Amazon-Reviews-on-NB_final

March 31, 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 point
# you can change the number to any other number based on your computing power

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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 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                      ProfileName  \
         60400    65655  B00410JCD6  A1B5ULSP1Z2MIY      Brian Edwards "B'More Bri"
         190210  206255  B000GGOBLQ   AUICIB1WWCAQ7               Jukeman "jukeman"
         197612  214180  B000EXA92M  A2JFNQ0A8AFB4K                          jwbems
         25315    27644  B000BF54MS   AXQIHSF9KK7CO                            Dody
         34874    37936  B000F6SNPS   AYRDJVQ3KCCDD  Rebecca M. Abrams "ramblinroz"

                 HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         60400                      2                       2      1  1286841600
         190210                     0                       0      1  1253750400
         197612                     0                       0      0  1331424000
         25315                      0                       0      1  1213142400
         34874                      2                       2      0  1333238400

                                  Summary  \
         60400                  Excellent
         190210                Astounding
         197612  Very low quality chocolate
         25315          Vegetarian Staple
         34874         More on "not natural"

                                                              Text
         60400   Peanuts and roasted red chilli peppers.  Defin...
         190210  The aroma is just incredible, the flavor is gr...
         197612  What a waste of money!!!!!! Based on other cus...
         25315   Here is a product that is so handy.  It is ful...
         34874   I purchased organic Good Earth (at a "whole fo...
```

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]:
```python
# 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)
```

```
Peanuts and roasted red chilli peppers.  Definitely spicy, but not unbearable.  Great flavor.
==================================================
The dark chocolate chips are a perfect match to the light and crunchy granola. This leads to "
==================================================
Fancy Feast is good cat food but it's tricky for me to get the flavor my cat will<br />always
==================================================
Very Natural flavor. Not loaded with sugars and other things not good for you. Has a fresh tas
==================================================
```

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

```
Peanuts and roasted red chilli peppers.  Definitely spicy, but not unbearable.  Great flavor.
```

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

```
Peanuts and roasted red chilli peppers.  Definitely spicy, but not unbearable.  Great flavor.
==================================================
The dark chocolate chips are a perfect match to the light and crunchy granola. This leads to "
==================================================
Fancy Feast is good cat food but it's tricky for me to get the flavor my cat willalways eat si
==================================================
Very Natural flavor. Not loaded with sugars and other things not good for you. Has a fresh tas
```

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)
```

```
Fancy Feast is good cat food but it is tricky for me to get the flavor my cat will<br />always
==================================================
```

```
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)
```

```
Peanuts and roasted red chilli peppers.  Definitely spicy, but not unbearable.  Great flavor.
```

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

```
Fancy Feast is good cat food but it is tricky for me to get the flavor my cat will br always ea
```

```
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', '
                     'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
                     's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
                     've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
                     "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                     "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                     'won', "won't", 'wouldn', "wouldn't"])
```

```
In [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 [00:46<00:00, 2170.31it/s]
```

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

Out[24]:
```
'fancy feast good cat food tricky get flavor cat willalways eat since gorgeous picky i
```

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                      ProfileName  \
60400    65655  B00410JCD6  A1B5ULSP1Z2MIY     Brian Edwards "B'More Bri"
190210  206255  B000GGOBLQ   AUICIB1WWCAQ7              Jukeman "jukeman"
197612  214180  B000EXA92M  A2JFNQ0A8AFB4K                         jwbems
25315    27644  B000BF54MS   AXQIHSF9KK7CO                           Dody
34874    37936  B000F6SNPS   AYRDJVQ3KCCDD  Rebecca M. Abrams "ramblinroz"

        HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
60400                      2                       2      1  1286841600
190210                     0                       0      1  1253750400
197612                     0                       0      0  1331424000
25315                      0                       0      1  1213142400
34874                      2                       2      0  1333238400

                          Summary  \
60400                   Excellent
190210                 Astounding
197612  Very low quality chocolate
25315           Vegetarian Staple
34874        More on "not natural"

                                                     Text  \
60400   Peanuts and roasted red chilli peppers.  Defin...
```

```
190210   The aroma is just incredible, the flavor is gr...
197612   What a waste of money!!!!!! Based on other cus...
25315    Here is a product that is so handy.  It is ful...
34874    I purchased organic Good Earth (at a "whole fo...

                                                  prepr_rev
60400    peanuts roasted red chilli peppers definitely ...
190210   aroma incredible flavor great also using make ...
197612   waste money based customer review gave try bou...
25315    product handy full protein fiber taste highly ...
34874    purchased organic good earth whole foods type ...
```

```
In [27]: 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 pyth
             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())
```

```
 22%|       | 22490/100000 [00:06<00:22, 3497.48it/s]/Volumes/Saida/Applications/Anaconda/anac
  ' Beautiful Soup.' % markup)
100%|| 100000/100000 [00:29<00:00, 3338.23it/s]
```

```
In [28]: prepr_rev = [i + ' ' + j for i, j in zip(prepr_rev,preprocessed_summary)]
         print(prepr_rev[1500])
```

```
fancy feast good cat food tricky get flavor cat willalways eat since gorgeous picky female bran
```

```
In [29]: X = np.array(prepr_rev)
         y = np.array(final['Score'])
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [30]: 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 [31]: 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 [32]: 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 [33]: # 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', 0.8455944657325745), ('fantastic', 0.8240172266960144), ('good', 0.80797564983367
==================================================
[('greatest', 0.7693896293640137), ('tastiest', 0.7564027309417725), ('best', 0.74852371215820
number of words that occured minimum 5 times  13042
```

```
In [34]: 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  13042
sample words  ['baby', 'not', 'like', 'proteins', 'containing', 'meat', 'flavor', 'big', 'hit'
```

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

[4.4.1.1] Avg W2v

```
In [35]: i=0
         sent_of_test_cv=[]
         for sentance in X_cv:
             sent_of_test_cv.append(sentance.split())
```

```
In [36]: # 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 [00:53<00:00, 413.84it/s]

(22110, 50)
[-0.50523017 -0.11479854 -0.03200787  0.13353468  0.13596142  0.50285689
  0.40782288 -0.59033072  0.11434755  0.51528694  0.1910308   0.73593499
 -0.38575987  0.7417411  -0.04513764  0.22732463 -0.73386303  0.31745143
 -0.64847784 -0.05479136 -0.4631531   0.33003085 -0.66081223 -0.30726053
  0.07974474  0.95825225  0.05713817 -0.16710636  0.64184181  0.41067642
  0.26957263 -0.59078255  0.83191122 -0.32974229 -0.8801244  -0.64844684
  0.02139316 -0.54254419 -0.02060822 -0.25215706 -0.51701852 -0.54127047
 -0.44874072 -0.17757444  0.11975331 -0.34313597  0.21253911  0.01452104
 -0.38813811  0.8206042 ]
```

```
In [37]: # 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 [01:23<00:00, 393.54it/s]

(33000, 50)
[ 0.01376235  0.28893085  0.03941018 -0.58727319 -0.83308503 -0.08106945
 -0.14920961 -0.14446366 -0.57953979 -0.41207326 -0.65595679  0.15573724
```

```
 -0.36329756  0.67266244  0.07016691  0.25953635 -0.406169    0.14319636
 -0.05551508  0.59413541 -0.18034051  0.23919755 -0.58935891 -0.18026038
  0.61633672  0.68402586 -0.15522986  0.23427888  0.52708331 -0.18574332
  0.49454857 -0.34103861  0.66434252 -0.65074359 -0.75230302  0.21625035
 -0.19442735 -0.77172362 -0.1656153  -0.28547813 -0.94779993 -0.13478697
 -0.29403704  0.02966803  0.12511257 -0.07849445  0.58964748 -0.47299296
  0.1422585  -0.39882051]
```

In [38]:
```
# 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 [01:50<00:00, 405.59it/s]

(44890, 50)
[-0.13721478  0.08010389 -0.15564712  0.73888799  0.27517669  0.62704756
  0.22560687 -0.5688567  -0.02041555  0.28398134 -0.2877662  -0.0728872
  0.31543689 -0.30603457  0.81506797  0.24122786 -0.26859527 -0.13208472
 -0.47742535  0.35914314  0.24498541 -0.30386619 -0.29857029  0.35966692
  0.36598904  0.53495216  0.0058044   0.28305701  0.37508121  0.44433947
  0.95063118  0.00493663  1.21274136 -0.92643568  0.72681641 -0.44839512
 -0.55025943 -0.47290625 -0.80632758 -0.06141111  0.04634775 -0.56206447
 -0.72001188 -0.44774448  0.31360364 -0.05130844  0.78579321  0.24604547
 -0.67943466 -0.5778594 ]
```

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>

Note: Data Leakage

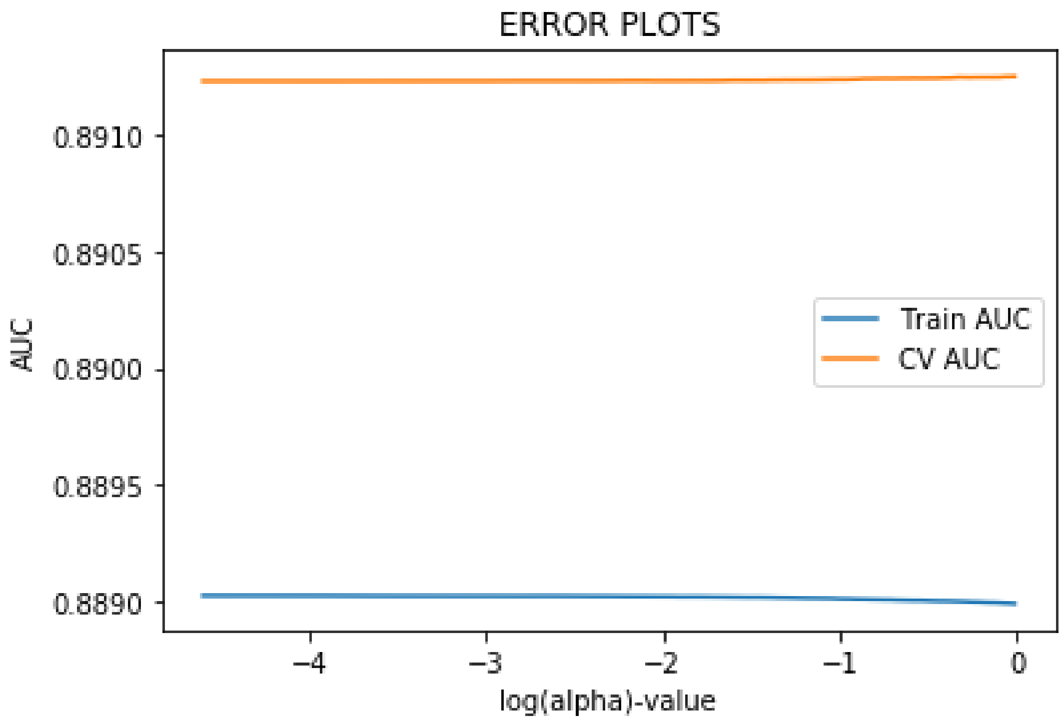
1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply 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 [39]: 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 [00:05<00:00, 17.69it/s]
```

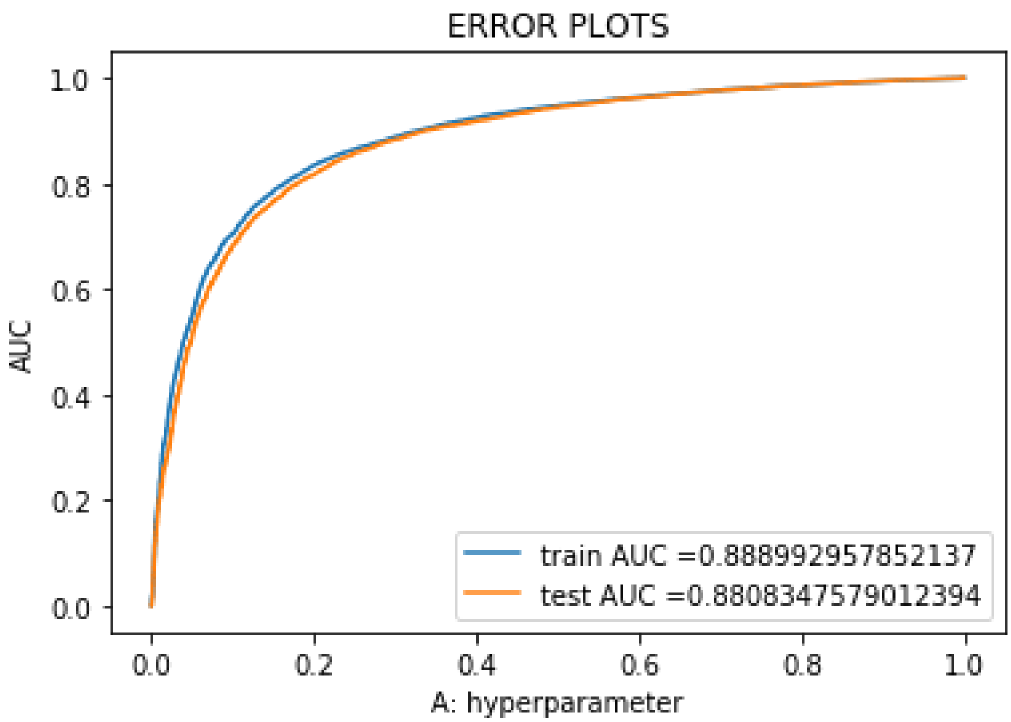


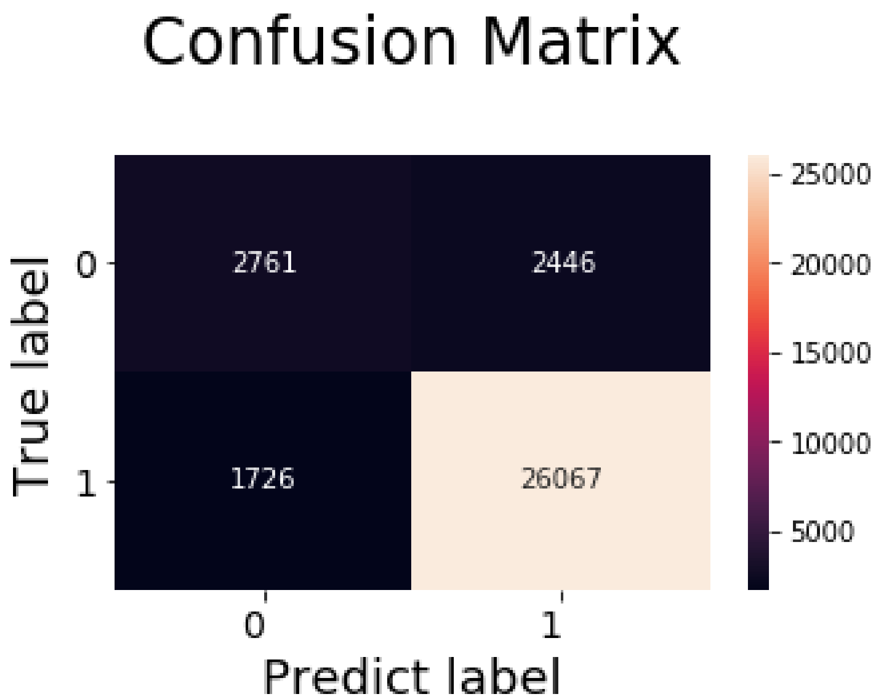

```
In [40]: opt_auc = alpha[cv_auc.index(max(cv_auc))]
         print(opt_auc)
```

0.99

```
In [41]: 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()
```





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

In [42]:
```
pos_sorted = nb.feature_log_prob_[1, :].argsort()
print(np.take(vectorizer.get_feature_names(), pos_sorted[-10:]))
```

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

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

In [43]:
```
# 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:]))
```

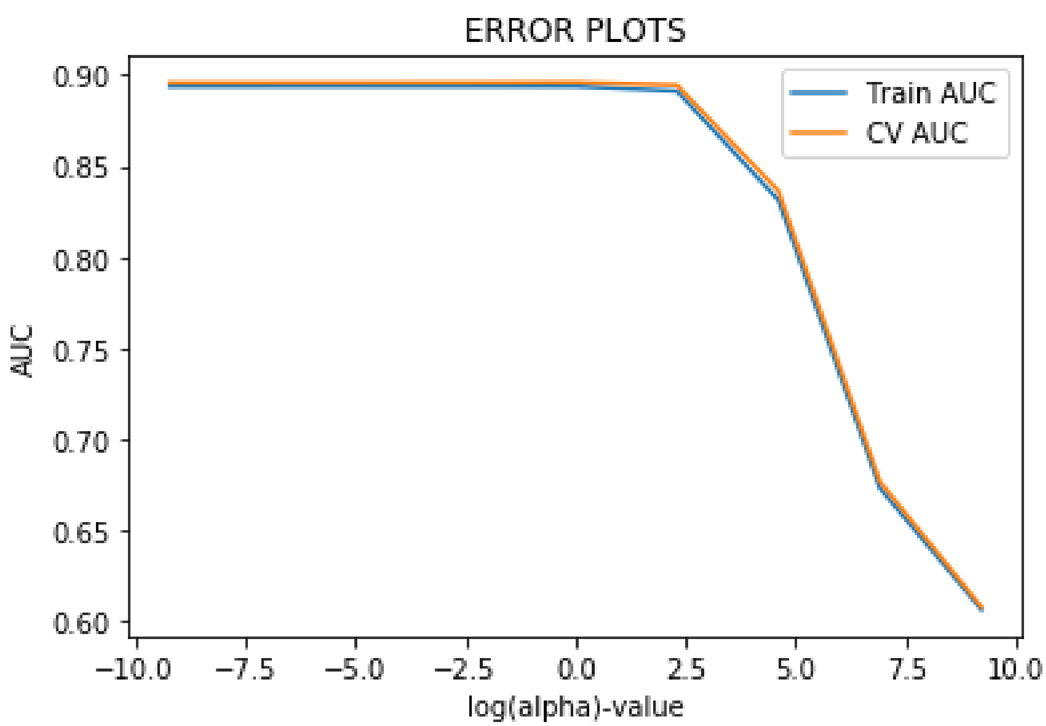
```
['no' 'flavor' 'good' 'coffee' 'one' 'product' 'would' 'taste' 'like'
 'not']
```

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

In [44]:
```
# 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()
```

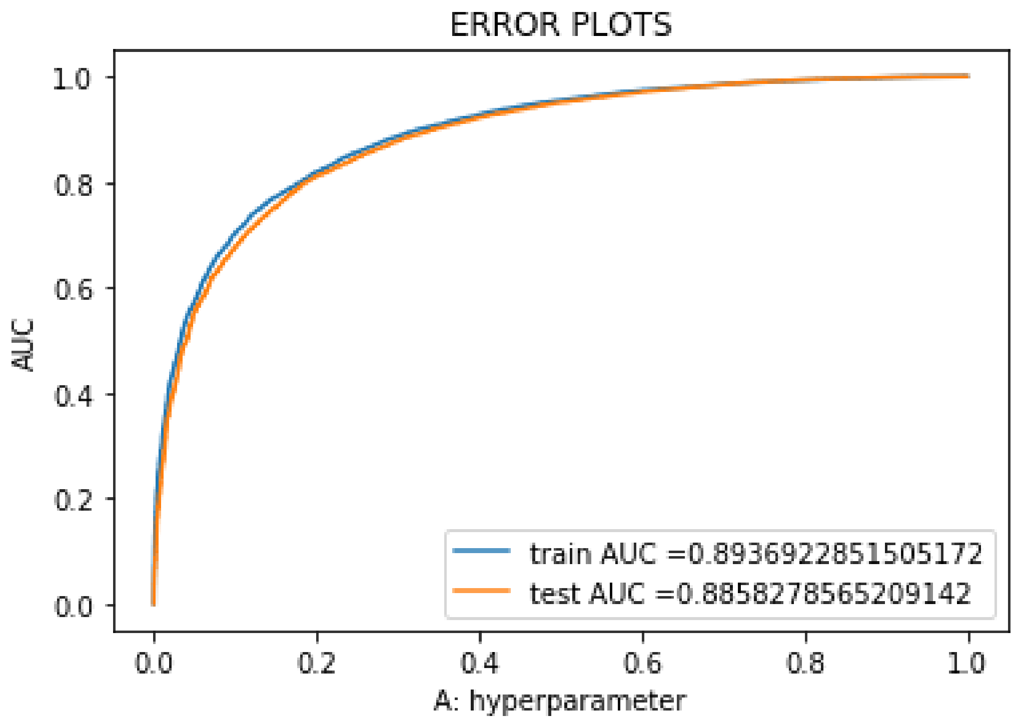
```
100%|| 9/9 [00:00<00:00, 21.03it/s]
```

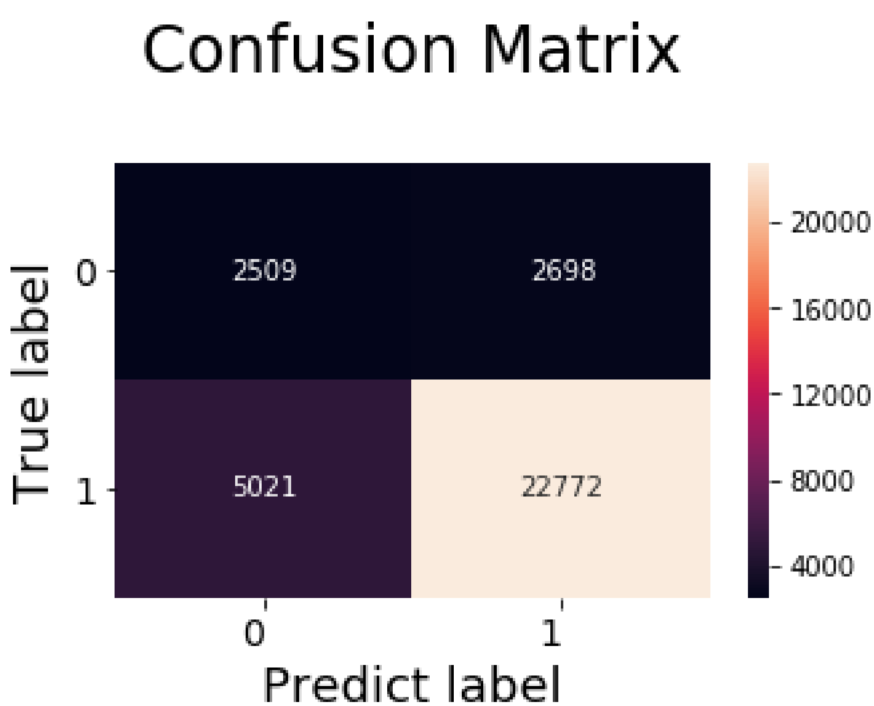


In [48]:
```
best_auc = alpha[cv_auc.index(max(cv_auc))]
print(best_auc)
```

1

In [49]:
```
nb = MultinomialNB(alpha=best_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',
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
0.0
0.2
0.4
0.6
0.8
1.0
A: hyperparameter
train AUC =0.8936922851505172
test AUC =0.8858278565209142


Confusion Matrix
2509
2698
5021
22772
0
1
True label
0
1
Predict label
20000
16000
12000
8000
4000

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

In [50]:
```
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 [51]:
```
# 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:]))
```

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

8 [6] Conclusions

In [53]:
```
from prettytable import PrettyTable

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


alpha=[0.99,1,0.99,1]

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 |  0.99 |
|   2   |    TFIDF     |   1   |
|   3   | Bag of Words |  0.99 |
|   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 0.99 where as Naive Bayes with TfIdf model has optimal value of alpha is 1. Vectorization of text optimal value may differ.