[1]. Reading Data

Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

Objective:

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

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

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

[1.1] 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 CSV dataset

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

In [1]:

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


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

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

from sklearn.metrics import accuracy_score
import seaborn as sn
from sklearn.metrics import classification_report

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

from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
from sklearn.model_selection import validation_curve

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

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

from tqdm import tqdm
import os
```

```
C:\Users\Adarsh\Anaconda3\lib\site-packages\gensim\utils.py:1212: UserWarning: detected Windows; a
liasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:

```
#loading train and test and validation dataset

file=open("x_train.pkl","rb")
x_train=pickle.load(file) # loading 'train' dataset

file=open("x_cv.pkl",'rb')
x_cv=pickle.load(file) # loading 'validation' dataset

file=open("x_test.pkl",'rb')
x_test=pickle.load(file) # loading 'test' dataset

file=open("y_train.pkl","rb")
y_train=pickle.load(file) # loading 'train' dataset

file=open("y_cv.pkl",'rb')
y_cv=pickle.load(file) # loading 'validation' dataset

file=open("y_test.pkl",'rb')
y_test=pickle.load(file) # loading 'test' dataset

#loading train_bow and test _bow
file=open('x_train_bow.pkl','rb')
x_train_bow=pickle.load(file)

file=open('x_test_bow.pkl','rb')
x_test_bow=pickle.load(file)

file=open('x_cv_bow.pkl','rb')
x_cv_bow=pickle.load(file)

#loading train_tf_idf and test_tf_idf
file=open('train_tf_idf.pkl','rb')
train_tf_idf=pickle.load(file)

file=open('cv_tf_idf.pkl','rb')
cv_tf_idf=pickle.load(file)
```

```
file=open('test_tf_idf.pkl','rb')
test_tf_idf=pickle.load(file)

#loading train_w2v and test_w2v
file=open('train_w2v.pkl','rb')
train_w2v=pickle.load(file)

file=open('cv_w2v.pkl','rb')
cv_w2v=pickle.load(file)

file=open('test_w2v.pkl','rb')
test_w2v=pickle.load(file)

#loading train_tf_idf_w2v and test_tf_idf_w2v
file=open('train_tf_idf_w2v.pkl','rb')
train_tf_idf_w2v=pickle.load(file)

file=open('cv_tf_idf_w2v.pkl','rb')
cv_tf_idf_w2v=pickle.load(file)

file=open('test_tf_idf_w2v.pkl','rb')
test_tf_idf_w2v=pickle.load(file)
```

In [7]:

```
# using csv Table to read data.

dataset=pd.read_csv("Reviews.csv")

print(dataset.shape)
dataset.head(3)
```

```
(568454, 10)
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all

In [8]:

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

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

# taking reviews whose score is not equal to 3
filtered_dataset=dataset[dataset['Score']!=3]
filtered_dataset.shape

#creating a function to filter the reviews (if score>3 --> positive , if score<3 --> negative)
def partition(x):
```

```
    if x>3:
        return 1
    return 0

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_dataset['Score']
positiveNegative = actualScore.map(partition)
filtered_dataset['Score'] = positiveNegative
print("Number of data points in our data", filtered_dataset.shape)
filtered_dataset.head(3)
```

```
Number of data points in our data (525814, 10)
```

Out[8]:

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

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

observation:

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

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

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

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

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

In [9]:

```
# sorting the value
sorted_data=filtered_dataset.sort_values(by='Id',inplace=True )
#finding the dublicate values using 'df.dublicated'
filtered_dataset[filtered_dataset.duplicated(subset={'ProfileName','HelpfulnessNumerator','Helpfuln
essDenominator','Score','Time'})].shape
#alternate way to drop dublicate values
dataset_no_dup=filtered_dataset.drop_duplicates(subset={'ProfileName','Score','Time','Summary'},kee
```

```
p='first')
print(f"before {dataset.shape}")
print(f"after removing duplicate values-->shape = {dataset_no_dup.shape}")
# %age of no. of review reamin in data set
print('percentage of data reamin after removing duplicate values and removing reviews with neutral scores % .2f'
      %((dataset_no_dup.size/dataset.size)*100))
```

```
before (568454, 10)
after removing duplicate values-->shape = (363255, 10)
percentage of data reamin after removing duplicate values and removing reviews with neutral scores 63.90
```

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 [10]:

```
# removing reviews where "HelpfulnessNumerator>HelpfulnessDenominator"
final=dataset_no_dup[dataset_no_dup['HelpfulnessNumerator']<=dataset_no_dup['HelpfulnessDenominator']]
```

In [11]:

```
#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()
```

```
(363253, 10)
```

Out[11]:

```
1    306222
0     57031
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

In [8]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-tags-from-an-element
from bs4 import BeautifulSoup

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

def decontracted(phrase):
```

```python
    # 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


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

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "y
ou're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having',
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', '
while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during',
'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under'
, 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'e
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll'
, 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "do
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [9]:

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

```
100%|██████████████████████████████████████████████████████████████████| 363253/363253
[02:56<00:00, 2063.41it/s]
```

In [10]:

```python
preprocessed_reviews[:5]
```

Out[10]:

```
['bought several vitality canned dog food products found good quality product looks like stew proc
essed meat smells better labrador finicky appreciates product better',
 'product arrived labeled jumbo salted peanuts peanuts actually small sized unsalted not sure erro
r vendor intended represent product jumbo',
 'confection around centuries light pillowy citrus gelatin nuts case filberts cut tiny squares lib
erally coated powdered sugar tiny mouthful heaven not chewy flavorful highly recommend yummy treat
familiar story c lewis lion witch wardrobe treat seduces edmund selling brother sisters witch',
 'looking secret ingredient robitussin believe found got addition root beer extract ordered good m
ade cherry soda flavor medicinal',
 'great taffy great price wide assortment yummy taffy delivery quick taffy lover deal']
```

In [11]:

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

In [12]:

```
# splitting the dataset in train , cv and test

n=final.shape[0] #size of final dataset

train=final.iloc[:round(0.60*n),:]
cv=final.iloc[round(0.60*n):round(0.80*n),:]
test=final.iloc[round(0.80*n):round(1.0*n),:]
```

In [13]:

```
from sklearn.model_selection import train_test_split
x_training,x_test,y_training,y_test=train_test_split(preprocessed_reviews,final["Score"]
,test_size=0.20, random_state=42)
x_train,x_cv,y_train,y_cv=train_test_split(x_training,y_training, test_size=0.25, random_state=42)
```

In [48]:

```
len(x_train),len(y_train),len(x_test),len(y_test),len(x_cv),len(y_cv)
```

Out[48]:

```
(217951, 217951, 72651, 72651, 72651, 72651)
```

In [14]:

```
# saving train and test dataset using pickle for fututre use

'''file=open("x_train.pkl","wb")
pickle.dump(x_train,file)
file.close()

file=open('x_cv.pkl','wb')
pickle.dump(x_cv,file)
file.close

file=open("x_test.pkl",'wb')
pickle.dump(x_test,file)
file.close()


file=open("y_train.pkl","wb")
pickle.dump(y_train,file)
file.close()

file=open('y_cv.pkl','wb')
pickle.dump(y_cv,file)
file.close

file=open("y_test.pkl",'wb')
pickle.dump(y_test,file)
file.close()

'''
```

In [2]:

```
#loading train and test and validation dataset

file=open("x_train.pkl","rb")
x_train=pickle.load(file) # loading 'train' dataset

file=open("x_cv.pkl",'rb')
x_cv=pickle.load(file) # loading 'validation' dataset

file=open("x_test.pkl",'rb')
x_test=pickle.load(file) # loading 'test' dataset

file=open("y_train.pkl","rb")
y_train=pickle.load(file) # loading 'train' dataset

file=open("y_cv.pkl",'rb')
y_cv=pickle.load(file) # loading 'validation' dataset

file=open("y_test.pkl",'rb')
y_test=pickle.load(file) # loading 'test' dataset
```

[4] Featurization

[4.1] BAG OF WORDS

In [4]:

```
#BoW

count_vect = CountVectorizer() #in scikit-learn

x_train_bow=count_vect.fit_transform(x_train)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*100)

# transform cv and test dataset
x_cv_bow=count_vect.transform(x_cv)
x_test_bow=count_vect.transform(x_test)
```

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaa', 'aaaaaaaaaaaa', 'aaaaaaaaaaaaa', 'aaa
aaaaaaaaaaa', 'aaaaaaaaaaaaaaa', 'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa']
====================================================================================================
```

In [16]:

```
x_train_bow.shape,x_test_bow.shape,x_cv_bow.shape
```

Out[16]:

```
((217951, 90000), (72651, 90000), (72651, 90000))
```

In [17]:

```
# saving train_bow and test_bow dataset using pickle for future use

'''file=open("x_train_bow.pkl","wb")
pickle.dump(x_train_bow,file)
file.close()

file=open("x_test_bow.pkl",'wb')
pickle.dump(x_test_bow,file)
file.close()

file=open("x_cv_bow.pkl",'wb')
pickle.dump(x_cv_bow,file)
```

```
file.close()
'''
```

In [15]:

```
#loading train_bow and test _bow
file=open('x_train_bow.pkl','rb')
x_train_bow=pickle.load(file)

file=open('x_test_bow.pkl','rb')
x_test_bow=pickle.load(file)

file=open('x_cv_bow.pkl','rb')
x_cv_bow=pickle.load(file)
```

[4.3] TF-IDF

In [5]:

```
# tf-idf "from sklearn.feature_extraction.text.TfidfVectorizer"
tf_idf=TfidfVectorizer()

train_tf_idf=tf_idf.fit_transform(x_train)
cv_tf_idf=tf_idf.transform(x_cv)
test_tf_idf=tf_idf.transform(x_test)
```

In [6]:

```
from sklearn.preprocessing import StandardScaler

sc=StandardScaler(with_mean=False)

train_tf_idf=sc.fit_transform(train_tf_idf)
cv_tf_idf=sc.transform(cv_tf_idf)
test_tf_idf=sc.transform(test_tf_idf)
```

In [21]:

```
# saving train_tf_idf and test_tf_idf dataset using pickle for fututre use

'''file=open("train_tf_idf.pkl","wb")
pickle.dump(train_tf_idf,file)
file.close()

file=open("cv_tf_idf.pkl",'wb')
pickle.dump(cv_tf_idf,file)
file.close()

file=open("test_tf_idf.pkl",'wb')
pickle.dump(test_tf_idf,file)
file.close()

'''
```

In [4]:

```
#loading train_tf_idf and test_tf_idf
file=open('train_tf_idf.pkl','rb')
train_tf_idf=pickle.load(file)

file=open('cv_tf_idf.pkl','rb')
cv_tf_idf=pickle.load(file)

file=open('test_tf_idf.pkl','rb')
test_tf_idf=pickle.load(file)
```

[4.4] Word2Vec

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

[4.4.1.1] Avg W2v

In [6]:

```
# converting our text-->vector using w2v with 50-dim
# more the dimension of each word = better the semantic of word
# using lib from "gensim.models.Word2Vec"
# to run w2v we need list of list of the words as w2v covert each world into number of dim


# for train_w2v
list_of_sent_train=[]
for sent in x_train:
    list_of_sent_train.append((str(sent)).split())
w2v_model=Word2Vec(list_of_sent_train,min_count=5,size=50)

# vocablary of w2v model of amazon dataset
vocab=w2v_model.wv.vocab
len(vocab)

#-----------------------------------------------------------------------------------------

# for test_w2v
list_of_sent_cv=[]
for sent in x_cv:
    list_of_sent_cv.append((str(sent)).split())

#-----------------------------------------------------------------------------------------

# for test_w2v
list_of_sent_test=[]
for sent in x_test:
    list_of_sent_test.append((str(sent)).split())
```

In [7]:

```
'''
    -->procedure to make avg w2v of each reviews
    1. find the w2v of each word
    2. sum-up w2v of each word in a sentence
    3. divide the total w2v of sentence by total no. of words in the sentence
'''

# average Word2Vec
# compute average word2vec for each review.
train_w2v = []; # the avg-w2v for each sentence/review in train dataset is stored in this list

for sent in list_of_sent_train: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    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 vocab:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_w2v.append(sent_vec)

print(len(train_w2v))

#---------------------------------------------------------------------------

cv_w2v = []; # the avg-w2v for each sentence/review in test dataset is stored in this list

for sent in list_of_sent_cv: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    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 vocab:
            vec = w2v_model.wv[word]
```

```
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    cv_w2v.append(sent_vec)

print(len(cv_w2v))


#-----------------------------------------------------------------------------------

test_w2v = []; # the avg-w2v for each sentence/review in test dataset is stored in this list

for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    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 vocab:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    test_w2v.append(sent_vec)

print(len(test_w2v))
```

```
217951
72651
72651
```

In [9]:

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler(with_mean=True)

train_w2v=sc.fit_transform(train_w2v)
cv_w2v=sc.transform(cv_w2v)
test_w2v=sc.transform(test_w2v)
```

In [10]:

```
# saving train_w2v and test_w2v dataset using pickle for fututre use

'''file=open("train_w2v.pkl","wb")
pickle.dump(train_w2v,file)
file.close()

file=open("cv_w2v.pkl",'wb')
pickle.dump(cv_w2v,file)
file.close()

file=open("test_w2v.pkl",'wb')
pickle.dump(test_w2v,file)
file.close()
'''
```

In [5]:

```
#loading train_w2v and test_w2v
file=open('train_w2v.pkl','rb')
train_w2v=pickle.load(file)

file=open('cv_w2v.pkl','rb')
cv_w2v=pickle.load(file)

file=open('test_w2v.pkl','rb')
test_w2v=pickle.load(file)
```

In [21]:

```
train_w2v[0]
```

Out[21]:

```
array([-0.0080363 , -0.55650226, -2.24174777,  1.02574886,  0.12327979,
       -0.19916425, -1.06522974,  0.89144715, -1.13231167,  2.54008377,
        0.8032532 ,  0.3404576 ,  1.6792167 , -0.98081078,  1.08851643,
       -0.72007858, -0.65714762, -0.56007184,  0.01985994,  2.12137305,
       -0.09203752, -0.23671867, -1.63326771,  1.04496922,  0.45004579,
        0.3219116 ,  0.78335079,  0.54301334, -2.4968575 ,  0.35478244,
        1.46397278, -0.01982212, -0.1817636 ,  1.35729521, -0.61338792,
       -1.68822842, -0.84256537, -0.59978494,  0.40587478, -0.49775708,
        0.31289323,  0.34938107, -0.18756661, -2.25982333,  0.01440547,
       -0.97699964, -0.10107761,  0.28043456,  1.88480264, -0.81507891])
```

In [12]:

```
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  26749
sample words  ['really', 'nice', 'seasoning', 'bought', 'product', 'sam', 'club', 'happy', 'able',
'purchase', 'cannot', 'get', 'anymore', 'use', 'meats', 'spaghetti', 'coffee', 'not', 'bad', 'defi
antly', 'anything', 'special', 'price', 'could', 'ethical', 'fair', 'trade', 'organic', 'shade', '
grown', 'etc', 'taste', 'ok', 'stick', 'dean', 'beans', 'smooth', 'flavorful', 'medium', 'roast',
'pleasantly', 'surprised', 'k', 'cup', 'would', 'deal', 'drew', 'glad', 'dogs', 'love']
```

[4.4.1.2] TFIDF weighted W2v

In [13]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(x_train)
# 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 [14]:

```
# TF-IDF weighted Word2Vec Train
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_tf_idf_w2v = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;

#list_of_sentence_train=list_of_sent_train[:30000] # reducing the size of train list due to comput
ational constrain

for sent in tqdm(list_of_sent_train[:60000]): # 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
    train_tf_idf_w2v.append(sent_vec)
    row += 1

len(train_tf_idf_w2v)
```

```
100%|██████████| 60000/60000 [51:13<00:00, 26.40it/s]
```

Out[14]:

```
60000
```

In [15]:

```
# TF-IDF weighted Word2Vec cv
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_tf_idf_w2v = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;

#list_of_sentence_train=list_of_sent_train[:30000] # reducing the size of train list due to comput
ational constrain

for sent in tqdm(list_of_sent_cv[:20000]): # 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
    cv_tf_idf_w2v.append(sent_vec)
    row += 1

len(cv_tf_idf_w2v)
```

```
100%|██████████| 20000/20000 [17:19<00:00, 19.23it/s]
```

Out[15]:

```
20000
```

In [16]:

```
# TF-IDF weighted Word2Vec Test
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_tf_idf_w2v = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;

#list_of_sentence_train=list_of_sent_train[:30000] # reducing the size of train list due to comput
ational constrain

for sent in tqdm(list_of_sent_test[:20000]): # 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
    test_tf_idf_w2v.append(sent_vec)
    row += 1

len(test_tf_idf_w2v)
```

```
100%|██████████| 20000/20000 [17:31<00:00, 19.03it/s]
```

Out[16]:

```
20000
```

In [15]:

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler(with_mean=True)

train_tf_idf_w2v=sc.fit_transform(train_tf_idf_w2v)
cv_tf_idf_w2v=sc.transform(cv_tf_idf_w2v)
test_tf_idf_w2v=sc.transform(test_tf_idf_w2v)
```

In [16]:

```
# saving train_tf_idf_w2v and test_tf_idf_w2v dataset using pickle for fututre use

'''file=open("train_tf_idf_w2v.pkl","wb")
pickle.dump(train_tf_idf_w2v,file)
file.close()

file=open("cv_tf_idf_w2v.pkl",'wb')
pickle.dump(cv_tf_idf_w2v,file)
file.close()

file=open("test_tf_idf_w2v.pkl",'wb')
pickle.dump(test_tf_idf_w2v,file)
file.close()

'''
```

In [6]:

```
#loading train_tf_idf_w2v and test_tf_idf_w2v
file=open('train_tf_idf_w2v.pkl','rb')
train_tf_idf_w2v=pickle.load(file)

file=open('cv_tf_idf_w2v.pkl','rb')
cv_tf_idf_w2v=pickle.load(file)

file=open('test_tf_idf_w2v.pkl','rb')
test_tf_idf_w2v=pickle.load(file)
```

[5] Assignment 4: Apply Naive Bayes

1. **Apply Multinomial NaiveBayes 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)
2. **The hyper paramter tuning(find best Alpha)**
    - Find the best hyper parameter which will give the maximum AUC value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning
3. **Feature importance**
    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using values of `feature_log_prob_` parameter of MultinomialNB and print their corresponding feature names
4. **Feature engineering**
    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.

- Considering some features from review summary as well.

5. **Representation of results**

   - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure. Here on X-axis you will have alpha values, since they have a wide range, just to represent those alpha values on the graph, apply log function on those alpha values.
   - Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
   - Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

6. **Conclusion**

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

Note: Data Leakage

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

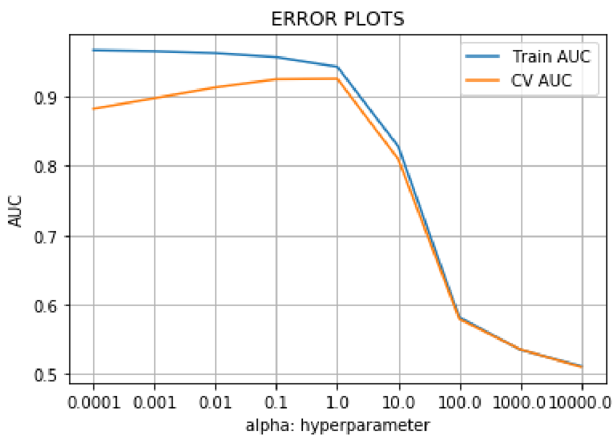
Applying Multinomial Naive Bayes

[5.1] Applying Naive Bayes on BOW, SET 1

In [19]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive class, confidence values, or no
n-thresholded measure of
decisions (as returned by "decision_function" on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.

"""

train_auc = []
cv_auc = []
alpha_range = [10e-5,10e-4,10e-3,10e-2,1,10,10e1,10e2,10e3]
for i in alpha_range:
    mnb=MultinomialNB(alpha=i, fit_prior=True, class_prior=None)
    mnb.fit(x_train_bow, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs


    #predicting on train and cv using blocks
    y_train_pred = []
    for i in range(0, x_train_bow.shape[0], 1000):
        y_train_pred.extend(mnb.predict_proba(x_train_bow[i:i+1000])[:,1])

    y_cv_pred = []
    for i in range(0, x_cv_bow.shape[0], 1000):
        y_cv_pred.extend(mnb.predict_proba(x_cv_bow[i:i+1000])[:,1])
```

```
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))


plt.plot(np.arange(1,10,1), train_auc, label='Train AUC')
plt.plot(np.arange(1,10,1), cv_auc, label='CV AUC')
plt.xticks( np.arange(1,10,1), (10e-5, 10e-4, 10e-3, 10e-2, 10e-1, 10e0, 10e1, 10e2, 10e3))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

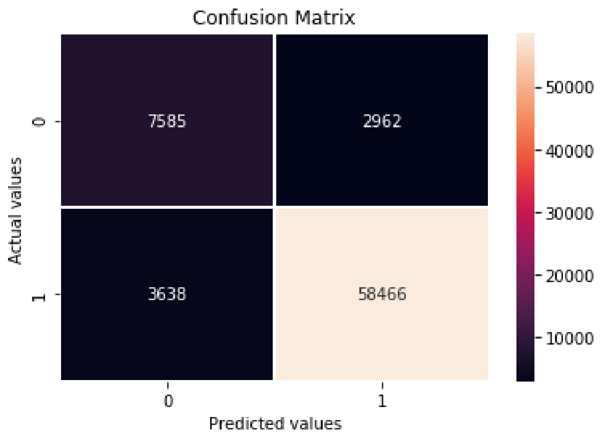


In [20]:

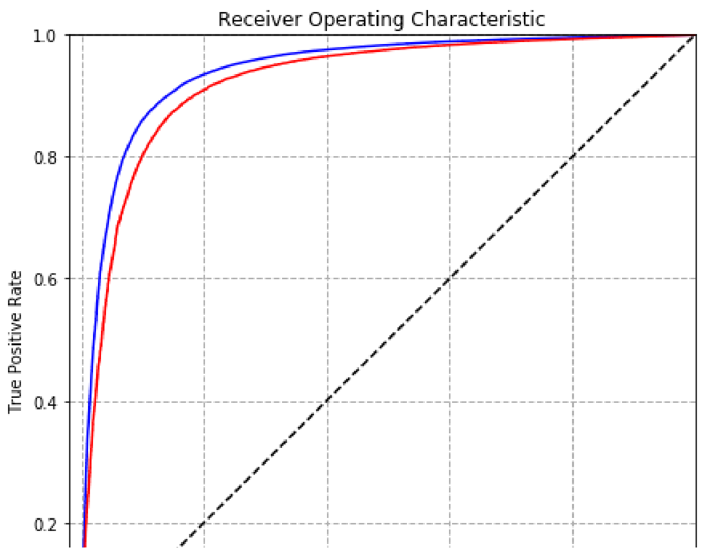
```
# Test dataset

from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt


#using optimum_k to find generalistion ROC AUC accuracy
optimum_alpha=1 #optimum 'alpha'

clf=MultinomialNB(alpha=optimum_alpha, fit_prior=True, class_prior=None)
clf.fit(x_train_bow,y_train)


y_pred = []
for i in range(0, x_test_bow.shape[0], 1000):
    y_pred.extend(clf.predict(x_test_bow[i:i+1000]))

y_pred_proba = []
for i in range(0, x_test_bow.shape[0], 1000):
    y_pred_proba.extend(clf.predict_proba(x_test_bow[i:i+1000])[:,1])


accuracy=accuracy_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred_proba)
print(f'\ngenearalisation roc_auc on best alpha-value at optimum_alpha = {optimum_alpha} is
{roc_auc:.2f}')
print(f'\nmisclassification percentage is {(1-accuracy):.2f}%')


#ploting confusion matrix
sn.heatmap(confusion_matrix(y_pred,y_test),annot=True, fmt="d",linewidths=.5)
plt.title('Confusion Matrix')
plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.show()
print("\n\nclassification report:\n",classification_report(y_test,y_pred))


# ROC Curve (reference:stack overflow with little modification)

y_train_pred_proba = []
```

```
for i in range(0, x_train_bow.shape[0], 1000):
    y_train_pred_proba.extend(clf.predict_proba(x_train_bow[i:i+1000])[:,1])


train_fpr, train_tpr, train_threshold =roc_curve(y_train, y_train_pred_proba)
test_fpr, test_tpr, test_threshold =roc_curve(y_test, y_pred_proba)

roc_auc_train = roc_auc_score(y_train,y_train_pred_proba)
roc_auc_test = roc_auc_score(y_test,y_pred_proba)

plt.figure(figsize=(7,7))
plt.title('Receiver Operating Characteristic')
plt.plot(train_fpr, train_tpr, 'b', label = 'train_AUC = %0.2f' % roc_auc_train)
plt.plot(test_fpr, test_tpr, 'r', label = 'test_AUC = %0.2f' % roc_auc_test)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'k--')
plt.xlim([-0.02, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.grid(linestyle='--', linewidth=1)
plt.show()
```

```
genearalisation roc_auc on best alpha-value at optimum_alpha = 1 is 0.92

misclassification percentage is 0.09%
```




```
classification report:
             precision    recall  f1-score   support

          0       0.72      0.68      0.70     11223
          1       0.94      0.95      0.95     61428

avg / total       0.91      0.91      0.91     72651
```



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

In [23]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

vectorizor=count_vect

clf=MultinomialNB(alpha=1, fit_prior=True, class_prior=None) # optimim_alpha=1
clf.fit(x_train_bow[:],y_train)
```

Out[23]:

```
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [24]:

```
# (clf.feature_log_prob_)[1] --> '1' for positive class label
features=pd.DataFrame({'log-prob':(clf.feature_log_prob_)
[1],'feature_name':vectorizor.get_feature_names()})
```

In [25]:

```
# negative feature importance of naive bayes
# using log probabilty as original probabilty values are too small

max_ind_neg=np.argsort((clf.feature_log_prob_)[1])[::-1][0:10]
pd.DataFrame({'log-prob':features.iloc[max_ind_neg,0],'positive_feature':features.iloc[max_ind_neg
,1]})
```

Out[25]:

	log-prob	positive_feature
53444	-3.735773	not
45238	-4.574322	like
33533	-4.687724	good
34245	-4.756608	great
55115	-4.913450	one
78198	-4.970295	taste
78481	-5.073596	tea
61931	-5.083465	product
29567	-5.094024	flavor
46287	-5.094525	love

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

In [28]:

```
# (clf.feature_log_prob_)[0] --> '0' for negative class label
features=pd.DataFrame({'log-prob':(clf.feature_log_prob_)
[0],'feature_name':vectorizor.get_feature_names()})
```

In [29]:

```
# negative feature importance of naive bayes
# using log probabilty as original probabilty values are too small

max_ind_neg=np.argsort((clf.feature_log_prob_)[0])[::-1][0:10]
pd.DataFrame({'log-prob':features.iloc[max_ind_neg,0],'negative_feature':features.iloc[max_ind_neg
,1]})
```

Out[29]:

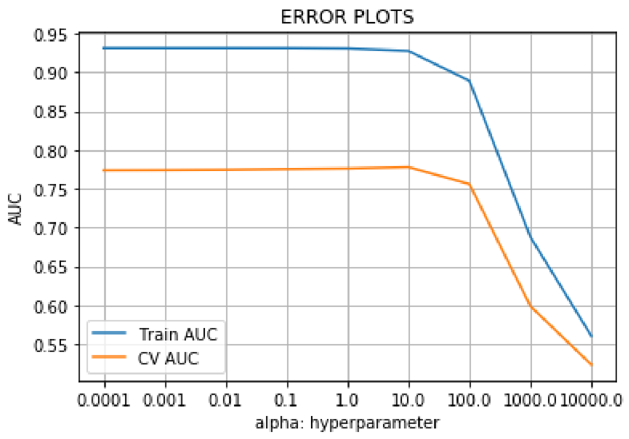
	log-prob	negative_feature
53444	-3.324656	not
45238	-4.456015	like
61931	-4.695314	product
88476	-4.715379	would
78198	-4.748106	taste
55115	-4.929418	one
53079	-5.180822	no
33533	-5.180936	good
29567	-5.220042	flavor
15557	-5.223142	coffee

[5.2] Applying Naive Bayes on TFIDF, SET 2

In [4]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive class, confidence values, or no
n-thresholded measure of
decisions (as returned by "decision_function" on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.

"""

train_auc = []
cv_auc = []
K = [10,25,35,50,75,100,125,150]
alpha_range = [10e-5,10e-4,10e-3,10e-2,1,10,10e1,10e2,10e3]
for i in alpha_range:
    mnb=MultinomialNB(alpha=i, fit_prior=True, class_prior=None)
    mnb.fit(train_tf_idf, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

    #predicting on train and cv using blocks
    y_train_pred = []
    for i in range(0, train_tf_idf.shape[0], 1000):
        y_train_pred.extend(mnb.predict_proba(train_tf_idf[i:i+1000])[:,1])

    y_cv_pred = []
    for i in range(0, cv_tf_idf.shape[0], 1000):
        y_cv_pred.extend(mnb.predict_proba(cv_tf_idf[i:i+1000])[:,1])


    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

```
plt.plot(np.arange(1,10,1), train_auc, label='Train AUC')
plt.plot(np.arange(1,10,1), cv_auc, label='CV AUC')
plt.xticks( np.arange(1,10,1), (10e-5, 10e-4, 10e-3, 10e-2, 10e-1, 10e0, 10e1, 10e2, 10e3))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

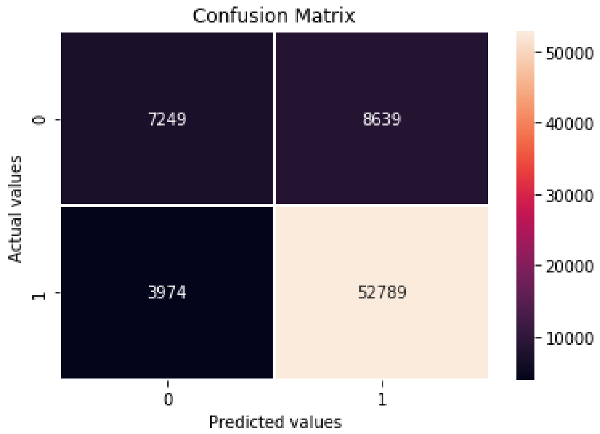


In [5]:

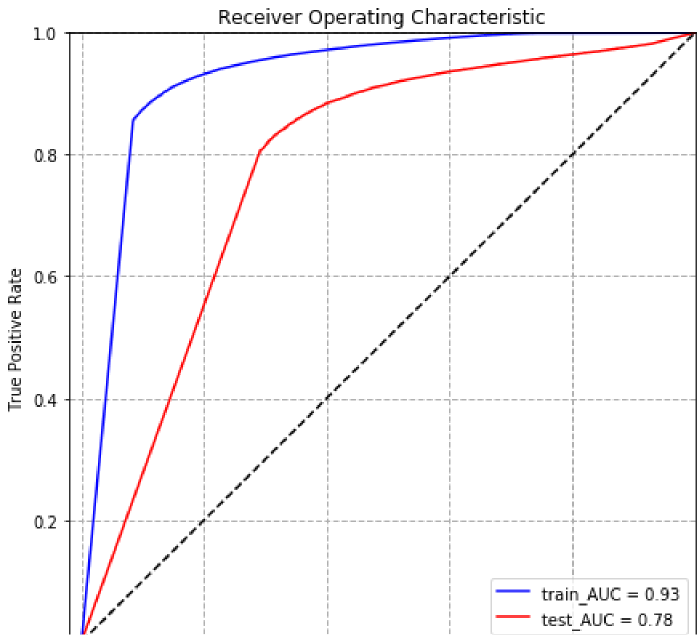
```
# Test dataset

from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt


#using optimum_k to find generalistion ROC AUC accuracy
optimum_alpha=10 #optimum 'alpha'

clf=MultinomialNB(alpha=optimum_alpha, fit_prior=True, class_prior=None)
clf.fit(train_tf_idf,y_train)


y_pred = []
for i in range(0, test_tf_idf.shape[0], 1000):
    y_pred.extend(clf.predict(test_tf_idf[i:i+1000]))

y_pred_proba = []
for i in range(0, test_tf_idf.shape[0], 1000):
    y_pred_proba.extend(clf.predict_proba(test_tf_idf[i:i+1000])[:,1])


accuracy=accuracy_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred_proba)
print(f'\ngenearalisation roc_auc on best alpha-value at optimum_alpha = {optimum_alpha} is
{roc_auc:.2f}')
print(f'\nmisclassification percentage is {(1-accuracy):.2f}%')


#ploting confusion matrix
sn.heatmap(confusion_matrix(y_pred,y_test),annot=True, fmt="d",linewidths=.5)
plt.title('Confusion Matrix')
plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.show()
print("\n\nclassification report:\n",classification_report(y_test,y_pred))


# ROC Curve (reference:stack overflow with little modification)

y_train_pred_proba = []
for i in range(0, train_tf_idf.shape[0], 1000):
    y_train_pred_proba.extend(clf.predict_proba(train_tf_idf[i:i+1000])[:,1])
```

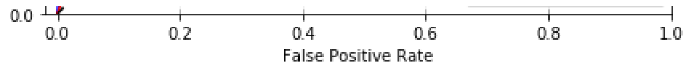
```
train_fpr, train_tpr, train_threshold =roc_curve(y_train, y_train_pred_proba)
test_fpr, test_tpr, test_threshold =roc_curve(y_test, y_pred_proba)

roc_auc_train = roc_auc_score(y_train,y_train_pred_proba)
roc_auc_test = roc_auc_score(y_test,y_pred_proba)

plt.figure(figsize=(7,7))
plt.title('Receiver Operating Characteristic')
plt.plot(train_fpr, train_tpr, 'b', label = 'train_AUC = %0.2f' % roc_auc_train)
plt.plot(test_fpr, test_tpr, 'r', label = 'test_AUC = %0.2f' % roc_auc_test)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'k--')
plt.xlim([-0.02, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.grid(linestyle='--', linewidth=1)
plt.show()
```

```
genearalisation roc_auc on best alpha-value at optimum_alpha = 10 is 0.78

misclassification percentage is 0.17%
```




```
classification report:
             precision    recall  f1-score   support

          0       0.46      0.65      0.53     11223
          1       0.93      0.86      0.89     61428

avg / total       0.86      0.83      0.84     72651
```





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

In [13]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

n=10
vectorizor=tf_idf

clf=MultinomialNB(alpha=10, fit_prior=True, class_prior=None) # optimim_alpha=10
clf.fit(train_tf_idf,y_train)
```

Out[13]:

```
MultinomialNB(alpha=10, class_prior=None, fit_prior=True)
```

In [19]:

```
# (clf.feature_log_prob_)[1] --> '1' for positive class label
features=pd.DataFrame({'log-prob':(clf.feature_log_prob_)
[1],'feature_name':vectorizor.get_feature_names()})
```

In [18]:

```
# positive feature importance of naive bayes
# using log probabilty as original probabilty values are too small

max_ind_pos=np.argsort((clf.feature_log_prob_)[1])[::-1][0:10]
pd.DataFrame({'log-prob':features.iloc[max_ind_pos,0],'positive_word':features.iloc[max_ind_pos,1]
})
```

Out[18]:

	log-prob	positive_word
53444	-6.669028	not
34245	-7.003078	great
33533	-7.023746	good
45238	-7.051448	like
46287	-7.185567	love
55115	-7.195117	one
78198	-7.235129	taste
29567	-7.281934	flavor
61931	-7.307256	product
88476	-7.338337	would

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

In [21]:

```
# (clf.feature_log_prob_)[0] --> '0' for negative class label
features=pd.DataFrame({'log-prob':(clf.feature_log_prob_)
[0],'feature_name':vectorizor.get_feature_names()})
```

In [22]:

```
# negative feature importance of naive bayes
# using log probabilty as original probabilty values are too small
```

```
max_ind_neg=np.argsort((clf.feature_log_prob_)[0])[::-1][0:10]
pd.DataFrame({'log-prob':features.iloc[max_ind_neg,0],'negative_word':features.iloc[max_ind_neg,1]
})
```

Out[22]:

	log-prob	negative_word
53444	-6.254634	not
88476	-6.976598	would
45238	-6.977966	like
78198	-7.066022	taste
61931	-7.137677	product
22377	-7.258200	disappointed
5791	-7.269828	bad
55115	-7.298566	one
53079	-7.304793	no
50646	-7.325043	money

[5.3] Feature Engineering

[5.3.1] Using length of reviews as feature and then check weather this perticular feature effect result of model or not

- Using DataFrameMapper from sklean-pandas library to combine length of reviews as additional feature with BOW and TFIDF featurizer

In [181]:

```
from sklearn_pandas import DataFrameMapper

# traning Dataframe
df_train=pd.DataFrame(x_train)
reviews_len_train=df_train[0].str.len() #storing length of reviews from traning reviews
df_train['review_len']=reviews_len_train

# validation Dataframe
df_cv=pd.DataFrame(x_cv)
reviews_len_cv=df_cv[0].str.len() #storing length of reviews from validation reviews
df_cv['review_len']=reviews_len_cv

# testing Dataframe
df_test=pd.DataFrame(x_test)
reviews_len_test=df_test[0].str.len() #storing length of reviews from validation reviews
df_test['review_len']=reviews_len_test
```

1. appying naive bayes on(BOW+reviews_length)

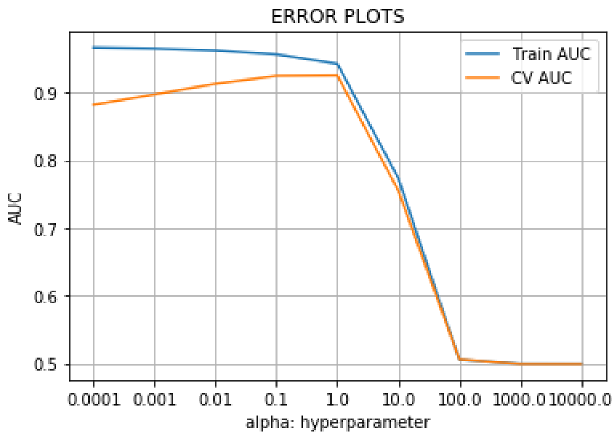
In [182]:

```
mapper_bow=DataFrameMapper([(0,CountVectorizer()),
                            ('review_len',None)],sparse=True)

train_with_len_feat_bow=mapper_bow.fit_transform(df_train)
cv_with_len_feat_bow=mapper_bow.transform(df_cv)
test_with_len_feat_bow=mapper_bow.transform(df_test)
```

In [180]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
```

```
import matplotlib.pyplot as plt

"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive class, confidence values, or no
n-thresholded measure of
decisions (as returned by “decision_function” on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.

"""

train_auc = []
cv_auc = []
K = [10,25,35,50,75,100,125,150]
alpha_range = [10e-5,10e-4,10e-3,10e-2,1,10,10e1,10e2,10e3]
for i in alpha_range:
    mnb=MultinomialNB(alpha=i, fit_prior=True, class_prior=None)
    mnb.fit(train_with_len_feat, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

    #predicting on train and cv using blocks
    y_train_pred = []
    for i in range(0, train_with_len_feat.shape[0], 1000):
        y_train_pred.extend(mnb.predict_proba(train_with_len_feat[i:i+1000])[:,1])

    y_cv_pred = []
    for i in range(0, cv_with_len_feat.shape[0], 1000):
        y_cv_pred.extend(mnb.predict_proba(cv_with_len_feat[i:i+1000])[:,1])


    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))




plt.plot(np.arange(1,10,1), train_auc, label='Train AUC')
plt.plot(np.arange(1,10,1), cv_auc, label='CV AUC')
plt.xticks( np.arange(1,10,1), (10e-5, 10e-4, 10e-3, 10e-2, 10e-1, 10e0, 10e1, 10e2, 10e3))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

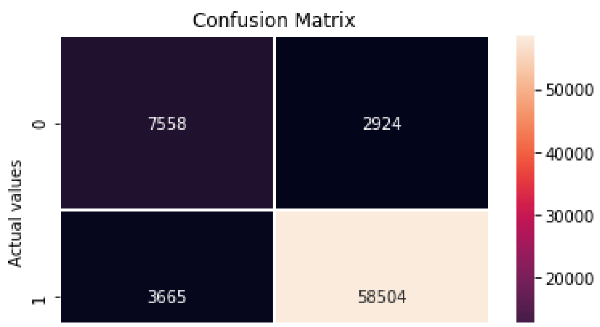


In [184]:

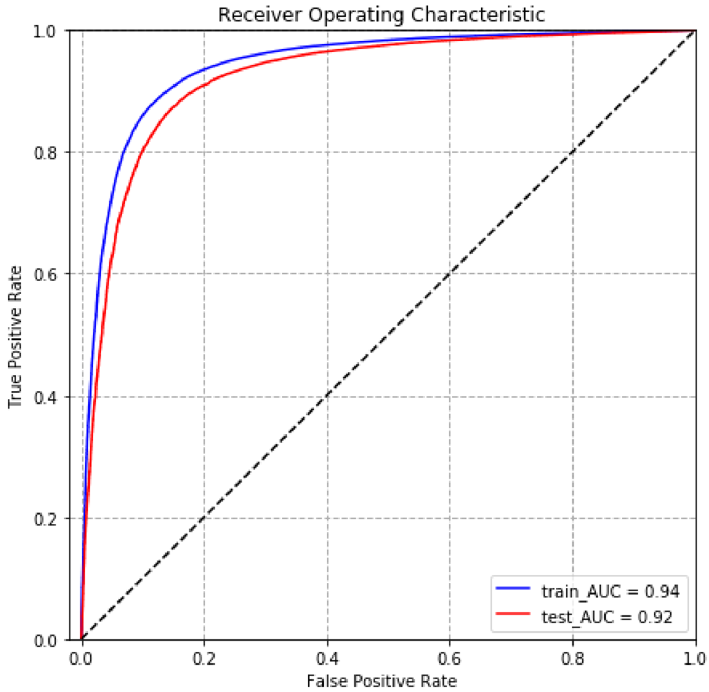
```
# Test dataset

from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
```

```python
#using optimum_k to find generalistion ROC AUC accuracy
optimum_alpha=1 #optimum 'alpha'

clf=MultinomialNB(alpha=optimum_alpha, fit_prior=True, class_prior=None)
clf.fit(train_with_len_feat_bow,y_train)


y_pred = []
for i in range(0, test_with_len_feat_bow.shape[0], 1000):
    y_pred.extend(clf.predict(test_with_len_feat_bow[i:i+1000]))

y_pred_proba = []
for i in range(0, test_with_len_feat_bow.shape[0], 1000):
    y_pred_proba.extend(clf.predict_proba(test_with_len_feat_bow[i:i+1000])[:,1])


accuracy=accuracy_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred_proba)
print(f'\ngenearalisation roc_auc on best alpha-value at optimum_alpha = {optimum_alpha} is
{roc_auc:.2f}')
print(f'\nmisclassification percentage is {(1-accuracy):.2f}%')


#ploting confusion matrix
sn.heatmap(confusion_matrix(y_pred,y_test),annot=True, fmt="d",linewidths=.5)
plt.title('Confusion Matrix')
plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.show()
print("\n\nclassification report:\n",classification_report(y_test,y_pred))


# ROC Curve (reference:stack overflow with little modification)

y_train_pred_proba = []
for i in range(0, train_with_len_feat_bow.shape[0], 1000):
    y_train_pred_proba.extend(clf.predict_proba(train_with_len_feat_bow[i:i+1000])[:,1])


train_fpr, train_tpr, train_threshold =roc_curve(y_train, y_train_pred_proba)
test_fpr, test_tpr, test_threshold =roc_curve(y_test, y_pred_proba)

roc_auc_train = roc_auc_score(y_train,y_train_pred_proba)
roc_auc_test = roc_auc_score(y_test,y_pred_proba)

plt.figure(figsize=(7,7))
plt.title('Receiver Operating Characteristic')
plt.plot(train_fpr, train_tpr, 'b', label = 'train_AUC = %0.2f' % roc_auc_train)
plt.plot(test_fpr, test_tpr, 'r', label = 'test_AUC = %0.2f' % roc_auc_test)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'k--')
plt.xlim([-0.02, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.grid(linestyle='--', linewidth=1)
plt.show()
```

```
genearalisation roc_auc on best alpha-value at optimum_alpha = 1 is 0.92

misclassification percentage is 0.09%
```




```
classification report:
             precision    recall  f1-score   support

          0       0.72      0.67      0.70     11223
          1       0.94      0.95      0.95     61428

avg / total       0.91      0.91      0.91     72651
```



2. appying naive bayes on (tfidf+reviews_length)

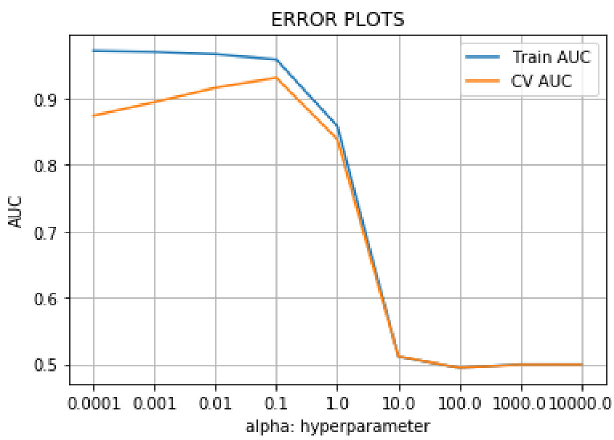
In [185]:

```
mapper_bow=DataFrameMapper([(0,TfidfVectorizer()),
                            ('review_len',None)],sparse=True)

train_with_len_feat_tfidf=mapper_bow.fit_transform(df_train)
cv_with_len_feat_tfidf=mapper_bow.transform(df_cv)
test_with_len_feat_tfidf=mapper_bow.transform(df_test)
```

In [177]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive class, confidence values, or no
n-thresholded measure of
decisions (as returned by "decision_function" on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.

"""

train_auc = []
```

```
cv_auc = []
K = [10,25,35,50,75,100,125,150]
alpha_range = [10e-5,10e-4,10e-3,10e-2,1,10,10e1,10e2,10e3]
for i in alpha_range:
    mnb=MultinomialNB(alpha=i, fit_prior=True, class_prior=None)
    mnb.fit(train_with_len_feat_tfidf, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

    #predicting on train and cv using blocks
    y_train_pred = []
    for i in range(0, train_with_len_feat_tfidf.shape[0], 1000):
        y_train_pred.extend(mnb.predict_proba(train_with_len_feat_tfidf[i:i+1000])[:,1])

    y_cv_pred = []
    for i in range(0, cv_with_len_feat.shape[0], 1000):
        y_cv_pred.extend(mnb.predict_proba(cv_with_len_feat_tfidf[i:i+1000])[:,1])


    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))




plt.plot(np.arange(1,10,1), train_auc, label='Train AUC')
plt.plot(np.arange(1,10,1), cv_auc, label='CV AUC')
plt.xticks( np.arange(1,10,1), (10e-5, 10e-4, 10e-3, 10e-2, 10e-1, 10e0, 10e1, 10e2, 10e3))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

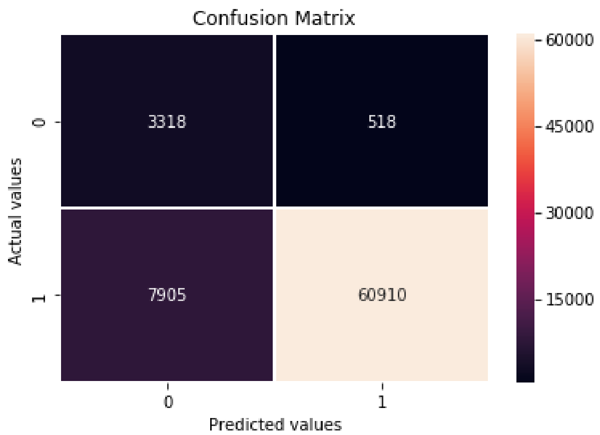


In [186]:

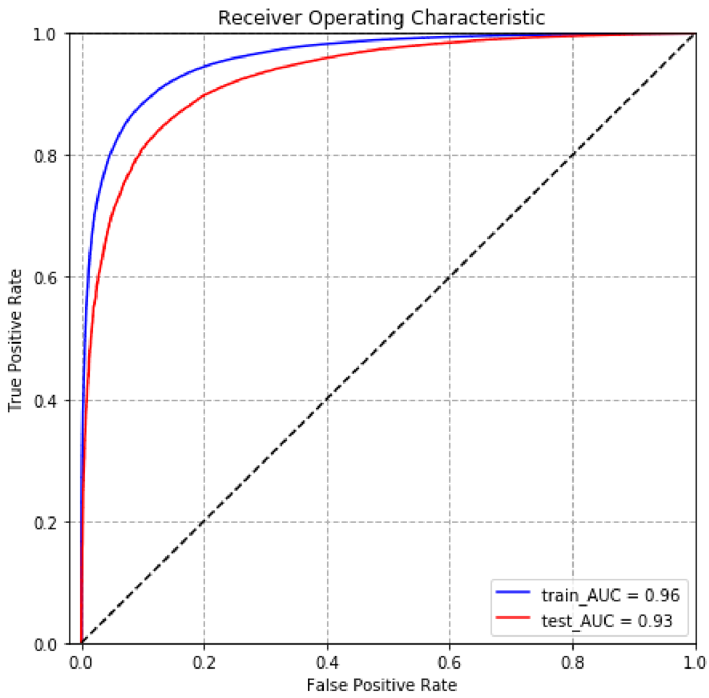
```
# Test dataset

from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt


#using optimum_k to find generalistion ROC AUC accuracy
optimum_alpha=0.1 #optimum 'alpha'

clf=MultinomialNB(alpha=optimum_alpha, fit_prior=True, class_prior=None)
clf.fit(train_with_len_feat_tfidf,y_train)


y_pred = []
for i in range(0, test_with_len_feat_tfidf.shape[0], 1000):
    y_pred.extend(clf.predict(test_with_len_feat_tfidf[i:i+1000]))

y_pred_proba = []
for i in range(0, test_with_len_feat_tfidf.shape[0], 1000):
```

```
    y_pred_proba.extend(clf.predict_proba(test_with_len_feat_tfidf[i:i+1000])[:,1])


accuracy=accuracy_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred_proba)
print(f'\ngenearalisation roc_auc on best alpha-value at optimum_alpha = {optimum_alpha} is
{roc_auc:.2f}')
print(f'\nmisclassification percentage is {(1-accuracy):.2f}%')


#ploting confusion matrix
sn.heatmap(confusion_matrix(y_pred,y_test),annot=True, fmt="d",linewidths=.5)
plt.title('Confusion Matrix')
plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.show()
print("\n\nclassification report:\n",classification_report(y_test,y_pred))


# ROC Curve (reference:stack overflow with little modification)

y_train_pred_proba = []
for i in range(0, train_with_len_feat_tfidf.shape[0], 1000):
    y_train_pred_proba.extend(clf.predict_proba(train_with_len_feat_tfidf[i:i+1000])[:,1])


train_fpr, train_tpr, train_threshold =roc_curve(y_train, y_train_pred_proba)
test_fpr, test_tpr, test_threshold =roc_curve(y_test, y_pred_proba)

roc_auc_train = roc_auc_score(y_train,y_train_pred_proba)
roc_auc_test = roc_auc_score(y_test,y_pred_proba)

plt.figure(figsize=(7,7))
plt.title('Receiver Operating Characteristic')
plt.plot(train_fpr, train_tpr, 'b', label = 'train_AUC = %0.2f' % roc_auc_train)
plt.plot(test_fpr, test_tpr, 'r', label = 'test_AUC = %0.2f' % roc_auc_test)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'k--')
plt.xlim([-0.02, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.grid(linestyle='--', linewidth=1)
plt.show()
```

```
genearalisation roc_auc on best alpha-value at optimum_alpha = 0.1 is 0.93

misclassification percentage is 0.12%
```




```
classification report:
              precision    recall  f1-score   support

          0       0.86      0.30      0.44     11223
          1       0.89      0.99      0.94     61428

avg / total       0.88      0.88      0.86     72651
```



observation:

- Adding length of reviews as additional feature helps improving performance of model.
- length of reviews as additional feature with TF-IDF improved ROC_AUC of model from 78% to 93%.

[6] Conclusions

In [1]:

```
# Please compare all your models using Prettytable library

from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["text featurization", "optimum_alpha", "generalization ROC AUC(%age) ",
"algorithm:Naive_bayes",]

x.add_row(["BOW", 1,92, "Multinomial"])
x.add_row(["TF_IDF", 10,78, "Multinomial"])
x.add_row(["BOW + reviews_length", 1,92, "Multinomial"])
x.add_row(["TF_IDF + reviews_length", 0.1,93, "Multinomial"])

print(x)
```

```
+-------------------------+---------------+---------------------------------+-----------------------+
|    text featurization   | optimum_alpha | generalization ROC AUC(%age)    | algorithm:Naive_bayes
|
+-------------------------+---------------+---------------------------------+-----------------------+
|           BOW           |       1       |                92               |      Multinomial      |
|          TF_IDF         |       10      |                78               |      Multinomial      |
|   BOW + reviews_length  |       1       |                92               |      Multinomial      |
| TF_IDF + reviews_length |      0.1      |                93               |      Multinomial      |
+-------------------------+---------------+---------------------------------+-----------------------+
```

Observation:

1. Runtime of Naive Bayes algorithm is much faster than KNN beacuse runtime complextity of naive Bayes is ~ O(d)
2. I am considering ROC AUC metric to compare the performance so best generalization ROC AUC is 93% on (TF_IDF + reviews_length) Featurization

3. Adding length of feature improved the result of the model and therefore we can add this feature to improve performance of the model

In [ ]:

```

```