04 Amazon Fine Food Reviews Analysis_NaiveBayes

June 14, 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 [86]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os

from bs4 import BeautifulSoup
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from prettytable import PrettyTable
import math
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

```
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 100

        # 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 (100000, 10)
```

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

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

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

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

```
        GROUP BY UserId
        HAVING COUNT(*)>1
        """, con)
```

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

```
(80668, 7)
```

```
Out[4]:                UserId   ProductId             ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
        3  #oc-R1105J5ZVQE25C  B005HG9ET0           Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B007OSBE1U   Christopher P. Presta  1348617600      1

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

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

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

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

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

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

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

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

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

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

   HelpfulnessDenominator  Score        Time  \
0                       2      5  1199577600
1                       2      5  1199577600
2                       2      5  1199577600

                              Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  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 ...
```

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]: (87775, 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]: 87.775

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()
```

```
(87773, 10)
```

```
Out[13]: 1    73592
         0    14181
         Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

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

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

1. Begin by removing the html tags

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

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

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

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

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

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

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

```
In [0]: # remove urls from text python: https://stackoverflow.com/a/40823105/4084039
        sent_0 = re.sub(r"http\S+", "", sent_0)
        sent_1000 = re.sub(r"http\S+", "", sent_1000)
        sent_150 = re.sub(r"http\S+", "", sent_1500)
        sent_4900 = re.sub(r"http\S+", "", sent_4900)

        print(sent_0)
```

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

```
In [0]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-
        # from bs4 import BeautifulSoup
```

```
soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

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

In [14]:
```
# 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 [0]:
```
sent_1500 = decontracted(sent_1500)
```

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

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

```
In [0]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
        sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
        print(sent_0)
```

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

```
In [0]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
        sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
        print(sent_1500)
```

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

```
In [15]: # 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 [16]: # Combining all the above stundents
         from tqdm import tqdm
         preprocessed_reviews = []
         # tqdm is for printing the status bar
         for sentance in tqdm(final['Text'].values):
             sentance = re.sub(r"http\S+", "", sentance)
```

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

```
100%|| 87773/87773 [00:35<00:00, 2469.01it/s]
```

```
In [17]: preprocessed_reviews[1500]
```

```
Out[17]: 'way hot blood took bite jig lol'
```

5 [4] Splitting the Data

Before splitting the data in train, cross validation and test , we put all the pre processed reviews in x and corresponding class labels into y.

```
In [18]: x = preprocessed_reviews
         y = final["Score"].values
```

Splitting the data as train data, cross validation data and test data

```
In [19]: # splitting the data into 3 parts for furhter process,
         # train data, cross validation data and test data

         x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30)         # t
         x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.30) # t
```

```
In [20]: # number of rows in earch data set, train, cross validation and test data respectivel
         print(len(x_train))
         print(len(x_cv))
         print(len(x_test))
```

```
43008
18433
26332
```

6 [5] Featurization

6.1 [5.1] BAG OF WORDS

```
In [24]: # BoW using scikit-learn
```

```
count_vect = CountVectorizer(min_df=10, max_features=10000)
count_vect.fit(x_train)

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

# we use the fitted CountVectorizer to convert the text to vector
x_train_bow = count_vect.transform(x_train)
x_cv_bow    = count_vect.transform(x_cv)
x_test_bow  = count_vect.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)
```

```
some feature names  ['ability', 'able', 'absence', 'absent', 'absolute', 'absolutely', 'absolu
==================================================
After vectorizations
(43008, 8076) (43008,)
(18433, 8076) (18433,)
(26332, 8076) (26332,)
```

6.2 [5.2] TF-IDF

In [23]:
```
# TFIDF using scikit-learn

tf_idf_vect = TfidfVectorizer(min_df=10, max_features=10000)               #in scikit
tf_idf_vect.fit(x_train)

print("some sample features",tf_idf_vect.get_feature_names()[0:10])
print('='*50)

# we use fit() method to learn the vocabulary from x_train
# and now transform text data to vectors using transform() method

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 featurization\n")

print(x_train_tfidf.shape, y_train.shape)
print(x_cv_tfidf.shape, y_cv.shape)
print(x_test_tfidf.shape, y_test.shape)
```

```
some sample features ['ability', 'able', 'absence', 'absent', 'absolute', 'absolutely', 'absolu
```

```
==================================================
After featurization

(43008, 8076) (43008,)
(18433, 8076) (18433,)
(26332, 8076) (26332,)
```

7 [6] 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.appliedaico
<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 f
    </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.

8 Applying Multinomial Naive Bayes

8.1 [6.1] Applying Naive Bayes on BOW, SET 1

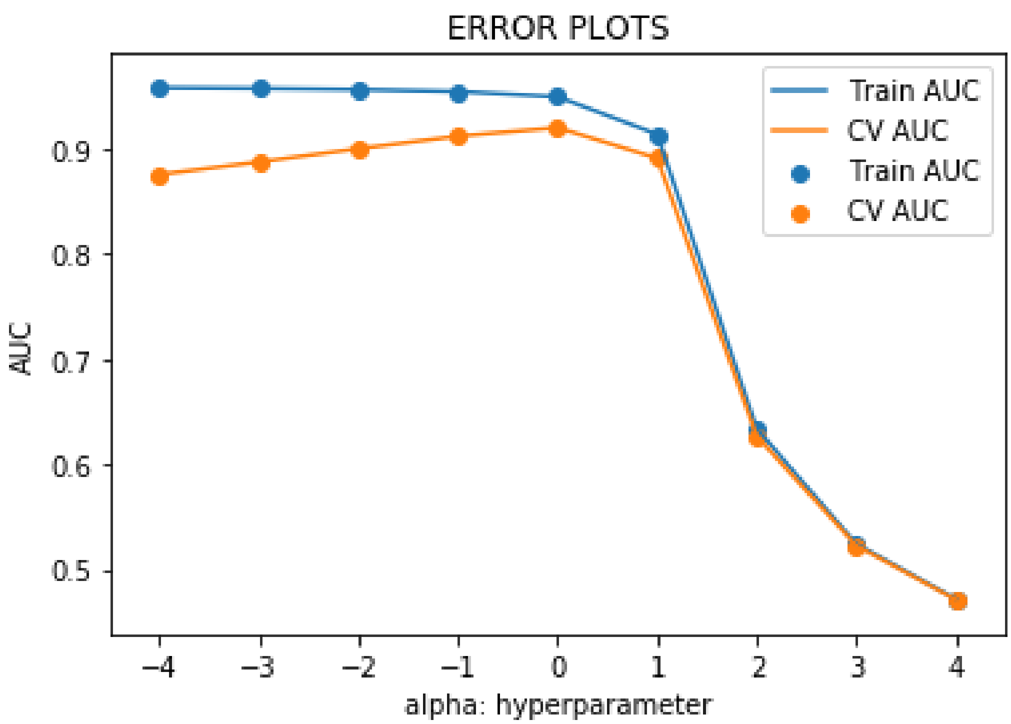
So let's find a best value for our hyperparameter here using GridSearch hyperparameter tuning.

```
In [44]: lg_alp = []
         alpha = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

         for i in alpha :
             lg_alp.append(math.log10(i))

         print(lg_alp)
```

```
[-4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]
```

```
In [40]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearc

         parameters = {'alpha':[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]}
         nb = MultinomialNB()

         grid = GridSearchCV(nb, parameters, cv=4, scoring='roc_auc', n_jobs=-1)
         grid.fit(x_train_bow, y_train)

         train_auc_bow      = grid.cv_results_['mean_train_score']
         cv_auc_bow         = grid.cv_results_['mean_test_score']
```

```
plt.plot(lg_alp, train_auc_bow, label='Train AUC')
plt.scatter(lg_alp, train_auc_bow, label='Train AUC')

plt.plot(lg_alp, cv_auc_bow, label='CV AUC')
plt.scatter(lg_alp, cv_auc_bow, label='CV AUC')

plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
print("Model with best parameters :\n",grid.best_estimator_)
```

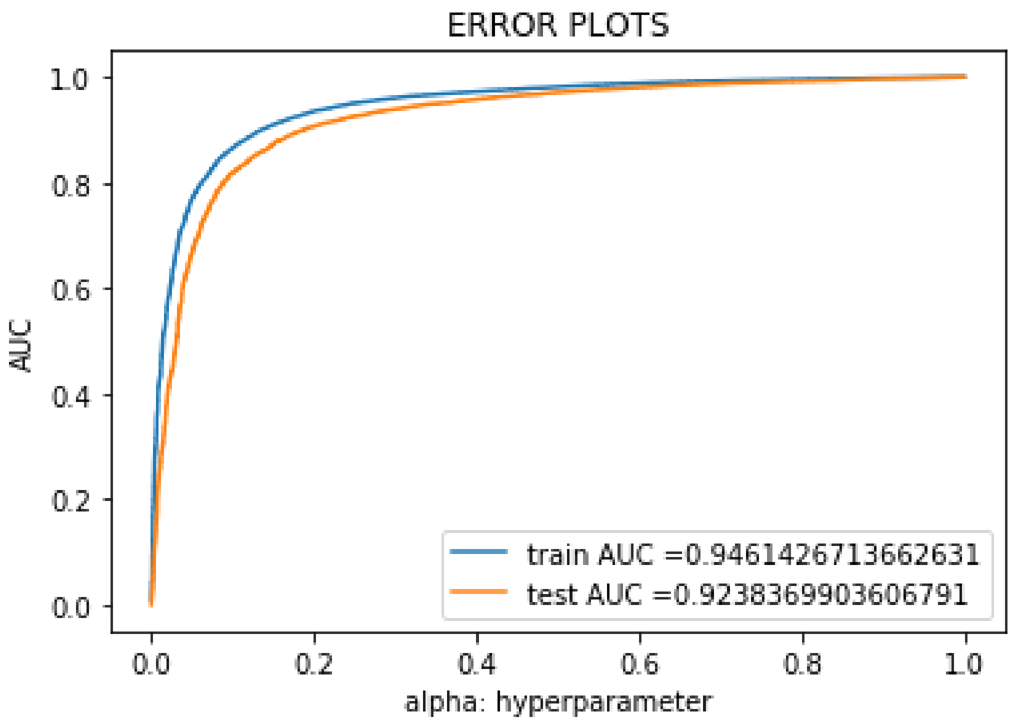



```
Model with best parameters :
 MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [41]:
```
best_alpha = 1
```

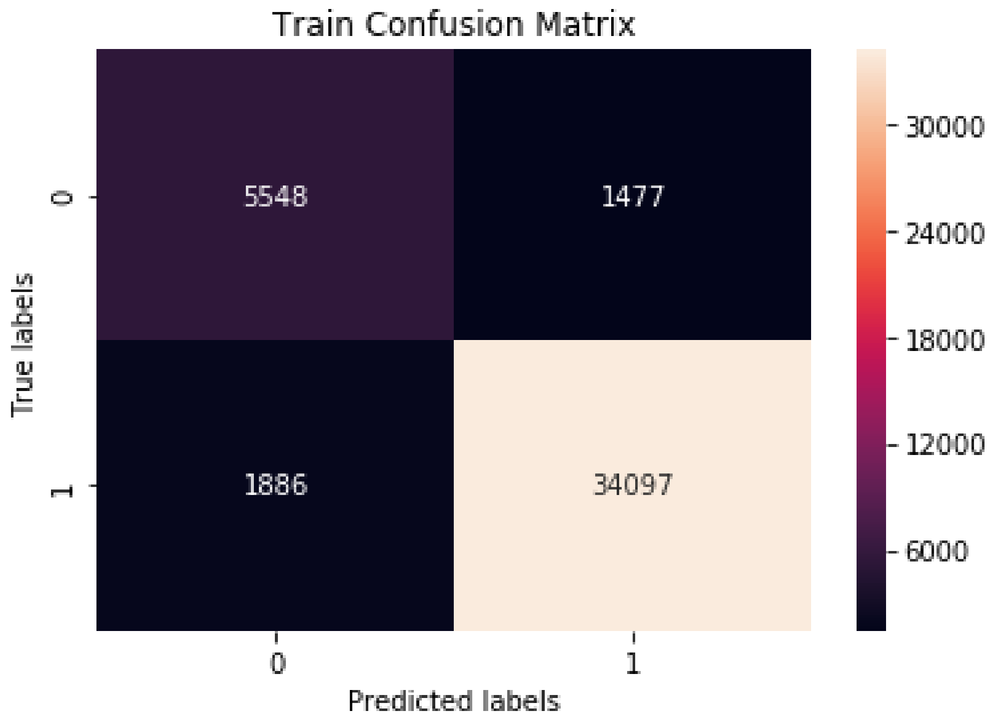
In [77]:
```
nb = MultinomialNB(alpha = best_alpha)
nb.fit(x_train_bow, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
```

```
# not the predicted outputs

train_fpr_bow, train_tpr_bow, thresholds_bow = roc_curve(y_train, nb.predict_proba(x_t
test_fpr_bow, test_tpr_bow, thresholds_bow = roc_curve(y_test, nb.predict_proba(x_tes

plt.plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, trai
plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tpr
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



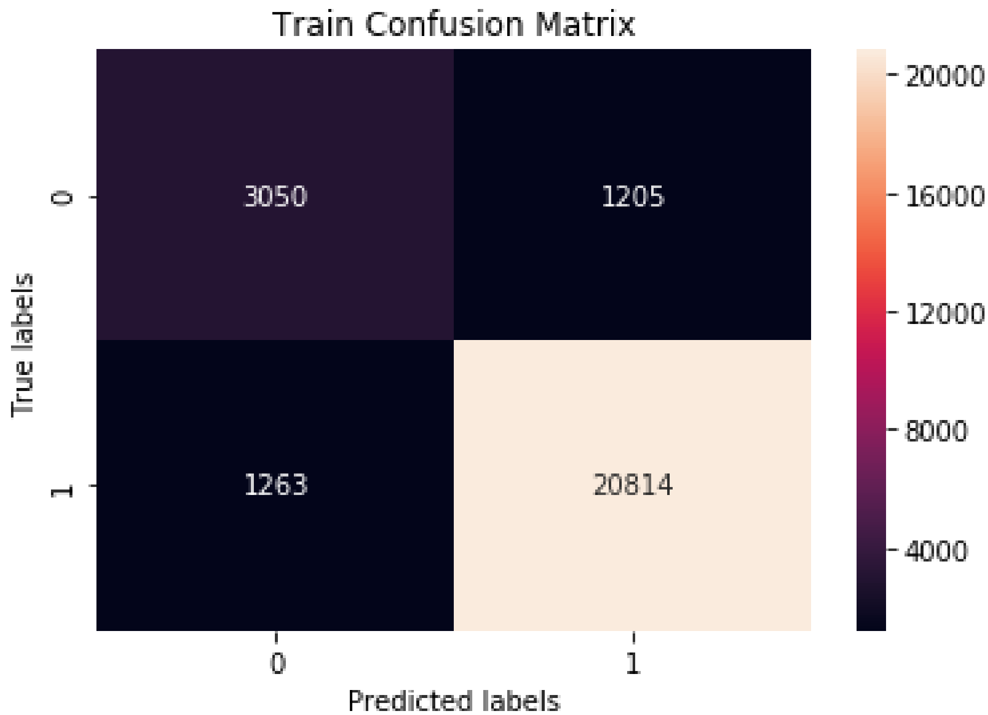

```
In [120]: print("Train Confusion Matrix")
          cm_tr = confusion_matrix(y_train, grid.predict(x_train_bow))
          sns.heatmap(cm_tr, annot=True, fmt= 'd') # annot=True to annotate cells

          # labels, title and ticks
          plt.xlabel('Predicted labels')
          plt.ylabel('True labels')
          plt.title('Train Confusion Matrix')
          plt.show()
```

```
Train Confusion Matrix
```




```
In [121]: print("Test Confusion Matrix")
          cm_te = confusion_matrix(y_test, grid.predict(x_test_bow))
          sns.heatmap(cm_te, annot=True, fmt='g')

          # labels, title and ticks
          plt.xlabel('Predicted labels')
          plt.ylabel('True labels')
          plt.title('Train Confusion Matrix')
          plt.show()
```

```
Test Confusion Matrix
```



8.1.1 [6.1.1] Top 10 important features of positive class from SET 1

In [82]:
```
nb.classes_
```

Out[82]:
```
array([0, 1], dtype=int64)
```

In [83]:
```
# Now we can find log probabilities of different features for both the classes
class_features = nb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

# Getting all feature names
feature_names = count_vect.get_feature_names()

# Sorting 'negative_features' and 'positive_features' in descending order using argso
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("\n\nTop 10 Important Features and their log probabilities For Positive Class :
for i in list(sorted_positive_features[0:10]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 10 Important Features and their log probabilities For Positive Class :


not          -->         -3.679396
like          -->         -4.480949
good          -->         -4.621951
great          -->         -4.676597
one          -->         -4.832851
taste          -->         -4.916672
coffee          -->         -4.930744
flavor          -->         -5.005918
would          -->         -5.020401
love          -->         -5.028871
```

8.1.2 [6.1.2] Top 10 important features of negative class from SET 1

```
In [84]: print("Top 10 Important Features and their log probabilities For Negative Class :\n\n
         for i in list(sorted_negative_features[0:10]):
             print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))
```

```
Top 10 Important Features and their log probabilities For Negative Class :


not          -->         -3.235728
like          -->         -4.350658
would          -->         -4.637823
taste          -->         -4.649252
product          -->         -4.691221
one          -->         -4.871003
good          -->         -5.062585
coffee          -->         -5.081188
flavor          -->         -5.137463
no          -->         -5.181554
```

```
In [114]: # evaluating train: accuracy, precison, recall and f1_score

          predictions = nb.predict(x_train_bow)

          acc_tr = accuracy_score(y_train, predictions)
          print('Accuracy score: ', acc_tr)

          pre_tr = precision_score(y_train, predictions)
          print('Precision score: ', pre_tr)
```

```
rec_tr = recall_score(y_train, predictions)
print('Recall score: ', rec_tr)

f1_tr = f1_score(y_train, predictions)
print('F1 score: ', f1_tr)
```

```
Accuracy score:  0.9190150669642857
Precision score:  0.9578238575533893
Recall score:  0.9448072700997693
F1 score:  0.9512710382360758
```

```
In [113]: # evaluating test: accuracy, precision, recall and f1_score
          predictions = nb.predict(x_test_bow)

          acc_te = accuracy_score(y_test, predictions)
          print('Accuracy score: ', acc_te)

          pre_te = precision_score(y_test, predictions)
          print('Precision score: ', pre_te)

          rec_te = recall_score(y_test, predictions)
          print('Recall score: ', rec_te)

          f1_te = f1_score(y_test, predictions)
          print('F1 score: ', f1_te)
```

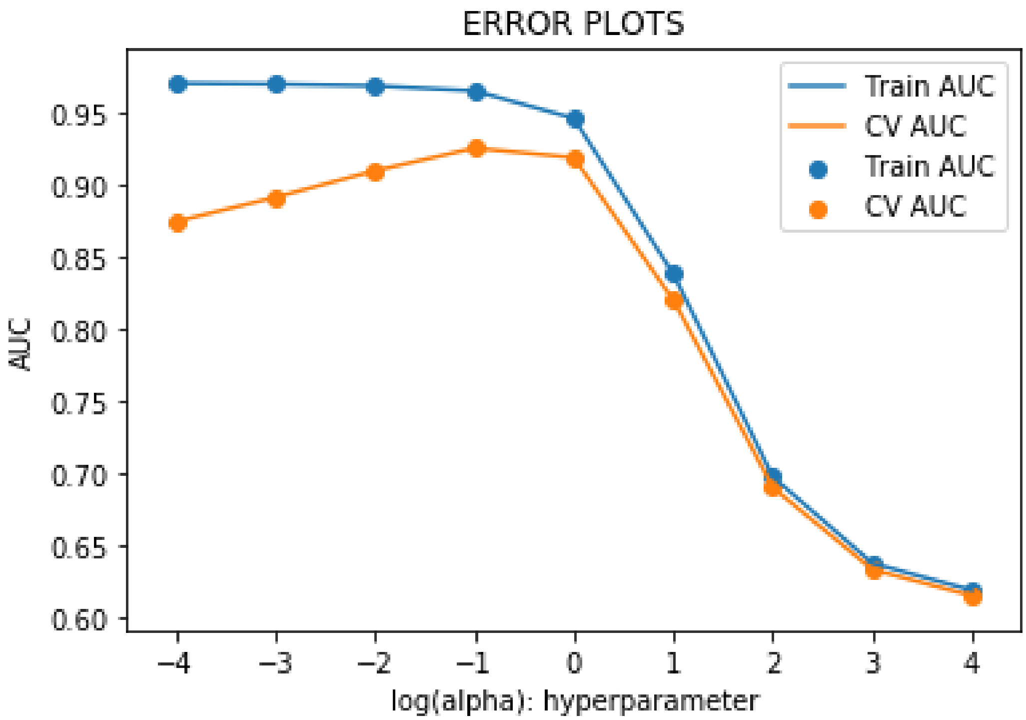
```
Accuracy score:  0.9011089169071852
Precision score:  0.9430716723549488
Recall score:  0.9387144992526159
F1 score:  0.9408880414056116
```

8.2 [6.2] Applying Naive Bayes on TFIDF, SET 2

Hyperparameter tuning using grid search

```
In [93]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearc

         nb = MultinomialNB()
         parameters = {'alpha':[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]}
         grid = GridSearchCV(nb, parameters, cv=3, scoring='roc_auc', n_jobs=-1)
         grid.fit(x_train_tfidf, y_train)

         train_auc_tfidf      = grid.cv_results_['mean_train_score']
         cv_auc_tfidf         = grid.cv_results_['mean_test_score']

         plt.plot(lg_alp, train_auc_tfidf, label='Train AUC')
```

```
plt.scatter(lg_alp, train_auc_tfidf, label='Train AUC')

plt.plot(lg_alp, cv_auc_tfidf, label='CV AUC')
plt.scatter(lg_alp, cv_auc_tfidf, label='CV AUC')

plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
print("Model with best parameters :\n",grid.best_estimator_)
```

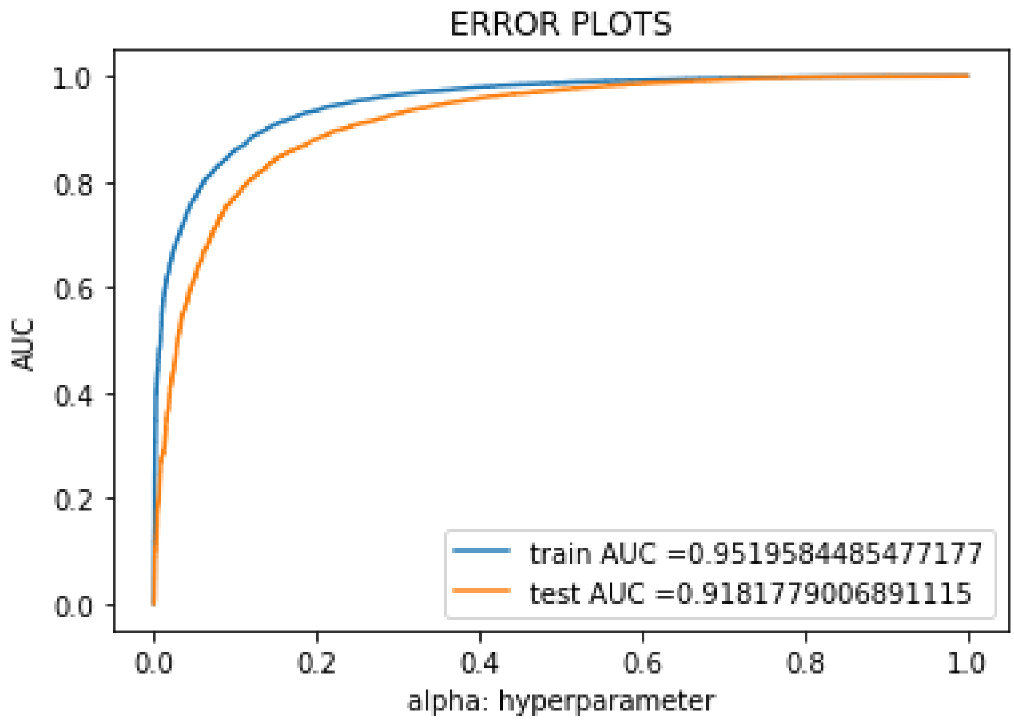



```
Model with best parameters :
 MultinomialNB(alpha=0.1, class_prior=None, fit_prior=True)
```

In [94]:
```
best_alpha_tfidf = 0.1
```

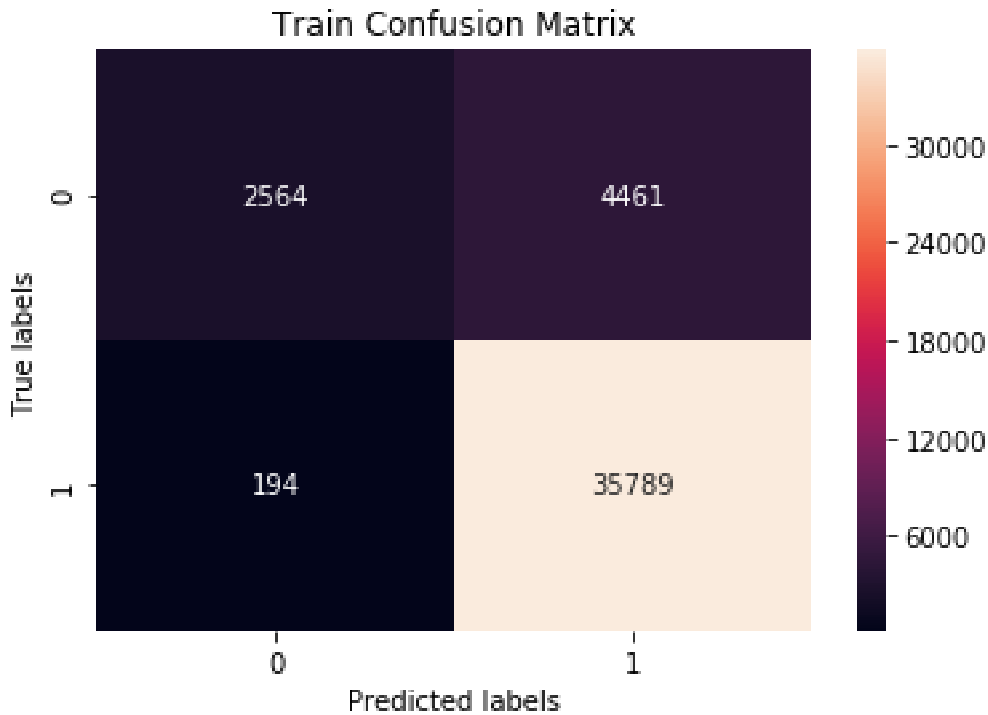
In [96]:
```
nb = MultinomialNB(alpha = best_alpha_tfidf)
nb.fit(x_train_bow, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
# not the predicted outputs

train_fpr_tfidf, train_tpr_tfidf, thresholds_tfidf = roc_curve(y_train, nb.predict_pro
```

```
test_fpr_tfidf, test_tpr_tfidf, thresholds_tfidf = roc_curve(y_test, nb.predict_proba

plt.plot(train_fpr_tfidf, train_tpr_tfidf, label="train AUC ="+str(auc(train_fpr_tfid
plt.plot(test_fpr_tfidf, test_tpr_tfidf, label="test AUC ="+str(auc(test_fpr_tfidf, te
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



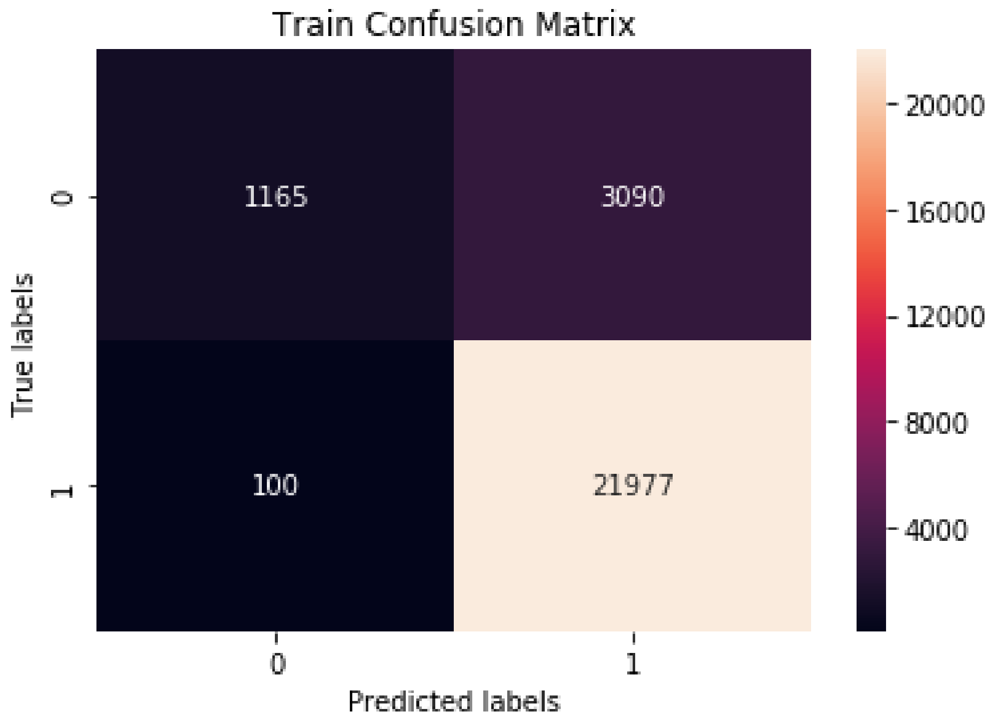

```
In [117]: print("Train Confusion Matrix")
          cm_tr = confusion_matrix(y_train, grid.predict(x_train_tfidf))
          sns.heatmap(cm_tr, annot=True, fmt= 'd') # annot=True to annotate cells

          # labels, title and ticks
          plt.xlabel('Predicted labels')
          plt.ylabel('True labels')
          plt.title('Train Confusion Matrix')
          plt.show()
```

```
Train Confusion Matrix
```



In [122]:
```
print("Train Confusion Matrix")
cm_te = confusion_matrix(y_test, grid.predict(x_test_tfidf))
sns.heatmap(cm_te, annot=True, fmt= 'd') # annot=True to annotate cells

# labels, title and ticks
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Train Confusion Matrix')
plt.show()
```

```
Train Confusion Matrix
```



8.2.1 [6.2.1] Top 10 important features of positive class from SET 2

```
In [ ]: # https://github.com/PushpendraSinghChauhan/Amazon-Fine-Food-Reviews/blob/master/Apply

In [97]: nb.classes_

Out[97]: array([0, 1], dtype=int64)

In [98]: # Now we can find log probabilities of different features for both the classes
         class_features = nb.feature_log_prob_

         #  row_0 is for 'negative' class and row_1 is for 'positive' class
         negative_features = class_features[0]
         positive_features = class_features[1]

         # Getting all feature names
         feature_names = tf_idf_vect.get_feature_names()

         # Sorting 'negative_features' and 'positive_features' in descending order using argso
         sorted_negative_features = np.argsort(negative_features)[::-1]
         sorted_positive_features = np.argsort(positive_features)[::-1]

In [99]: print("\n\nTop 10 Important Features and their log probabilities For Positive Class :
         for i in list(sorted_positive_features[0:10]):
             print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 10 Important Features and their log probabilities For Positive Class :


not          -->         -3.673939
like          -->         -4.475525
good          -->         -4.616536
great          -->         -4.671185
one          -->         -4.827452
taste          -->         -4.911280
coffee          -->         -4.925353
flavor          -->         -5.000535
would          -->         -5.015020
love          -->         -5.023491
```

8.2.2 [6.2.2] Top 10 important features of negative class from SET 2

```
In [100]: print("Top 10 Important Features and their log probabilities For Negative Class :\n\n
          for i in list(sorted_negative_features[0:10]):
              print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))
```

```
Top 10 Important Features and their log probabilities For Negative Class :


not          -->         -3.211281
like          -->         -4.326367
would          -->         -4.613610
taste          -->         -4.625042
product          -->         -4.667025
one          -->         -4.846872
good          -->         -5.038536
coffee          -->         -5.057148
flavor          -->         -5.113451
no          -->         -5.157564
```

```
In [111]: # evaluating train: accuracy, precison, recall and f1_score

          predictions1 = nb.predict(x_train_tfidf)

          acc_tr1 = accuracy_score(y_train, predictions1)
          print('Accuracy score: ', acc_tr1)

          pre_tr1 = precision_score(y_train, predictions1)
          print('Precision score: ', pre_tr1)
```

```
rec_tr1 = recall_score(y_train, predictions1)
print('Recall score: ', rec_tr1)

f1_tr1 = f1_score(y_train, predictions1)
print('F1 score: ', f1_tr1)
```

```
Accuracy score:  0.8858119419642857
Precision score:  0.8829619404456714
Recall score:  0.9954700830947948
F1 score:  0.9358466904416665
```

```
In [112]: # evaluating test accuracy, precison, recall, f1_score

          predictions1 = nb.predict(x_test_tfidf)
          acc_te1 = accuracy_score(y_test, predictions1)
          print('Accuracy score: ', acc_te1)

          pre_te1 = precision_score(y_test, predictions1)
          print('Precision score: ', pre_te1)

          rec_te1 = recall_score(y_test, predictions1)
          print('Recall score: ', rec_te1)

          f1_te1 = f1_score(y_test, predictions1)
          print('F1 score: ', f1_te1)
```

```
Accuracy score:  0.873310041014735
Precision score:  0.8712412344994256
Recall score:  0.996104543189745
F1 score:  0.9294982881778604
```

9 [7] Conclusions

```
In [115]: # Creating table using PrettyTable library

          names = ["MultinomialNB for BoW", "MultinomialNB for TFIDF"]

          optimal_alpha = [ best_alpha, best_alpha_tfidf]

          #train_acc = [ train_auc_bow, train_auc_tfidf]

          train_acc = [ acc_tr, acc_tr1]
          test_acc  = [ acc_te, acc_te1]

          numbering = [1,2]
```

```python
# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",names)
ptable.add_column("Best Alpha",optimal_alpha)
ptable.add_column("Train Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)
#ptable.add_column("Training Accuracy",train_acc)
#ptable.add_column("Test Accuracy",test_acc)

# Printing the Table
print(ptable)
```

```
+--------+-------------------------+------------+--------------------+--------------------+
| S.NO.  |          MODEL          | Best Alpha |   Train Accuracy   |   Test Accuracy    |
+--------+-------------------------+------------+--------------------+--------------------+
|   1    |  MultinomialNB for BoW  |     1      | 0.9190150669642857 | 0.9011089169071852 |
|   2    | MultinomialNB for TFIDF |    0.1     | 0.8858119419642857 | 0.873310041014735  |
+--------+-------------------------+------------+--------------------+--------------------+
```