y_prob_train > 0.5, 1, 0)
            auc_roc_train = roc_auc_score(train_y , y_prob_train)
            print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(
            w2v_train_auc.append(auc_roc_train)
            # CV
            y_prob_cv = LR.predict_proba(w2v_cv)[:,1]
            y_pred = np.where(y_prob_cv > 0.5, 1, 0)
            auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
            print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
            w2v_cv_auc.append(auc_roc_cv)
            print("="*50)
```

```
Train AUC for  = 0.0001 is 82.41%

CV AUC for  = 0.0001 is 82.78%
==================================================

Train AUC for  = 0.001 is 89.60%

CV AUC for  = 0.001 is 89.57%
==================================================

Train AUC for  = 0.01 is 90.71%

CV AUC for  = 0.01 is 90.58%
==================================================

Train AUC for  = 0.1 is 91.25%

CV AUC for  = 0.1 is 90.99%
==================================================

Train AUC for  = 1 is 91.49%

CV AUC for  = 1 is 91.12%
==================================================

Train AUC for  = 10 is 91.52%

CV AUC for  = 10 is 91.14%
==================================================

Train AUC for  = 100 is 91.52%

CV AUC for  = 100 is 91.14%
==================================================
```

```
Train AUC for  = 1000 is 91.52%

CV AUC for  = 1000 is 91.14%
==================================================
```

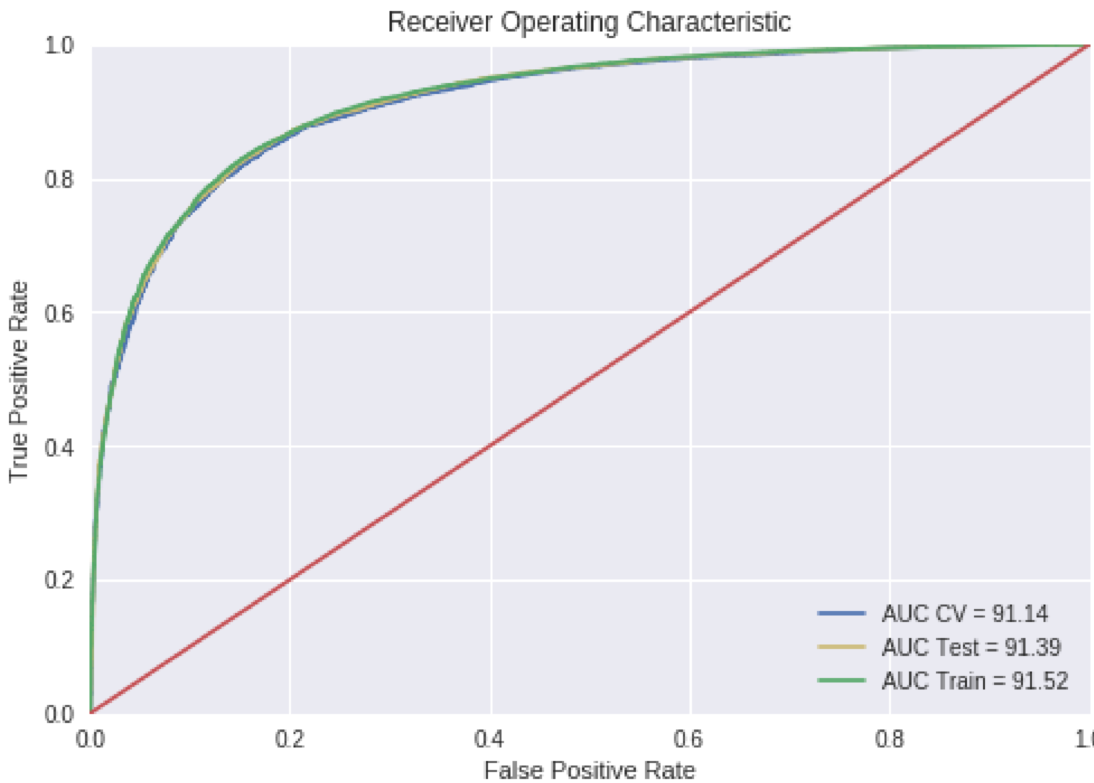
```
In [30]: hyper = [str(pow(10,j)) for j in range(-4,4)]
         # https://www.dataquest.io/blog/learning-curves-machine-learning/

         import matplotlib.pyplot as plt
         %matplotlib inline

         plt.style.use('seaborn')

         plt.plot(hyper,w2v_train_auc,label = 'Training AUC')
         plt.plot(hyper, w2v_cv_auc, label = 'Validation AUC')

         plt.ylabel('AUC', fontsize = 14)
         plt.xlabel('\u03BB-values', fontsize = 14)
         plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03)
         plt.legend()
```

```
Out[30]: <matplotlib.legend.Legend at 0x7fe9c1283ba8>
```

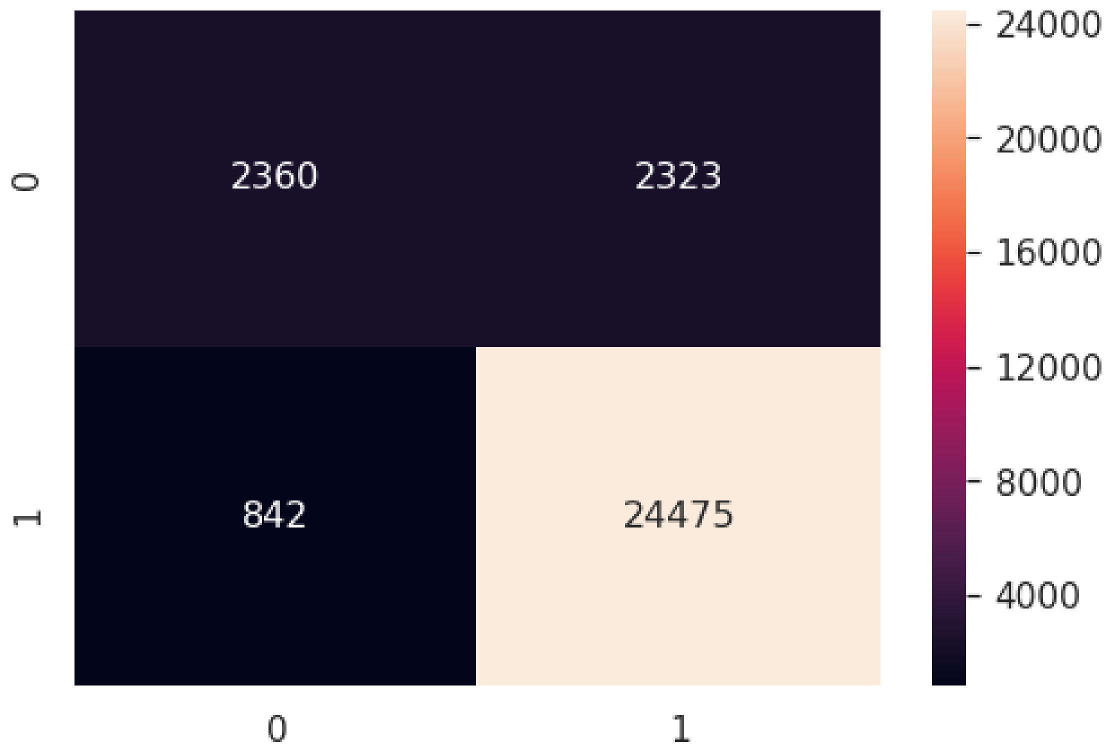
```
In [31]: i = 10
         LR = LogisticRegression(C=i , penalty="l2")
         LR.fit(w2v_train, train_y)
         # train data
         y_prob_train = LR.predict_proba(w2v_train)[:,1]
         fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
         y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
         auc_roc_train = roc_auc_score(train_y , y_prob_train)
         print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
         # CV
         y_prob_cv = LR.predict_proba(w2v_cv)[:,1]
         fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
         y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
         auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
         print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
         # Test
         y_prob_test = LR.predict_proba(w2v_test)[:,1]
         fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
         y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
         auc_roc_test = roc_auc_score(test_y , y_prob_test)
         print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

```
Train AUC for  = 10 is 91.52%

CV AUC for  = 10 is 91.14%

Test AUC for  = 10 is 91.39%
```

```
In [32]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

         import matplotlib.pyplot as plt
         plt.clf()
         plt.title('Receiver Operating Characteristic')
         plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
         plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
         plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
         plt.legend(loc = 'lower right')
         plt.plot([0, 1], [0, 1],'r')
         plt.xlim([0, 1])
         plt.ylim([0, 1])
         plt.ylabel('True Positive Rate')
         plt.xlabel('False Positive Rate')
         plt.show()
```




```
In [33]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))

F1-Score on test set: 0.94


In [34]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe9c1121c50>
```



7.4 [5.4] Logistic Regression on TFIDF W2V, SET 4

In [35]:
```
model = TfidfVectorizer()
#tf_idf_matrix = model.fit_transform(train)

print("================Train Data===========")
final_tf_idf_train = model.fit_transform(train)
print("the type of count vectorizer ",type(final_tf_idf_train))
print("the shape of out text TFIDF vectorizer ",final_tf_idf_train.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_tf_idf_
print("================CV Data===========")
final_tf_idf_cv = model.transform(cv)
print("the type of count vectorizer ",type(final_tf_idf_cv))
print("the shape of out text TFIDF vectorizer ",final_tf_idf_cv.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_tf_idf_
print("================Test Data===========")
final_tf_idf_test = model.transform(test)
print("the type of count vectorizer ",type(final_tf_idf_test))
print("the shape of out text TFIDF vectorizer ",final_tf_idf_test.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_tf_idf_

# we are converting a dictionary with word as a key, and the idf as a value
```

```
        dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
================Train Data===========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (49000, 42951)
the number of unique words including both unigrams and bigrams  42951
================CV Data===========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (21000, 42951)
the number of unique words including both unigrams and bigrams  42951
================Test Data===========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (30000, 42951)
the number of unique words including both unigrams and bigrams  42951
```

In [37]:
```
######## Train #######
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

train_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
row=0;
for sent in tqdm(list_of_train_sentance): # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            #tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    train_tfidf_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|| 49000/49000 [37:33<00:00, 21.75it/s]
```

In [38]:
```
######## CV #######
# TF-IDF weighted Word2Vec
#tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
```

```
cv_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in thi
row=0;
for sent in tqdm(list_of_cv_sentance): # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            #tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    cv_tfidf_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|| 21000/21000 [15:30<00:00, 19.62it/s]
```

In [39]:
```
######## Train #######
# TF-IDF weighted Word2Vec
#tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

test_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in th
row=0;
for sent in tqdm(list_of_test_sentance): # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            #tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    test_tfidf_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|| 30000/30000 [22:19<00:00, 22.40it/s]
```

```
In [40]: # save the datasets as numpy array
         tfidf_w2v_train = np.array(train_tfidf_sent_vectors)
         tfidf_w2v_cv = np.array(cv_tfidf_sent_vectors)
         tfidf_w2v_test = np.array(test_tfidf_sent_vectors)
```

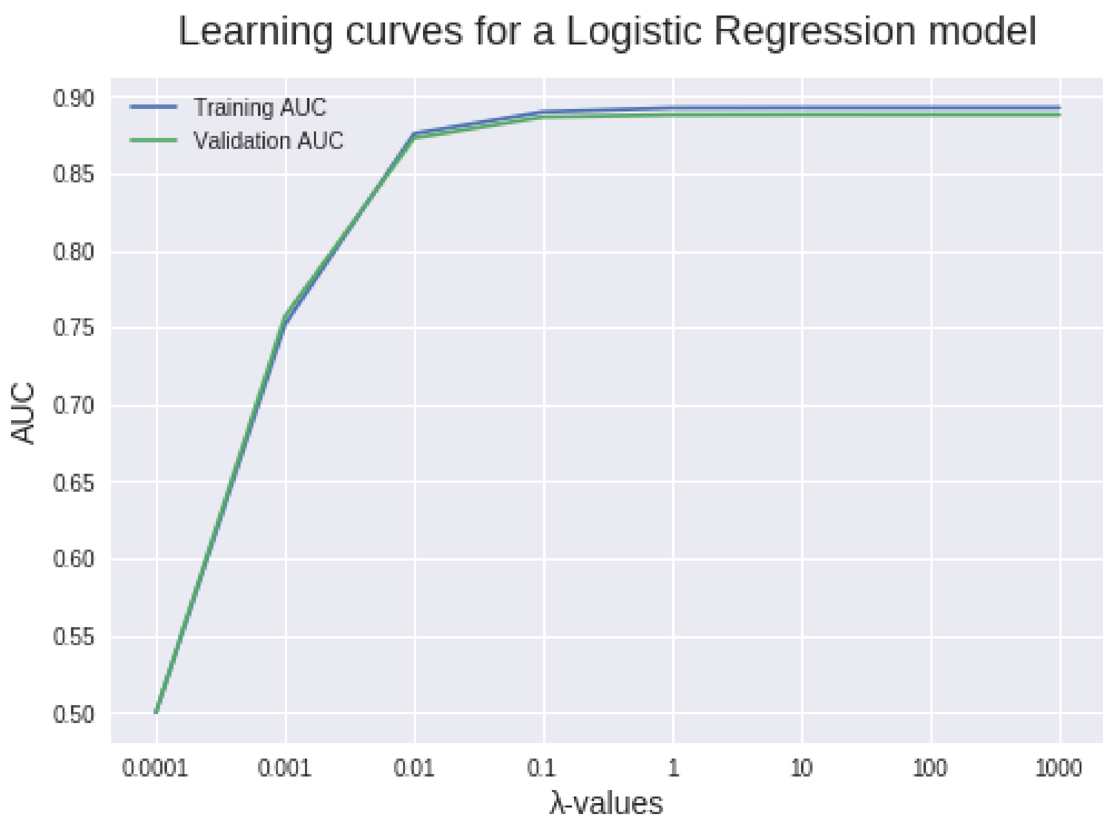
7.4.1 [5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

```
In [42]: # Please write all the code with proper documentation
         # Please write all the code with proper documentation
         # Please write all the code with proper documentation
         C = [pow(10,j) for j in range(-4,4,1)]
         tfidf_w2v_train_auc = []
         tfidf_w2v_cv_auc = []
         for i in C:
             LR = LogisticRegression(C=i , penalty="l1")
             LR.fit(tfidf_w2v_train, train_y)
             # train data
             y_prob_train = LR.predict_proba(tfidf_w2v_train)[:,1]
             y_pred = np.where(y_prob_train > 0.5, 1, 0)
             auc_roc_train = roc_auc_score(train_y , y_prob_train)
             print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(
             tfidf_w2v_train_auc.append(auc_roc_train)
             # CV
             y_prob_cv = LR.predict_proba(tfidf_w2v_cv)[:,1]
             y_pred = np.where(y_prob_cv > 0.5, 1, 0)
             auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
             print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
             tfidf_w2v_cv_auc.append(auc_roc_cv)
             print("="*50)
```

```
Train AUC for  = 0.0001 is 50.00%

CV AUC for  = 0.0001 is 50.00%
==================================================

Train AUC for  = 0.001 is 75.20%

CV AUC for  = 0.001 is 75.72%
==================================================

Train AUC for  = 0.01 is 87.58%

CV AUC for  = 0.01 is 87.29%
==================================================
```

```
Train AUC for  = 0.1 is 88.99%

CV AUC for  = 0.1 is 88.66%
==================================================

Train AUC for  = 1 is 89.25%

CV AUC for  = 1 is 88.80%
==================================================

Train AUC for  = 10 is 89.26%

CV AUC for  = 10 is 88.81%
==================================================

Train AUC for  = 100 is 89.26%

CV AUC for  = 100 is 88.81%
==================================================

Train AUC for  = 1000 is 89.26%

CV AUC for  = 1000 is 88.81%
==================================================
```

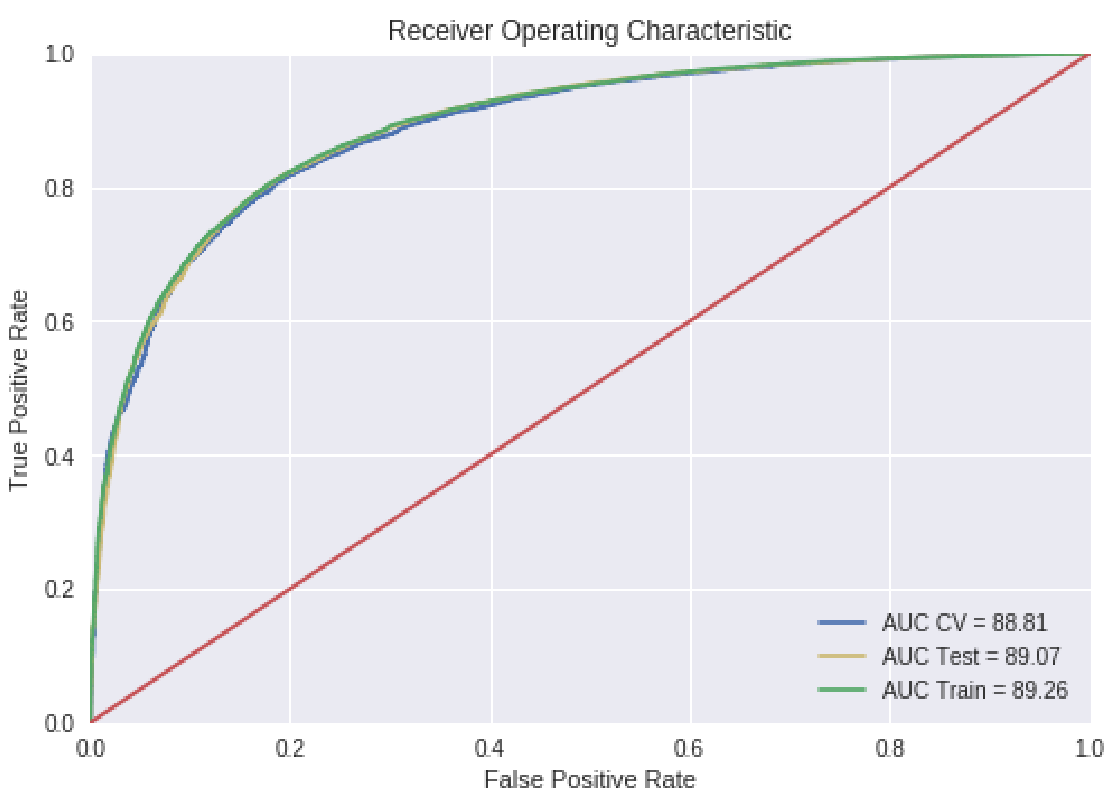
```
In [43]: hyper = [str(pow(10,j)) for j in range(-4,4)]
         # https://www.dataquest.io/blog/learning-curves-machine-learning/

         import matplotlib.pyplot as plt
         %matplotlib inline

         plt.style.use('seaborn')

         plt.plot(hyper,tfidf_w2v_train_auc,label = 'Training AUC')
         plt.plot(hyper, tfidf_w2v_cv_auc, label = 'Validation AUC')

         plt.ylabel('AUC', fontsize = 14)
         plt.xlabel('\u03BB-values', fontsize = 14)
         plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03)
         plt.legend()

Out[43]: <matplotlib.legend.Legend at 0x7fe98ee3a080>
```



In [44]:
```
i = 100
LR = LogisticRegression(C=i , penalty="l1")
LR.fit(tfidf_w2v_train, train_y)
# train data
y_prob_train = LR.predict_proba(tfidf_w2v_train)[:,1]
fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
# CV
y_prob_cv = LR.predict_proba(tfidf_w2v_cv)[:,1]
fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
# Test
y_prob_test = LR.predict_proba(tfidf_w2v_test)[:,1]
fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test)
print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

```
Train AUC for  = 100 is 89.26%

CV AUC for  = 100 is 88.81%

Test AUC for  = 100 is 89.07%
```

```
In [45]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

         import matplotlib.pyplot as plt
         plt.clf()
         plt.title('Receiver Operating Characteristic')
         plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
         plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
         plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
         plt.legend(loc = 'lower right')
         plt.plot([0, 1], [0, 1],'r')
         plt.xlim([0, 1])
         plt.ylim([0, 1])
         plt.ylabel('True Positive Rate')
         plt.xlabel('False Positive Rate')
         plt.show()
```

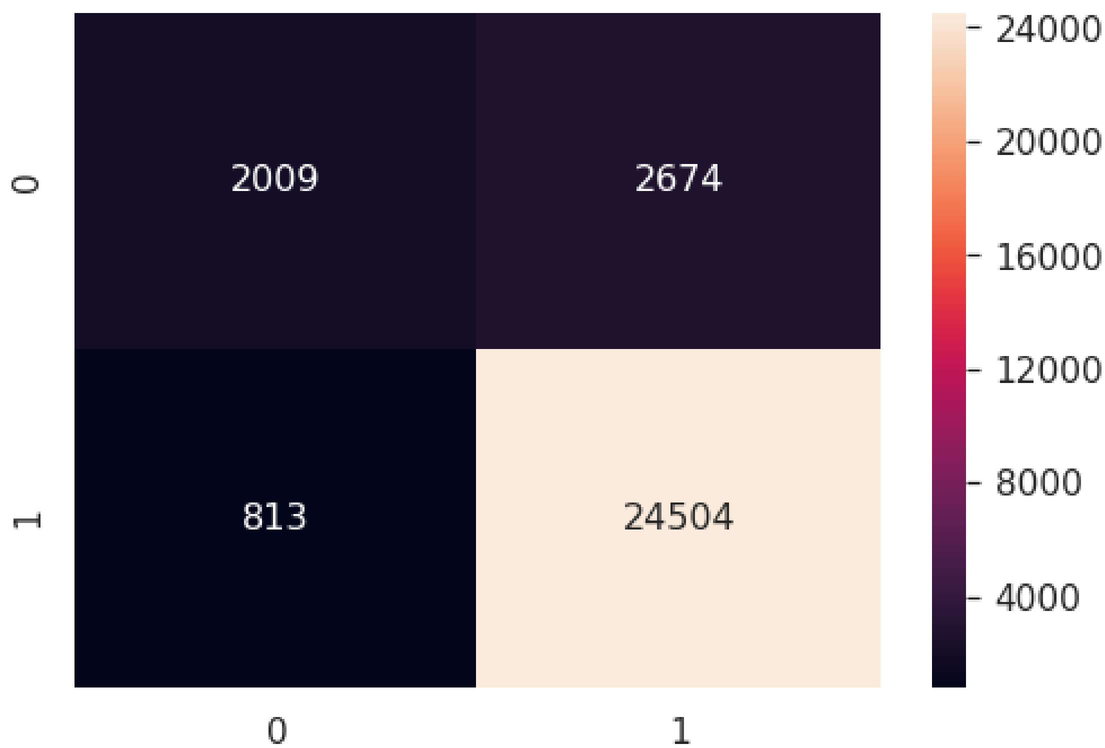


```
In [46]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.93
```

```
In [47]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

```
Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe98a1c19e8>
```




```
In [48]: # number of non-zero weights
         w = LR.coef_
         print("Number of weights : ", w.shape[1])
         print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  100
Number of non-zero weights :  100
```

7.4.2 [5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

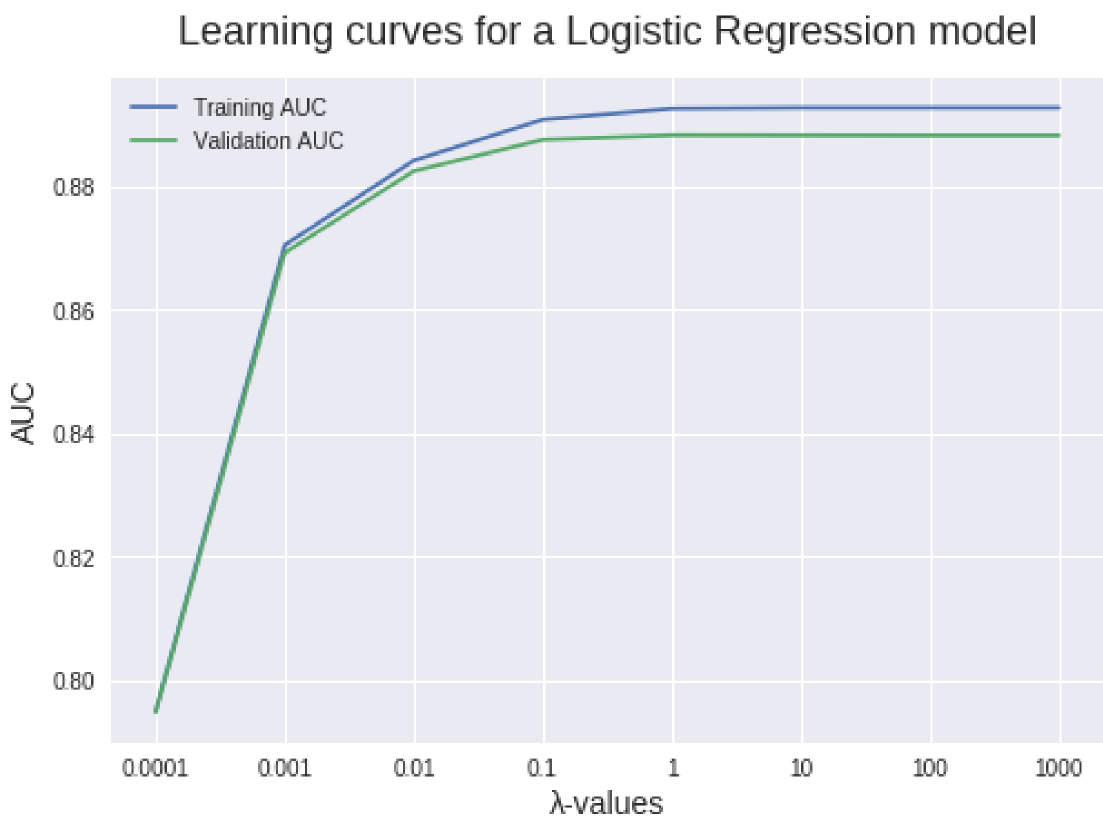
In [49]:
```
# Please write all the code with proper documentation
C = [pow(10,j) for j in range(-4,4,1)]
tfidf_w2v_train_auc = []
tfidf_w2v_cv_auc = []
for i in C:
    LR = LogisticRegression(C=i , penalty="l2")
    LR.fit(tfidf_w2v_train, train_y)
    # train data
    y_prob_train = LR.predict_proba(tfidf_w2v_train)[:,1]
    y_pred = np.where(y_prob_train > 0.5, 1, 0)
    auc_roc_train = roc_auc_score(train_y , y_prob_train)
    print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(
    tfidf_w2v_train_auc.append(auc_roc_train)
    # CV
    y_prob_cv = LR.predict_proba(tfidf_w2v_cv)[:,1]
    y_pred = np.where(y_prob_cv > 0.5, 1, 0)
    auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
    print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
    tfidf_w2v_cv_auc.append(auc_roc_cv)
    print("="*50)
```

```
Train AUC for  = 0.0001 is 79.52%

CV AUC for  = 0.0001 is 79.49%
==================================================

Train AUC for  = 0.001 is 87.04%

CV AUC for  = 0.001 is 86.92%
==================================================

Train AUC for  = 0.01 is 88.41%

CV AUC for  = 0.01 is 88.24%
==================================================

Train AUC for  = 0.1 is 89.07%

CV AUC for  = 0.1 is 88.74%
==================================================

Train AUC for  = 1 is 89.25%

CV AUC for  = 1 is 88.82%
==================================================
```

```
Train AUC for  = 10 is 89.26%

CV AUC for  = 10 is 88.82%
==================================================

Train AUC for  = 100 is 89.26%

CV AUC for  = 100 is 88.81%
==================================================

Train AUC for  = 1000 is 89.26%

CV AUC for  = 1000 is 88.81%
==================================================
```

In [50]:
```
hyper = [str(pow(10,j)) for j in range(-4,4)]
# https://www.dataquest.io/blog/learning-curves-machine-learning/

import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')

plt.plot(hyper,tfidf_w2v_train_auc,label = 'Training AUC')
plt.plot(hyper, tfidf_w2v_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC', fontsize = 14)
plt.xlabel('\u03BB-values', fontsize = 14)
plt.title('Learning curves for a Logistic Regression model', fontsize = 18, y = 1.03)
plt.legend()
```

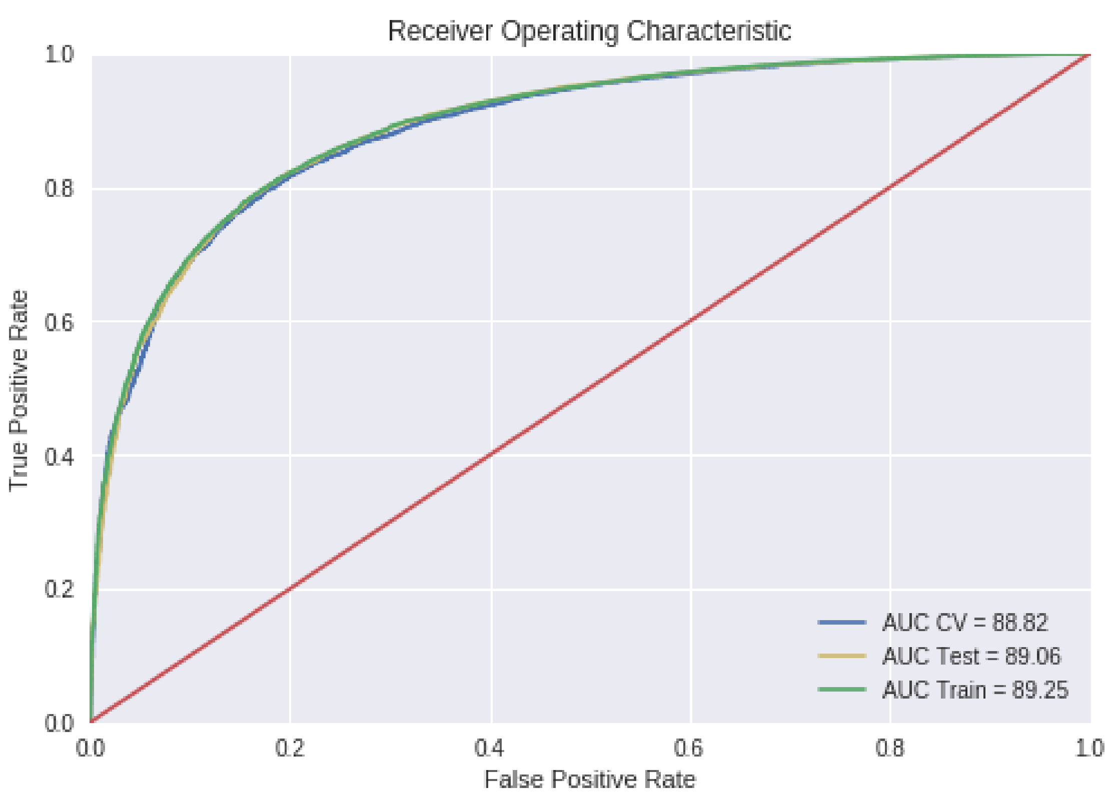
Out[50]:
```
<matplotlib.legend.Legend at 0x7fe98a0adc18>
```



In [51]:
```
i = 1
LR = LogisticRegression(C=i , penalty="l2")
LR.fit(tfidf_w2v_train, train_y)
# train data
y_prob_train = LR.predict_proba(tfidf_w2v_train)[:,1]
fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
# CV
y_prob_cv = LR.predict_proba(tfidf_w2v_cv)[:,1]
fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
# Test
y_prob_test = LR.predict_proba(tfidf_w2v_test)[:,1]
fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test)
print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

```
Train AUC for  = 1 is 89.25%

CV AUC for  = 1 is 88.82%

Test AUC for  = 1 is 89.06%
```

In [52]:
```python
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

import matplotlib.pyplot as plt
plt.clf()
plt.title('Receiver Operating Characteristic')
plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

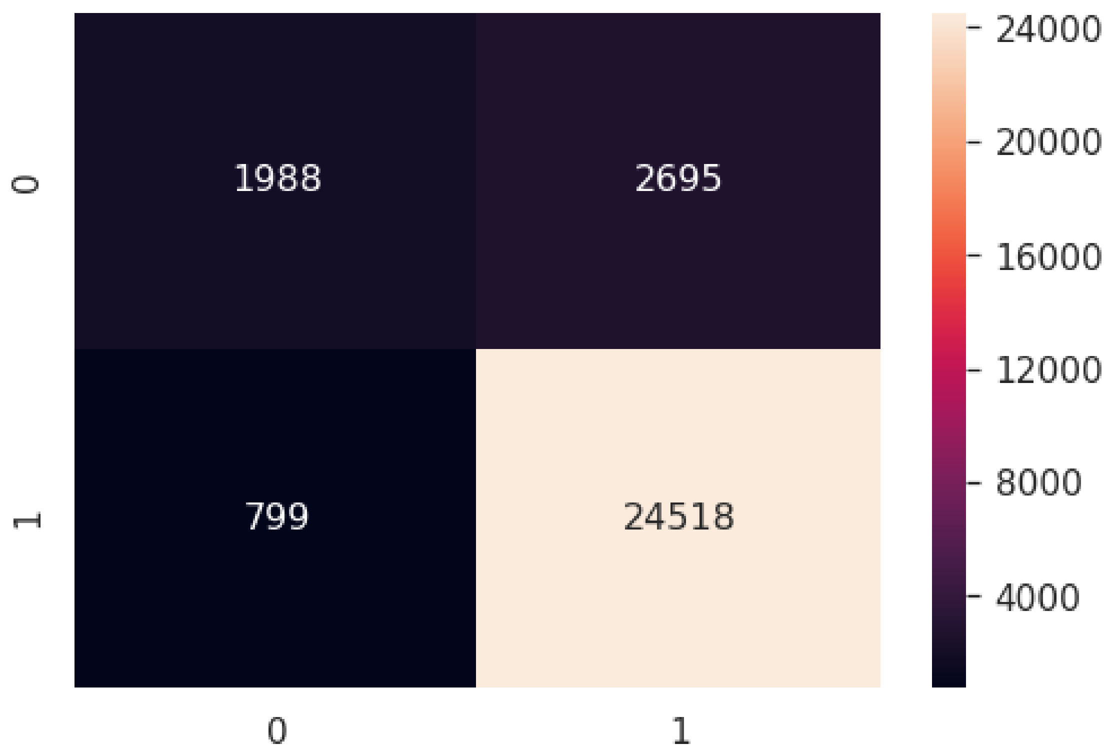


```
In [53]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.93
```

```
In [54]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

```
Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe98a05b940>
```




```
In [55]: # number of non-zero weights
         w = LR.coef_
         print("Number of weights : ", w.shape[1])
         print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  100
Number of non-zero weights :  100
```

7.4.3 Feature engineeering

Taking length of reviews as another feature

```
In [57]: # new featrue function text leangth
         def get_text_length(x):
             return np.array([len(t) for t in x]).reshape(-1, 1)
```

```
In [58]: # adding a new feature to dataframe as text_length
         df['text_length'] = get_text_length(df["CleanedText"].values)
```

```
In [59]: # take 100k sample data randomly
         sample_data = df.sample(100000)
         sample_data.shape

         # sorted the data using time based
         sorted_data = sample_data.sort_values('Time', axis=0, inplace=False)
         sorted_data.shape

         sorted_data['Score'].value_counts()

         from sklearn.model_selection import train_test_split
         text_length = np.array(sorted_data['text_length'])
         X = np.array(sorted_data['CleanedText'])
         y = np.array(sorted_data['Score'])
         print(X.shape)
         print(y.shape)
         print(text_length.shape)
```

```
(100000,)
(100000,)
(100000,)
```

```
In [60]: # Simple cross validation
         # split the data sent into train and test
         train , test, train_text, test_text , train_y , test_y = train_test_split(X,text_leng

         # split the train data set into cross validation train and cross validation test
         train, cv , train_text, cv_text, train_y, cv_y = train_test_split(train, train_text, t

         print("train data = ", train.shape)
         print("cros validation = ", cv.shape)
         print("test data = ", test.shape)
         print("train text = ",train_text.shape)
         print("cv text = ",cv_text.shape)
         print("test text = ", test_text.shape)
```

```
train data =  (49000,)
cros validation =  (21000,)
```

```
test data =  (30000,)
train text =  (49000,)
cv text =  (21000,)
test text =  (30000,)
```

```
In [61]: #BoW
         count_vect = CountVectorizer(min_df=15, ngram_range=(1,1)) #in scikit-learn
         count_vect.fit(train)
         print("some feature names ", count_vect.get_feature_names()[:10])
         print('='*50)

         bow_train = count_vect.fit_transform(train)
         bow_cv = count_vect.transform(cv)
         bow_test = count_vect.transform(test)
         print("============Train Data=========")
         print("the type of count vectorizer ",type(bow_train))
         print("the shape of out text BOW vectorizer ",bow_train.get_shape())
         print("the number of unique words ", bow_train.get_shape()[1])
         print("============Cross validation Data=========")
         print("the type of count vectorizer ",type(bow_cv))
         print("the shape of out text BOW vectorizer ",bow_cv.get_shape())
         print("the number of unique words ", bow_cv.get_shape()[1])
         print("============Test Data=========")
         print("the type of count vectorizer ",type(bow_test))
         print("the shape of out text BOW vectorizer ",bow_test.get_shape())
         print("the number of unique words ", bow_test.get_shape()[1])
```

```
some feature names  ['abandoned', 'ability', 'able', 'absence', 'absolute', 'absolutely', 'abs
==================================================
============Train Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 7030)
the number of unique words  7030
============Cross validation Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (21000, 7030)
the number of unique words  7030
============Test Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 7030)
the number of unique words  7030
```

```
In [62]: # adding a text_length feature to sparse matrix
         from scipy.sparse import hstack
         bow_train = hstack((bow_train,train_text[:,None]))
         bow_cv = hstack((bow_cv,cv_text[:,None]))
         bow_test = hstack((bow_test,test_text[:,None]))
```

```
In [63]: #after adding new feature to sparce matrix
         print("bow train shape = ", bow_train.shape)
         print("bow cv shape = ", bow_cv.shape)
         print("bow text shape = ",bow_test.shape)
```

```
bow train shape =  (49000, 7031)
bow cv shape =  (21000, 7031)
bow text shape =  (30000, 7031)
```

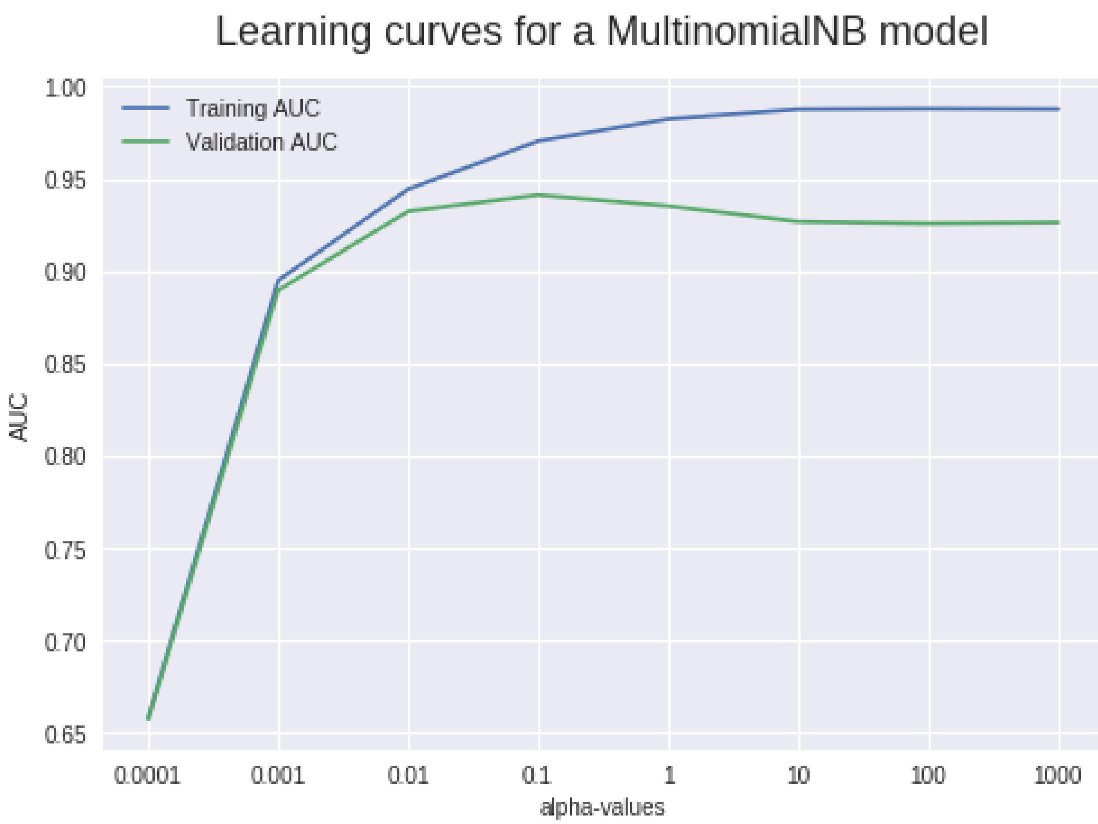
```
In [66]: bow_train_auc = []
         bow_cv_auc = []
         for i in C:
             LR = LogisticRegression(C=i , penalty="l2")
             LR.fit(bow_train, train_y)
             # train data
             y_prob_train = LR.predict_proba(bow_train)[:,1]
             y_pred = np.where(y_prob_train > 0.5, 1, 0)
             auc_roc_train = roc_auc_score(train_y , y_prob_train)
             print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(1
             bow_train_auc.append(auc_roc_train)
             # CV
             y_prob_cv = LR.predict_proba(bow_cv)[:,1]
             y_pred = np.where(y_prob_cv > 0.5, 1, 0)
             auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
             print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
             bow_cv_auc.append(auc_roc_cv)
             print("="*50)
```

```
Train AUC for  = 0.0001 is 65.86%

CV AUC for  = 0.0001 is 65.76%
==================================================

Train AUC for  = 0.001 is 89.51%

CV AUC for  = 0.001 is 88.98%
==================================================

Train AUC for  = 0.01 is 94.45%

CV AUC for  = 0.01 is 93.24%
==================================================

Train AUC for  = 0.1 is 97.05%

CV AUC for  = 0.1 is 94.13%
```

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

Train AUC for  = 1 is 98.23%

CV AUC for  = 1 is 93.53%
=====================================================

Train AUC for  = 10 is 98.76%

CV AUC for  = 10 is 92.68%
=====================================================

Train AUC for  = 100 is 98.80%

CV AUC for  = 100 is 92.58%
=====================================================

Train AUC for  = 1000 is 98.77%

CV AUC for  = 1000 is 92.64%
=====================================================
```

In [68]:
```python
# https://www.dataquest.io/blog/learning-curves-machine-learning/

import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')

plt.plot(hyper,bow_train_auc,label = 'Training AUC')
plt.plot(hyper, bow_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC')
plt.xlabel('alpha-values', fontsize = 10)
plt.title('Learning curves for a MultinomialNB model', fontsize = 18, y = 1.03)
plt.legend()
```

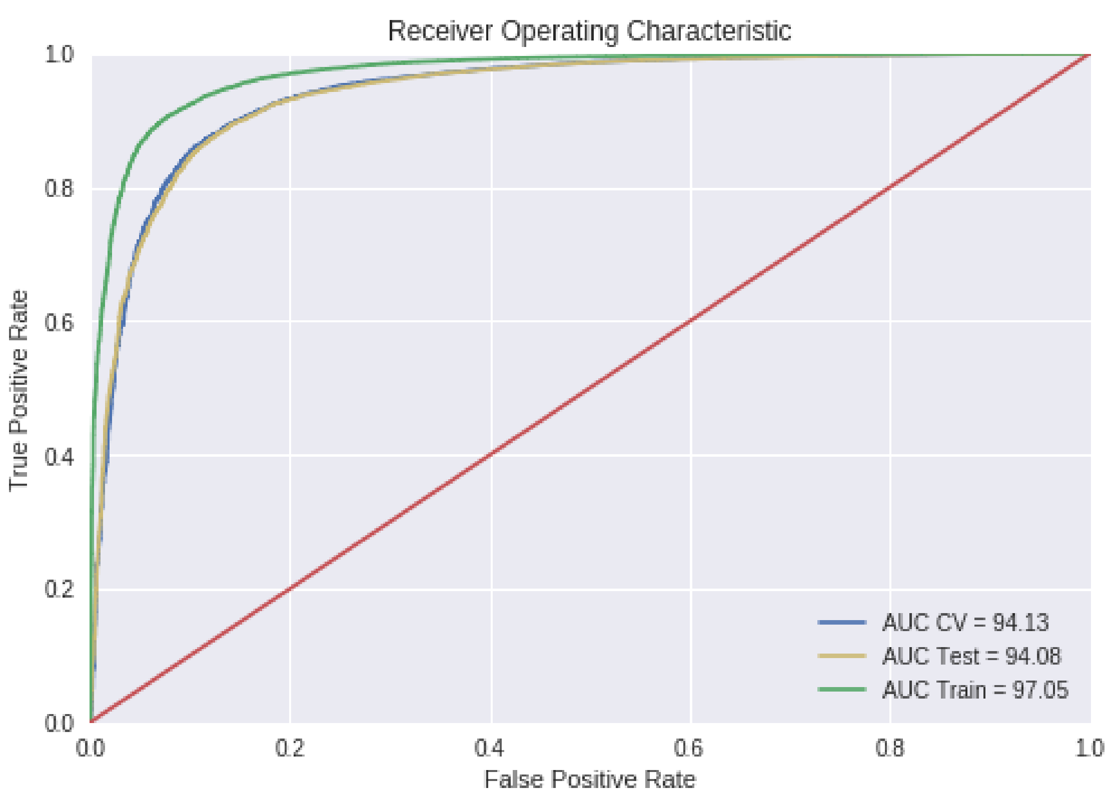
Out[68]:
```
<matplotlib.legend.Legend at 0x7fe989adef98>
```



In [69]:
```
i = 0.1
LR = LogisticRegression(C=i)
LR.fit(bow_train, train_y)
# train data
y_prob_train = LR.predict_proba(bow_train)[:,1]
fprt, tprt, throsholdt = roc_curve(train_y, y_prob_train)
y_pred_train = np.where(y_prob_train > 0.5, 1, 0)
auc_roc_train = roc_auc_score(train_y , y_prob_train)
print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(100)
# CV
y_prob_cv = LR.predict_proba(bow_cv)[:,1]
fprc, tprc, throsholdc = roc_curve(cv_y, y_prob_cv)
y_pred_cv = np.where(y_prob_cv > 0.5, 1, 0)
auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100))))
# Test
y_prob_test = LR.predict_proba(bow_test)[:,1]
fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test)
y_pred_test = np.where(y_prob_test > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test)
print('\nTest AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100)))
```

```
Train AUC for  = 0.1 is 97.05%

CV AUC for  = 0.1 is 94.13%

Test AUC for  = 0.1 is 94.08%
```

```
In [70]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python

         import matplotlib.pyplot as plt
         plt.clf()
         plt.title('Receiver Operating Characteristic')
         plt.plot(fprc, tprc, 'b' , label ='AUC CV = %0.2f' % (auc_roc_cv * float(100)))
         plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
         plt.plot(fprt, tprt, 'g', label='AUC Train = %0.2f' % (auc_roc_train * float(100)))
         plt.legend(loc = 'lower right')
         plt.plot([0, 1], [0, 1],'r')
         plt.xlim([0, 1])
         plt.ylim([0, 1])
         plt.ylabel('True Positive Rate')
         plt.xlabel('False Positive Rate')
         plt.show()
```

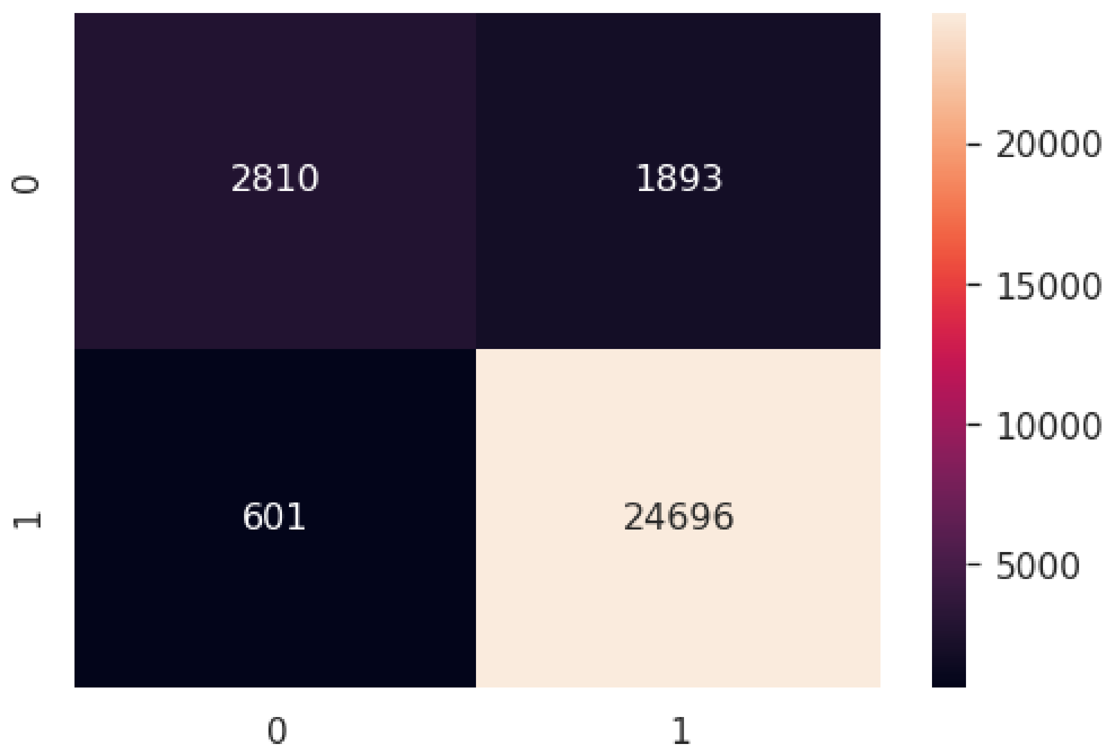


```
In [71]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))
```

```
F1-Score on test set: 0.95
```

```
In [72]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

```
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe989b37da0>
```




```
In [73]: # number of non-zero weights
         w = LR.coef_
         print("Number of weights : ", w.shape[1])
         print("Number of non-zero weights : ",np.count_nonzero(w))
```

```
Number of weights :  7031
Number of non-zero weights :  7031
```

7.4.4 Considering some features from review summary as well.

taking review summary as second model train bow model and take average averages of review text model and summary model

```
In [74]: X_review = np.array(sorted_data['CleanedText'])
         X_summary = np.array(sorted_data['Summary'])
         y = np.array(sorted_data['Score'])
         print(X_review.shape)
         print(X_summary.shape)
         print(y.shape)
```

```
(100000,)
(100000,)
(100000,)
```

```
In [75]: # Simple cross validation
         # split the data sent into train and test
         train_review , test_review, train_summary, test_summary , train_y , test_y = train_tes

         # split the train data set into cross validation train and cross validation test
         train_review, cv_review, train_summary, cv_summary , train_y, cv_y = train_test_split

         print("train review", train_review.shape)
         print("cv review", cv_review.shape)
         print("test review", test_review.shape)
         print("train summary", train_summary.shape)
         print("cv summary", cv_summary.shape)
         print("test summary", test_summary.shape)
```

```
train review (49000,)
cv review (21000,)
test review (30000,)
train summary (49000,)
cv summary (21000,)
test summary (30000,)
```

```
In [76]: # bow for summary
         # Please write all the code with proper documentation
         #BoW
         count_vect = CountVectorizer(min_df=15, ngram_range=(1,2)) #in scikit-learn
         count_vect.fit(train_summary)
         print("some feature names ", count_vect.get_feature_names()[:10])
         print('='*50)

         bow_train_summary = count_vect.fit_transform(train_summary)
         bow_cv_summary = count_vect.transform(cv_summary)
```

```
bow_test_summary = count_vect.transform(test_summary)
print("============Train Data=========")
print("the type of count vectorizer ",type(bow_train_summary))
print("the shape of out text BOW vectorizer ",bow_train_summary.get_shape())
print("the number of unique words ", bow_train_summary.get_shape()[1])
print("============Cross validation Data=========")
print("the type of count vectorizer ",type(bow_cv_summary))
print("the shape of out text BOW vectorizer ",bow_cv_summary.get_shape())
print("the number of unique words ", bow_cv_summary.get_shape()[1])
print("============Test Data=========")
print("the type of count vectorizer ",type(bow_test_summary))
print("the shape of out text BOW vectorizer ",bow_test_summary.get_shape())
print("the number of unique words ", bow_test_summary.get_shape()[1])
```

```
some feature names  ['10', '100', '11', '12', '16', '20', '24', '2nd', '40', '50']
==================================================
============Train Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 2292)
the number of unique words  2292
============Cross validation Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (21000, 2292)
the number of unique words  2292
============Test Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 2292)
the number of unique words  2292
```

In [78]:

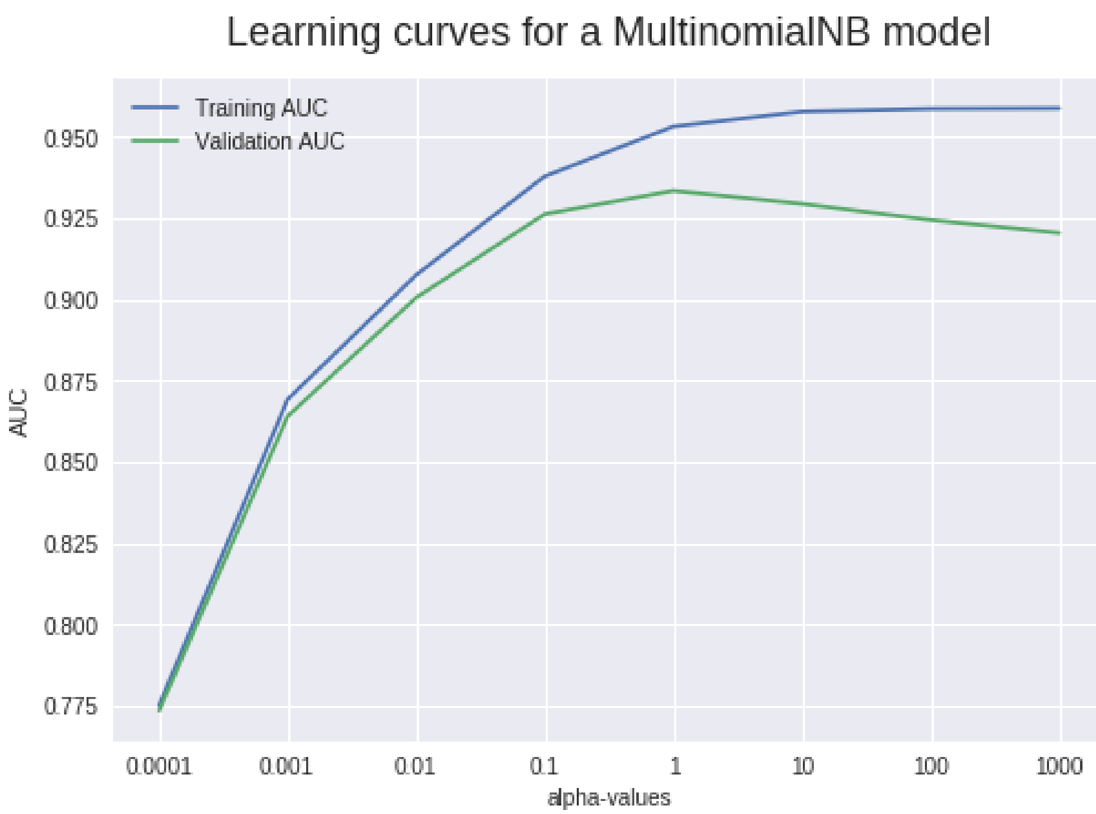
```
bow_train_auc = []
bow_cv_auc = []
for i in C:
    LR = LogisticRegression(C=i , penalty="l2")
    LR.fit(bow_train_summary, train_y)
    # train data
    y_prob_train = LR.predict_proba(bow_train_summary)[:,1]
    y_pred = np.where(y_prob_train > 0.5, 1, 0)
    auc_roc_train = roc_auc_score(train_y , y_prob_train)
    print('\nTrain AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_train * float(
    bow_train_auc.append(auc_roc_train)
    # CV
    y_prob_cv = LR.predict_proba(bow_cv_summary)[:,1]
    y_pred = np.where(y_prob_cv > 0.5, 1, 0)
    auc_roc_cv = roc_auc_score(cv_y , y_prob_cv)
    print('\nCV AUC for \u03BB = %s is %0.2f%%' % (str(i), (auc_roc_cv * float(100)))
    bow_cv_auc.append(auc_roc_cv)
    print("="*50)
```

```
Train AUC for  = 0.0001 is 77.51%

CV AUC for  = 0.0001 is 77.34%
==================================================

Train AUC for  = 0.001 is 86.92%

CV AUC for  = 0.001 is 86.40%
==================================================

Train AUC for  = 0.01 is 90.75%

CV AUC for  = 0.01 is 90.05%
==================================================

Train AUC for  = 0.1 is 93.78%

CV AUC for  = 0.1 is 92.62%
==================================================

Train AUC for  = 1 is 95.31%

CV AUC for  = 1 is 93.34%
==================================================

Train AUC for  = 10 is 95.77%

CV AUC for  = 10 is 92.94%
==================================================

Train AUC for  = 100 is 95.86%

CV AUC for  = 100 is 92.44%
==================================================

Train AUC for  = 1000 is 95.87%

CV AUC for  = 1000 is 92.04%
==================================================
```

In [80]:
```
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')

plt.plot(hyper,bow_train_auc,label = 'Training AUC')
```

```
plt.plot(hyper, bow_cv_auc, label = 'Validation AUC')

plt.ylabel('AUC')
plt.xlabel('alpha-values', fontsize = 10)
plt.title('Learning curves for a MultinomialNB model', fontsize = 18, y = 1.03)
plt.legend()
```

Out[80]: <matplotlib.legend.Legend at 0x7fe989afaa58>



In [83]:
```
# summary text
i = 1
LR = LogisticRegression(C=i)
LR.fit(bow_train_summary, train_y)
# Test
y_prob_test_summary = LR.predict_proba(bow_test_summary)[:,1]
fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test_summary)
y_pred_test = np.where(y_prob_test_summary > 0.5, 1, 0)
auc_roc_test = roc_auc_score(test_y , y_prob_test_summary)
print('\nTest AUC for alpha = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100))))
```

```
Test AUC for alpha = 1 is 93.14%
```

```
In [85]: # bow for review
         # Please write all the code with proper documentation
         #BoW
         count_vect = CountVectorizer(min_df=15, ngram_range=(1,2)) #in scikit-learn
         count_vect.fit(train_review)
         print("some feature names ", count_vect.get_feature_names()[:10])
         print('='*50)

         bow_train_review = count_vect.fit_transform(train_review)
         bow_cv_review = count_vect.transform(cv_review)
         bow_test_review = count_vect.transform(test_review)
         print("============Train Data=========")
         print("the type of count vectorizer ",type(bow_train_review))
         print("the shape of out text BOW vectorizer ",bow_train_review.get_shape())
         print("the number of unique words ", bow_train_review.get_shape()[1])
         print("============Cross validation Data=========")
         print("the type of count vectorizer ",type(bow_cv_review))
         print("the shape of out text BOW vectorizer ",bow_cv_review.get_shape())
         print("the number of unique words ", bow_cv_review.get_shape()[1])
         print("============Test Data=========")
         print("the type of count vectorizer ",type(bow_test_review))
         print("the shape of out text BOW vectorizer ",bow_test_review.get_shape())
         print("the number of unique words ", bow_test_review.get_shape()[1])
```

```
some feature names  ['aa', 'abandoned', 'abdominal', 'ability', 'able', 'able buy', 'able drin
==================================================
============Train Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 18484)
the number of unique words  18484
============Cross validation Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (21000, 18484)
the number of unique words  18484
============Test Data=========
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 18484)
the number of unique words  18484
```

```
In [87]: # review text
         i = 1
         LR = LogisticRegression(C=i)
         LR.fit(bow_train_review, train_y)
         # Test
         y_prob_test_review = LR.predict_proba(bow_test_review)[:,1]
         fprts, tprts, throsholdts = roc_curve(test_y, y_prob_test_review)
         y_pred_test = np.where(y_prob_test_review > 0.5, 1, 0)
```

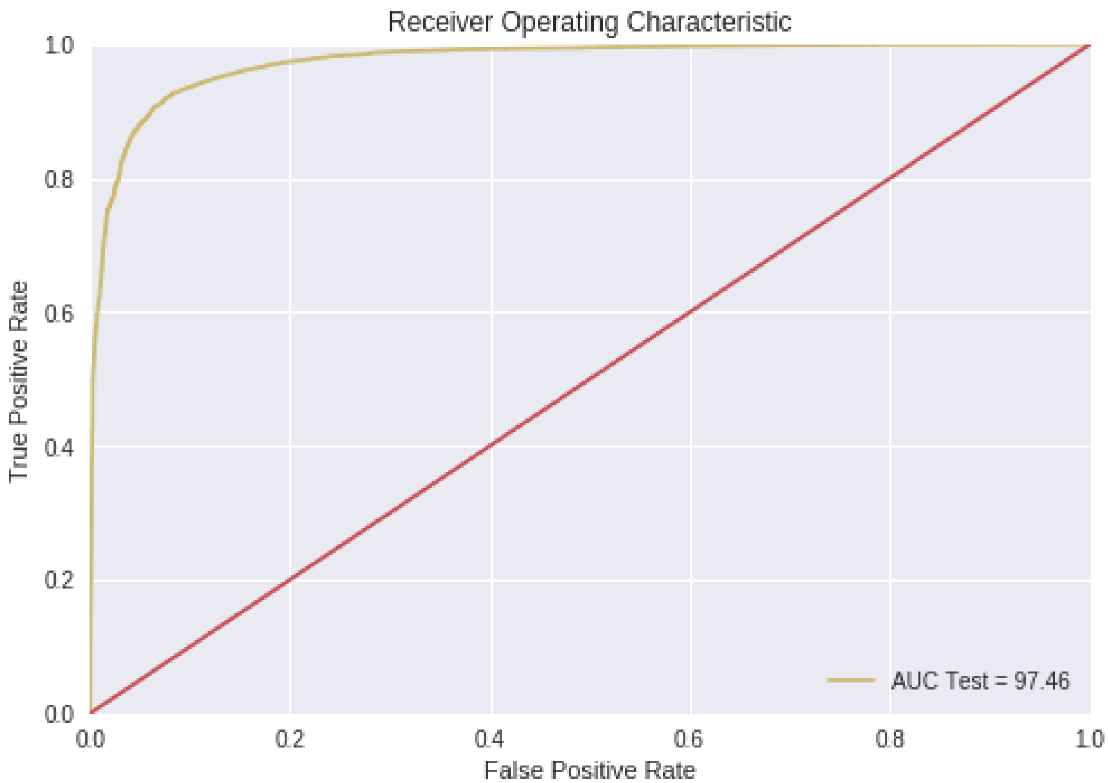
```
auc_roc_test = roc_auc_score(test_y , y_prob_test_review)
print('\nTest AUC for alpha = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100))))
```

```
Test AUC for alpha = 1 is 94.73%
```

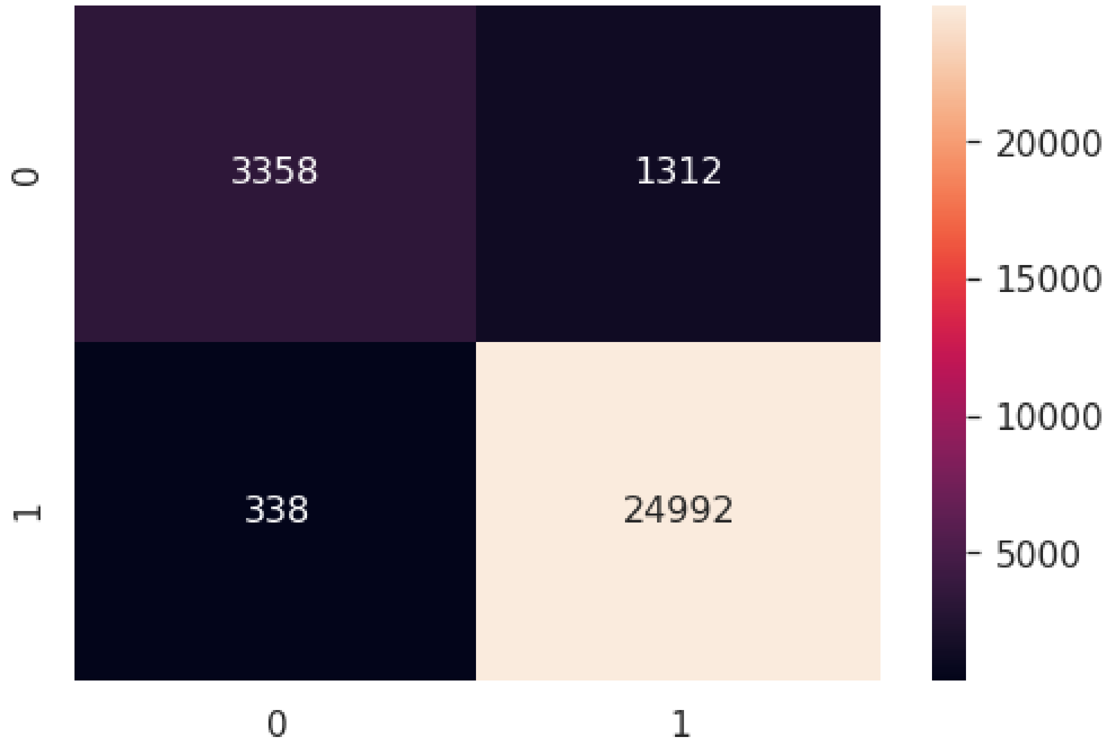
```
In [88]: # adding both summary and review test probabilitys and average
         new_proba = (y_prob_test_review + y_prob_test_summary) / 2

In [89]: fprts, tprts, throsholdts = roc_curve(test_y, new_proba)
         y_pred_test = np.where(new_proba > 0.5, 1, 0)
         auc_roc_test = roc_auc_score(test_y , new_proba)
         print('\nTest AUC for alpha = %s is %0.2f%%' % (str(i), (auc_roc_test * float(100))))
```

```
Test AUC for alpha = 1 is 97.46%
```

```
In [92]: import matplotlib.pyplot as plt
         plt.clf()
         plt.title('Receiver Operating Characteristic')
         plt.plot(fprts, tprts, 'y' , label ='AUC Test = %0.2f' % (auc_roc_test * float(100)))
         plt.legend(loc = 'lower right')
         plt.plot([0, 1], [0, 1],'r')
         plt.xlim([0, 1])
         plt.ylim([0, 1])
         plt.ylabel('True Positive Rate')
         plt.xlabel('False Positive Rate')
         plt.show()
```




```
In [93]: print("F1-Score on test set: %0.2f"%(f1_score(test_y, y_pred_test)))

F1-Score on test set: 0.97


In [94]: df_cm = pd.DataFrame(confusion_matrix(test_y, y_pred_test), range(2), range(2))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe98a1c1f60>
```



Observation : : adding two models we get better results. we see the 97.46% AUC and F1 score is 0.97

8 [6] Conclusions

```
In [95]: # Please compare all your models using Prettytable library
         from prettytable import PrettyTable

         x = PrettyTable(["Vectorizer" , "Regularization","Hyper parameter \u03BB", "AUC", "F1

         x.add_row(["BOW", "L2" ,0.1, "95.19%", 0.96])
         x.add_row(["BOW","L1" , 1,"95.06%", 0.96])
         x.add_row(["TFIDF", "L1" ,1, "95.36%", 0.96])
         x.add_row(["TFIDF","L2" , 1,"95.89%", 0.96])
         x.add_row(["AVG-W2V", "L1" ,10, "91.39%", 0.94])
         x.add_row(["AVG-W2V","L2" , 1,"91.39%", 0.94])
         x.add_row(["TFIDF-W2V", "L1" ,100, "89.07%", 0.93])
         x.add_row(["TFIDF-W2V","L2" , 1,"89.06%", 0.93])

         print(x.get_string(title="LR Model"))
```

```
+------------+----------------+-------------------+--------+----------+
| Vectorizer | Regularization | Hyper parameter   |  AUC   | F1 Score |
```

```
+------------+---------------+-------------------+--------+----------+
|    BOW     |       L2      |        0.1        | 95.19% |   0.96   |
|    BOW     |       L1      |         1         | 95.06% |   0.96   |
|   TFIDF    |       L1      |         1         | 95.36% |   0.96   |
|   TFIDF    |       L2      |         1         | 95.89% |   0.96   |
|  AVG-W2V   |       L1      |         10        | 91.39% |   0.94   |
|  AVG-W2V   |       L2      |         1         | 91.39% |   0.94   |
| TFIDF-W2V  |       L1      |        100        | 89.07% |   0.93   |
| TFIDF-W2V  |       L2      |         1         | 89.06% |   0.93   |
+------------+---------------+-------------------+--------+----------+
```

8.0.1 Feature engineering

```
In [96]: x = PrettyTable(["Feature" , "Vectorizer" , "Regularization","Hyper parameter \u03BB"

         x.add_row(["Test length", "BOW", "L2", 0.1, "94.08%", 0.95])
         x.add_row(["Summary + Review", "BOW", "L2",1 , "97.46%", 0.97])

         print(x.get_string(title="MNB Model"))
```

```
+------------------+------------+----------------+-------------------+--------+----------+
|     Feature      | Vectorizer | Regularization | Hyper parameter   |  AUC   | F1 Score |
+------------------+------------+----------------+-------------------+--------+----------+
|   Test length    |    BOW     |       L2       |        0.1        | 94.08% |   0.95   |
| Summary + Review |    BOW     |       L2       |         1         | 97.46% |   0.97   |
+------------------+------------+----------------+-------------------+--------+----------+
```

```
In [ ]:
```