Final_Amazon-Reviews-on-NB

March 17, 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 [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

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

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

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

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import NearestNeighbors
from sklearn.naive_bayes import BernoulliNB,MultinomialNB
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 sklearn.metrics import confusion_matrix,precision_score,recall_score,f1_score,roc_

from tqdm import tqdm
import os
```

In [2]:
```
# using SQLite Table to read data.
```

```
con = sqlite3.connect('database.sqlite')

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

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 200

# 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 (200000, 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  B005ZBZLT4                  Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ESG  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B005ZBZLT4         Kim Cieszykowski  1348531200      1
        3  #oc-R11O5J5ZVQE25C  B005HG9ESG            Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B007OSBEV0    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  B001ATMQK2  undertheshrine "undertheshrine"  1296691200

               Score                                               Text  COUNT(*)
        80638      5  I bought this 6 pack because for the price tha...         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]: (160178, 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]: 80.089

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()
```

```
(160176, 10)
```

Out[13]:
```
1    134799
0     25377
Name: Score, dtype: int64
```

In [14]:
```
##Sorting data for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, ki


final = time_sorted_data.take(np.random.permutation(len(final))[:100000])
print(final.shape)
final.head()
```

```
(100000, 10)
```

Out[14]:
```
            Id   ProductId          UserId  \
130970  142214  B001E50XBQ   AR3CEBCEZVGRE
51082    55453  B003J9Y4DS  A19SFWMII69UKH
4394      4775  B00139TT72  A3JEO703YA9U2H
184204  199810  B001FA1DR8  A3LR3IVEOPW1OL
328        360  B0041QJSJS  A221AFCU6AE0QO

                              ProfileName  HelpfulnessNumerator  \
130970                                 dj                     0
51082                           CBergmann                     0
4394    Coleen R. Kyser "Colleen R. Kyser"                    38
184204       Annie Coleman "LEGACYBUILDER"                     0
328                           Sarah Bowman                     3

        HelpfulnessDenominator  Score        Time  \
130970                       0      1  1345680000
51082                        0      1  1332115200
4394                        43      0  1262995200
184204                       0      1  1325808000
328                          5      1  1318204800

                                                  Summary  \
130970                                    Best I have tried
51082                              Firey hot by the handful!
4394    Something has changed. Quality control must ha...
184204                                              So good
328                                            Make My Day

                                                     Text
130970  We have used this product in making jams for w...
51082   These are my favorite jelly beans to get at an...
4394    We have been using Newman's organic dry dog fo...
184204  This chocolate is so good,It is hard for me to...
328     Having always been a strict Peet's Coffee love...
```

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 [15]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

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

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

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

```
We have used this product in making jams for well over 10 years with great results, the only t
==================================================
I tried this because it was cheaper than my usual xyletol.  This product is too sweet.  One cu
==================================================
Yes, so good even the Swiss Water process decaf version of these is totally delicious. Great f
==================================================
I ALSO LIKE THE BLEND OF FRENCH VANILLA. IT TASTES JUST LIKE THE NAME. I HAVE AT LEAST 1 CUP A
==================================================
```

In [16]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
```

```
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
We have used this product in making jams for well over 10 years with great results, the only t
```

In [17]:
```
# 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)
```

```
We have used this product in making jams for well over 10 years with great results, the only t
==================================================
I tried this because it was cheaper than my usual xyletol.  This product is too sweet.  One cup
==================================================
Yes, so good even the Swiss Water process decaf version of these is totally delicious. Great fl
==================================================
I ALSO LIKE THE BLEND OF FRENCH VANILLA. IT TASTES JUST LIKE THE NAME. I HAVE AT LEAST 1 CUP A
```

In [18]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

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

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
```

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

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

```
Yes, so good even the Swiss Water process decaf version of these is totally delicious. Great fl
==================================================
```

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

```
We have used this product in making jams for well over  years with great results, the only tim
```

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

```
Yes so good even the Swiss Water process decaf version of these is totally delicious Great fla
```

In [22]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
            "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', 'h
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'o
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'an
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
```

```
                  "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mig
                  "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                  'won', "won't", 'wouldn', "wouldn't"])
```

```
In [23]: # Combining all the above stundents
         from tqdm import tqdm
         prepr_rev = []
         # 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
             prepr_rev.append(sentance.strip())
```

```
100%|| 100000/100000 [01:12<00:00, 1379.36it/s]
```

```
In [24]: prepr_rev[1500]
```

```
Out[24]: 'yes good even swiss water process decaf version totally delicious great flavor pod co
```

```
In [25]: print(len(prepr_rev))
         final.shape
```

```
100000
```

```
Out[25]: (100000, 10)
```

```
In [26]: final ['prepr_rev']= prepr_rev
         final.head(5)
```

```
Out[26]:             Id   ProductId          UserId  \
         130970  142214  B001E50XBQ   AR3CEBCEZVGRE
         51082    55453  B003J9Y4DS  A19SFWMII69UKH
         4394      4775  B00139TT72  A3JEO703YA9U2H
         184204  199810  B001FA1DR8  A3LR3IVEOPW1OL
         328        360  B0041QJSJS  A221AFCU6AE0QO

                                       ProfileName  HelpfulnessNumerator  \
         130970                                 dj                     0
         51082                           CBergmann                     0
         4394    Coleen R. Kyser "Colleen R. Kyser"                    38
         184204         Annie Coleman "LEGACYBUILDER"                   0
         328                              Sarah Bowman                     3
```

```
        HelpfulnessDenominator  Score        Time  \
130970                       0      1  1345680000
51082                        0      1  1332115200
4394                        43      0  1262995200
184204                       0      1  1325808000
328                          5      1  1318204800

                                               Summary  \
130970                                 Best I have tried
51082                          Firey hot by the handful!
4394    Something has changed. Quality control must ha...
184204                                           So good
328                                          Make My Day

                                                  Text  \
130970  We have used this product in making jams for w...
51082   These are my favorite jelly beans to get at an...
4394    We have been using Newman's organic dry dog fo...
184204  This chocolate is so good,It is hard for me to...
328     Having always been a strict Peet's Coffee love...

                                             prepr_rev
130970  used product making jams well years great resu...
51082   favorite jelly beans get candy store period hu...
4394    using newman organic dry dog food years godsen...
184204  chocolate good hard eat moderation know health...
328     always strict peet coffee lover reticent switc...
```

In [32]:
```python
preprocessed_summary = []
# tqdm is for printing the status bar
for summary in tqdm(final['Summary'].values):
    summary = re.sub(r"http\S+", "", summary) # remove urls from text python: https:/
    summary = BeautifulSoup(summary, 'lxml').get_text() # https://stackoverflow.com/q
    summary = decontracted(summary)
    summary = re.sub("\S*\d\S*", "", summary).strip() #remove words with numbers pytho
    summary = re.sub('[^A-Za-z]+', ' ', summary) #remove spacial character: https://s
    # https://gist.github.com/sebleier/554280
    summary = ' '.join(e.lower() for e in summary.split() if e.lower() not in stopword
    preprocessed_summary.append(summary.strip())
```

```
 76%|  | 75954/100000 [00:41<00:11, 2112.56it/s]/Volumes/Saida/Applications/Anaconda/anaconda3/
  ' Beautiful Soup.' % markup)
100%|| 100000/100000 [00:57<00:00, 1749.28it/s]
```

In [33]:
```python
prepr_rev = [i + ' ' + j for i, j in zip(prepr_rev,preprocessed_summary)]
print(prepr_rev[1500])
```

```
yes good even swiss water process decaf version totally delicious great flavor pod coffee btw :
```

```
In [34]: X = np.array(prepr_rev)
         y = np.array(final['Score'])
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [35]: from sklearn.model_selection import train_test_split
         #splitting data into Train, C.V and Test
         X_train, X_test, y_train, y_test = train_test_split(final ['prepr_rev'], final['Score
         X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33)
         print("Train:",X_train.shape,y_train.shape)
         print("CV:",X_cv.shape,y_cv.shape)
         print("Test:",X_test.shape,y_test.shape)
```

```
Train: (44890,) (44890,)
CV: (22110,) (22110,)
Test: (33000,) (33000,)
```

```
In [36]: vectorizer = CountVectorizer(min_df=10, max_features=500)
         vectorizer.fit(X_train)
         #vectorizer.fit(X_train) # fit has to happen only on train data
         # we use the fitted CountVectorizer to convert the text to vector
         X_train_bow = vectorizer.transform(X_train)
         X_cv_bow = vectorizer.transform(X_cv)
         X_test_bow = vectorizer.transform(X_test)
         print("After vectorizations")
         print(X_train_bow.shape, y_train.shape)
         print(X_cv_bow.shape, y_cv.shape)
         print(X_test_bow.shape, y_test.shape)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

5.2 [4.3] TF-IDF

```
In [37]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
         tf_idf_vect.fit(X_train)
         # we use the fitted CountVectorizer to convert the text to vector
         X_train_tfidf = tf_idf_vect.transform(X_train)
         X_cv_tfidf = tf_idf_vect.transform(X_cv)
```

```
X_test_tfidf = tf_idf_vect.transform(X_test)
print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

5.3 [4.4] Word2Vec

In [38]:
```
# List of sentence in X_train text
sent_of_train=[]
for sent in X_train:
    sent_of_train.append(sent.split())

# List of sentence in X_test text
sent_of_test=[]
for sent in X_test:
    sent_of_test.append(sent.split())

# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)
print(w2v_model.wv.most_similar('great'))
print('='*50)
print(w2v_model.wv.most_similar('worst'))

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

```
[('awesome', 0.8788270950317383), ('good', 0.8186123371124268), ('fantastic', 0.817271828651428
==================================================
[('greatest', 0.7455554008483887), ('best', 0.7162259817123413), ('coolest', 0.683574080467224
number of words that occured minimum 5 times  12927
```

In [39]:
```
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  12927
sample words  ['purchased', 'less', 'expensive', 'alternative', 'tazo', 'passion', 'tea', 'plea
```

5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

```
In [40]: i=0
         sent_of_test_cv=[]
         for sentance in X_cv:
             sent_of_test_cv.append(sentance.split())
```

```
In [41]: # 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(sent_of_test_cv): # 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_cv.append(sent_vec)
         sent_vectors_cv = np.array(sent_vectors_cv)
         print(sent_vectors_cv.shape)
         print(sent_vectors_cv[0])
```

```
100%|| 22110/22110 [00:57<00:00, 384.54it/s]


(22110, 50)
[ 0.19199993 -0.29407681  0.92449721  0.15846253 -0.36790845 -0.26286564
  0.04207576  0.20968506  1.37369584 -1.82506164  0.51702488  0.29793135
 -0.12275548 -0.38225815 -0.11999584 -0.42558273  0.25003184 -1.27453481
 -0.81123311  0.37732364  0.66592627 -0.28213093  0.58667845  0.21038186
 -0.57486579 -0.53712685  0.25060931  0.390779    0.68374295  0.03096677
  0.09322316  0.30294733  1.16590351  0.60147912  0.6491013   0.44650899
  0.6512808  -0.69204267 -0.19216131  0.4625052   1.05057556 -0.03454629
  0.42324315  0.04905395 -0.19583231  0.11350721 -0.15608551 -0.24238636
  0.18510017 -0.02904165]
```

```
In [42]: # compute average word2vec for X_test .
         test_vectors = [];
         for sent in tqdm(sent_of_test):
             sent_vec = np.zeros(50)
             cnt_words =0;
             for word in sent: #
                 if word in w2v_words:
```

```
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        test_vectors.append(sent_vec)

    test_vectors = np.array(test_vectors)

    print(test_vectors.shape)
    print(test_vectors[0])
```

```
100%|| 33000/33000 [01:25<00:00, 335.28it/s]


(33000, 50)
[ 0.08677215 -0.23706726  0.68873633  0.1273033  -0.41815118  0.53121682
 -0.00388464 -0.12524754  0.28712401 -0.23442388  0.3900425  -0.33106879
  0.31176421 -0.43840219 -0.11820709  0.24618783  0.0524349  -0.42876442
  0.09677469  0.0886221   0.905075   -0.00303469  0.91329132 -0.12822156
 -0.37168133 -0.26537812  0.4944671   1.22570266  0.30096825  0.17413199
 -0.16856462  0.85607429  0.45451306  0.40068359 -0.16984371  0.4818911
 -0.03063187  0.1297784   0.32039866  0.12374933  0.4354547  -0.43695882
 -0.34301766  0.04469348 -0.24790298 -1.1890433  -0.52990319 -0.66982248
  0.19505132  0.10374413]
```

```
In [43]: # compute average word2vec for X_train .
    train_vectors = [];
    for sent in tqdm(sent_of_train):
        sent_vec = np.zeros(50)
        cnt_words =0;
        for word in sent: #
            if word in w2v_words:
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        train_vectors.append(sent_vec)

    train_vectors = np.array(train_vectors)

    print(train_vectors.shape)
    print(train_vectors[0])
```

```
100%|| 44890/44890 [01:56<00:00, 384.02it/s]

(44890, 50)
[-0.00468704 -0.26135934  0.53963485 -0.11883838 -0.55703393  1.16081494
```

```
 0.3143321   0.377136    0.61150758 -0.18449253  0.20232891  0.29535889
-0.37260273 -1.00253875  0.01323561  0.06268538  0.16788791 -0.35325816
 0.65363836  0.04015986 -0.18062311 -0.3658476   0.41738255  0.70651884
-0.76683886 -0.55240434 -0.20979986  0.75165505  0.74869671 -0.38610962
-0.07607628  0.21213904 -0.0661008   0.36161974 -0.40895205  0.00461417
 0.61376625 -0.18523529  0.20062299  0.19852224  0.24164803 -0.05915351
-0.07394799 -0.22243072 -0.51935086 -0.58294051 -0.27524277 -1.16664622
-0.08330683  0.39608173]
```

6 [5] Assignment 4: Apply Naive Bayes

```
<li><strong>Apply Multinomial NaiveBayes on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
    </ul>
</li>
<br>
<li><strong>The hyper paramter tuning(find best Alpha)</strong>
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001</l
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Find the top 10 features of positive class and top 10 features of negative class for both i
    </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.

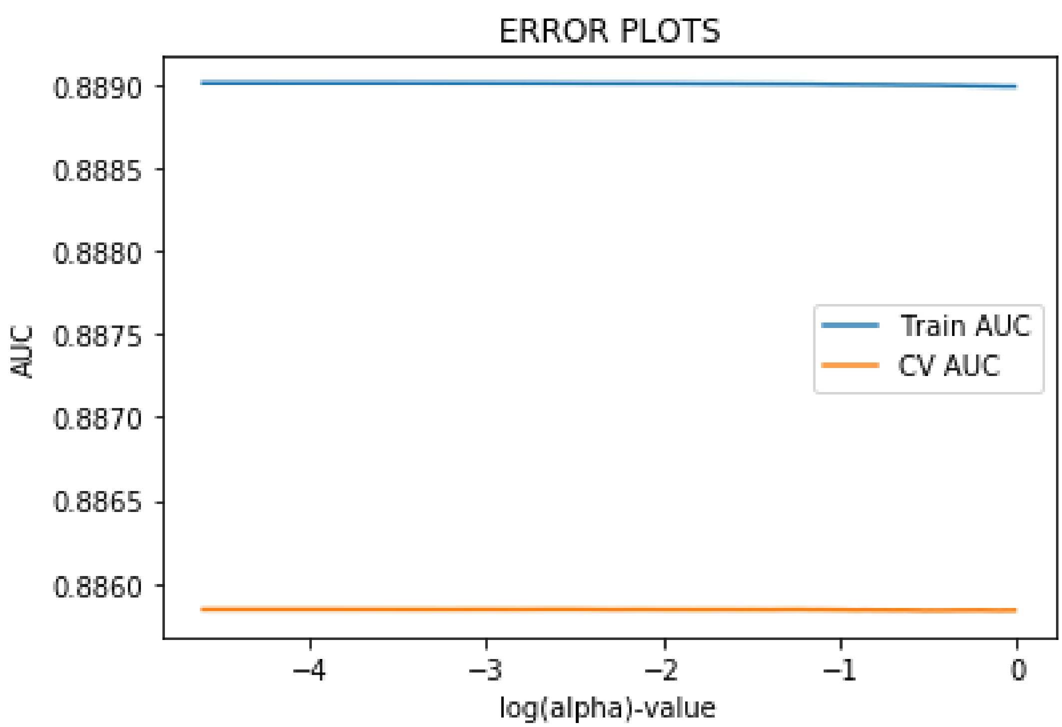
7 Applying Multinomial Naive Bayes

7.0.1 [5.1.1] Applying Naive Bayes on BOW, SET 1

In [45]:
```python
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
from math import log


train_auc = []
cv_auc = []
alpha = np.arange(0.01, 1.0, 0.01)
logalpha = [log(y) for y in alpha]
for i in tqdm(alpha):
    nb = MultinomialNB(alpha=i, class_prior=None, fit_prior=True)
    nb.fit(X_train_bow,y_train)

    y_train_pred =  nb.predict_log_proba(X_train_bow)[:,1]
    y_cv_pred = nb.predict_log_proba(X_cv_bow)[:,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(logalpha, train_auc, label='Train AUC')
        plt.plot(logalpha, cv_auc, label='CV AUC')
        plt.legend()
        plt.xlabel("log(alpha)-value")
        plt.ylabel("AUC")
        plt.title("ERROR PLOTS")
        plt.show()
```

```
100%|| 99/99 [00:06<00:00, 14.90it/s]
```

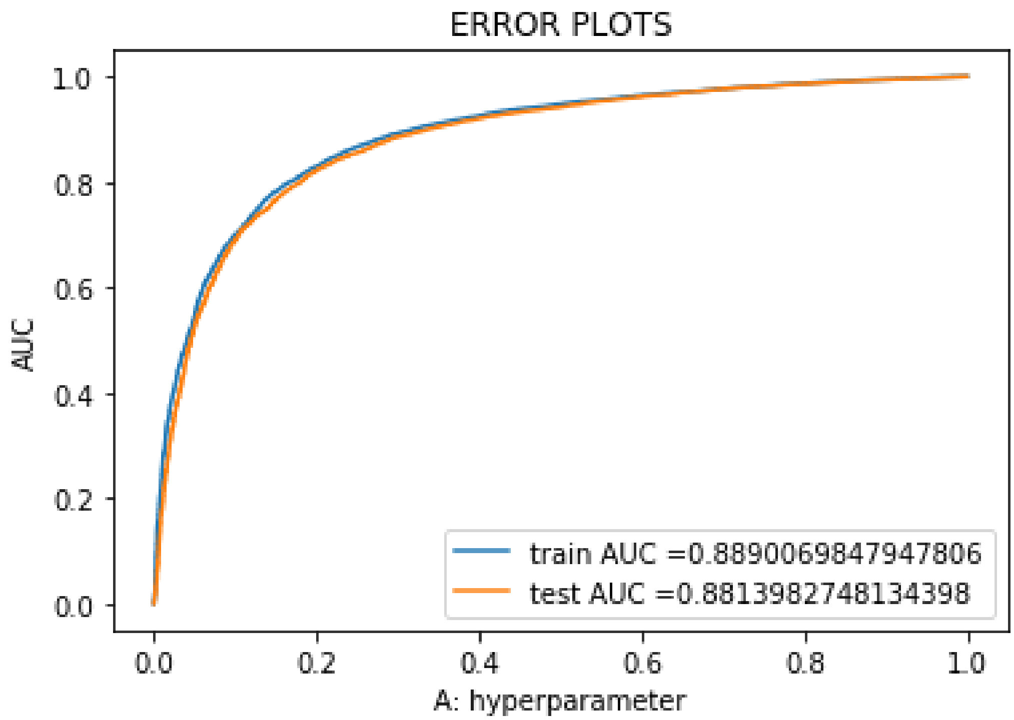


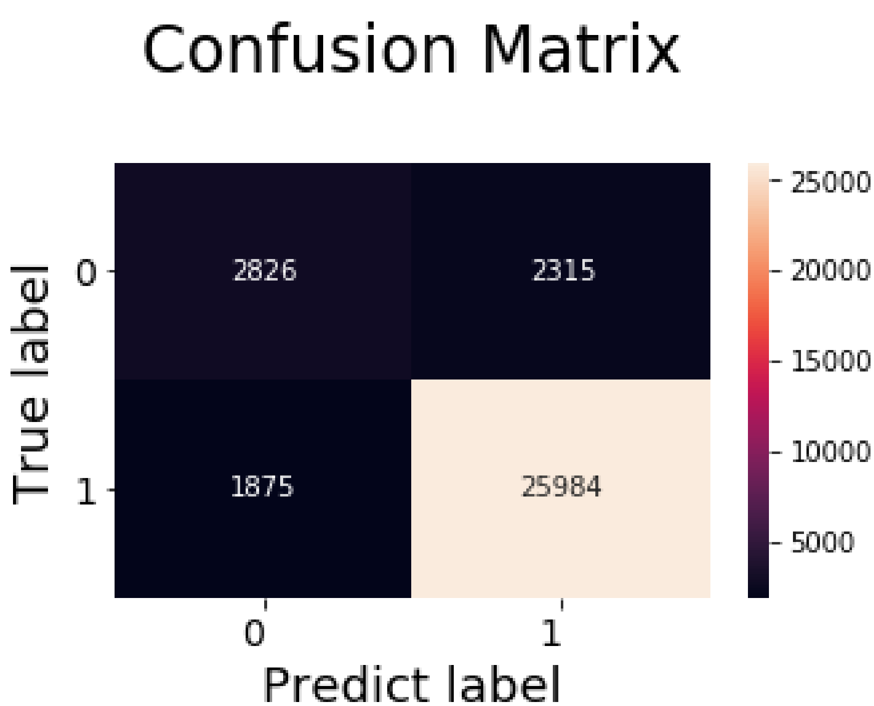
In [47]:
```
opt_auc = alpha[cv_auc.index(max(cv_auc))]
print(opt_auc)
```

```
0.08
```

In [48]:
```
nb = MultinomialNB(alpha=opt_auc, class_prior=None, fit_prior=True)
nb.fit(X_train_bow,y_train)


train_fpr, train_tpr, thresholds = roc_curve(y_train, nb.predict_proba(X_train_bow)[:
```

```
test_fpr, test_tpr, thresholds = roc_curve(y_test, nb.predict_proba(X_test_bow)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("A: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()


#Confusion Matrix

cm = confusion_matrix(y_train, nb.predict(X_train_bow))
cm = confusion_matrix(y_test, nb.predict(X_test_bow))
tn, fp, fn, tp = cm.ravel()
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
# Code for drawing seaborn heatmaps
class_names = ['0','1']
df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
fig = plt.figure(figsize=(5,3))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', 
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
plt.ylabel('True label',size=18)
plt.xlabel('Predict label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```


ERROR PLOTS
1.0
0.8
0.6
0.4
0.2
0.0
AUC
train AUC =0.8890069847947806
test AUC =0.8813982748134398
0.0
0.2
0.4
0.6
0.8
1.0
A: hyperparameter


Confusion Matrix
True label
0
1
2826
2315
1875
25984
0
1
Predict label
25000
20000
15000
10000
5000

7.0.2 [5.1.1] Top 10 important features of positive class from SET 1

In [50]:
```
pos_sorted = nb.feature_log_prob_[1, :].argsort()
print(np.take(vectorizer.get_feature_names(), pos_sorted[-10:]))
```

```
['flavor' 'product' 'love' 'coffee' 'taste' 'one' 'great' 'good' 'like'
 'not']
```

7.0.3 [5.1.2] Top 10 important features of negative class from SET 1

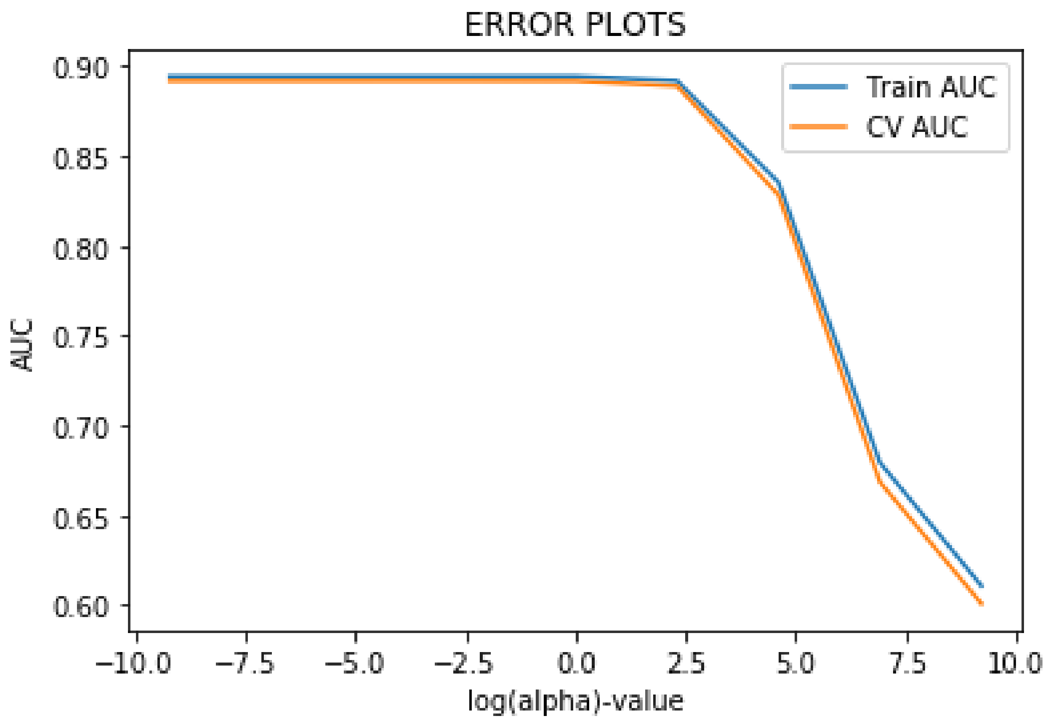
In [51]:
```
# Please write all the code with proper documentation
neg_sorted = nb.feature_log_prob_[0, :].argsort()
print(np.take(vectorizer.get_feature_names(), neg_sorted[-10:]))
```

```
['no' 'flavor' 'good' 'coffee' 'one' 'product' 'taste' 'would' 'like'
 'not']
```

7.1 [5.2] Applying Naive Bayes on TFIDF, SET 2

In [52]:
```
# Please write all the code with proper documentation
from math import log

train_auc = []
cv_auc = []
alpha = [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]
logalpha = [log(y) for y in alpha]
for i in tqdm(alpha):
    nb = MultinomialNB(alpha=i, class_prior=None, fit_prior=True)
    nb.fit(X_train_tfidf, y_train)

    y_train_pred =  nb.predict_log_proba(X_train_tfidf)[:,1]
    y_cv_pred =  nb.predict_log_proba(X_cv_tfidf)[:,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(logalpha, train_auc, label='Train AUC')
plt.plot(logalpha, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha)-value")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

```
100%|| 9/9 [00:00<00:00, 19.22it/s]
```

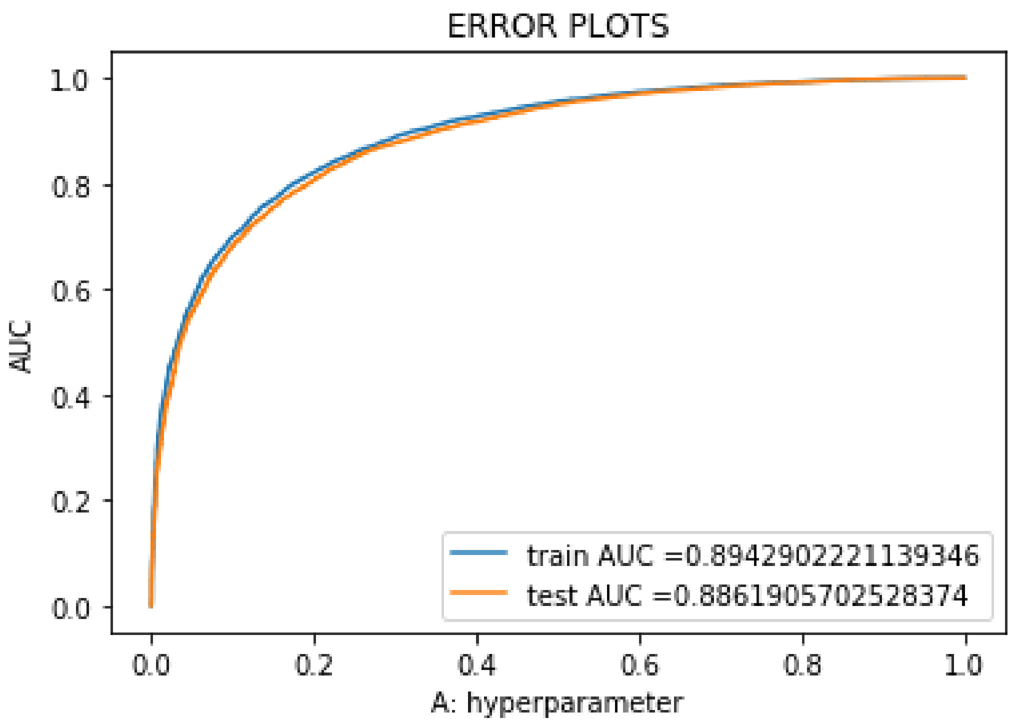


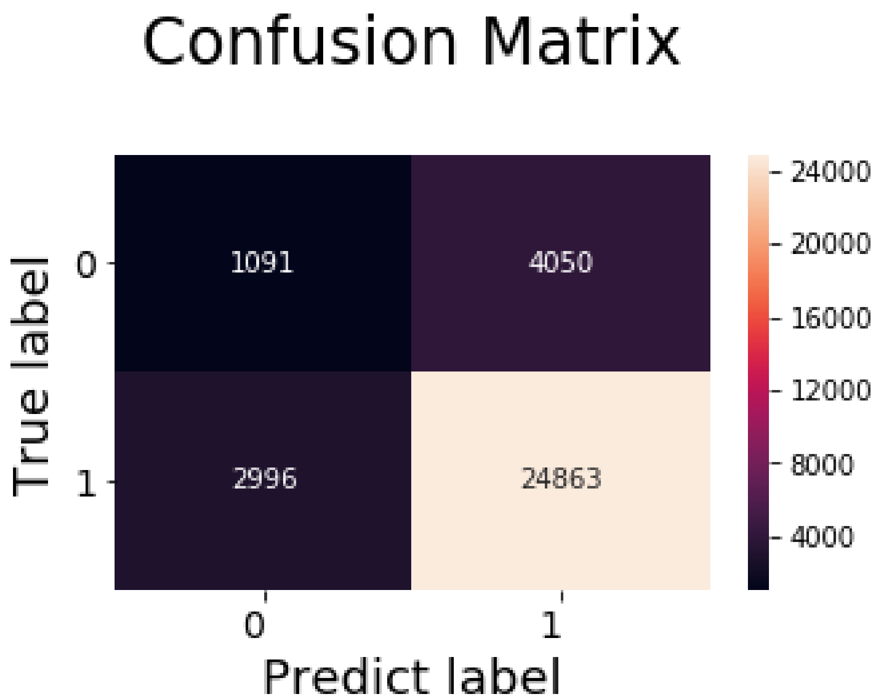
In [53]:
```
best_auc = alpha[cv_auc.index(max(cv_auc))]
print(best_auc)
```

```
0.1
```

In [54]:
```
nb = MultinomialNB(alpha=opt_auc, class_prior=None, fit_prior=True)
nb.fit(X_train_tfidf,y_train)


train_fpr, train_tpr, thresholds = roc_curve(y_train, nb.predict_proba(X_train_tfidf)
test_fpr, test_tpr, thresholds = roc_curve(y_test, nb.predict_proba(X_test_tfidf)[:,1]

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("A: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()


#Confusion Matrix
```

```
cm = confusion_matrix(y_train, nb.predict(X_train_bow))
cm = confusion_matrix(y_test, nb.predict(X_test_bow))
tn, fp, fn, tp = cm.ravel()
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
# Code for drawing seaborn heatmaps
class_names = ['0','1']
df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
fig = plt.figure(figsize=(5,3))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('True label',size=18)
plt.xlabel('Predict label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```





7.1.1 [5.2.1] Top 10 important features of positive class from SET 2

In [56]:
```
pos_sorted = nb.feature_log_prob_[1, :].argsort()
print(np.take(tf_idf_vect.get_feature_names(), pos_sorted[-10:]))
```

```
['taste' 'one' 'product' 'tea' 'love' 'coffee' 'like' 'good' 'great' 'not']
```

7.1.2 [5.2.2] Top 10 important features of negative class from SET 2

In [57]:
```
# Please write all the code with proper documentation

neg_sorted = nb.feature_log_prob_[0, :].argsort()
print(np.take(tf_idf_vect.get_feature_names(), neg_sorted[-10:]))
```

```
['buy' 'flavor' 'no' 'one' 'coffee' 'would' 'taste' 'product' 'like' 'not']
```

8 [6] Conclusions

In [60]:
```
from prettytable import PrettyTable

# Names of models
featurization = ['Bag of Words','TFIDF ','Bag of Words','TFIDF ']
```

```
alpha=[0.8,1,0.8,1]

numbering = [1,2,3,4]
# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",featurization)
ptable.add_column("alpha",alpha)


print(ptable)
```

```
+-------+--------------+-------+
| S.NO. |    MODEL     | alpha |
+-------+--------------+-------+
|   1   | Bag of Words |  0.8  |
|   2   |    TFIDF     |   1   |
|   3   | Bag of Words |  0.8  |
|   4   |    TFIDF     |   1   |
+-------+--------------+-------+
```

9 Summary

9.0.1 1:What I observed firstly is that naive Bayes is faster than the KNN and gives faster and better result.

9.0.2 2: TFIDF and BOW gave more than 85% AUC value.

9.0.3 3: Naive Bayes with Bow model has optimal value of alpha 0.08 where as Naive Bayes with TfIdf model has optimal value of alpha is 1. Vectorization of text optimal value may differ.

10 Note

10.0.1 What I also noticed here is when ever I run the code there is some changes for the percentages of AUC and the values of Alpha.

```
In [ ]:
```