04 Amazon Fine Food Reviews Analysis_NaiveBayes

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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 tqdm import tqdm
import os
from joblib import dump, load
from sklearn_pandas import DataFrameMapper
from sklearn.metrics import f1_score,recall_score,precision_score

from sklearn.naive_bayes import MultinomialNB
# importing Cross validation libs
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn import model_selection
```

```
# Python script for confusion matrix creation.
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
# ROC , AUC curve
# roc curve and auc
from sklearn.datasets import make_classification
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot
from sklearn.metrics import roc_curve, auc
# kFold
from sklearn.model_selection import KFold

from sklearn.model_selection import GridSearchCV

import seaborn as sns

from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import RandomizedSearchCV
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect(r'/home/pranay/ML datasource/amazon-fine-food-reviews/database.s

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

In [4]:
```python
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]:
```python
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]: (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 [14]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
```

```
    print("="*50)

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

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

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraic
==================================================
```

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

print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its
```

In [16]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
from bs4 import BeautifulSoup

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

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

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

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

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil smell. So if you are afraid
```

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

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

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

In [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
was way to hot for my blood, took a bite and did a jig  lol
==================================================
```

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

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its
```

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

```
was way to hot for my blood took a bite and did a jig lol
```

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

         stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', '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 [22]: #filtered out whole reviews

         from bs4 import BeautifulSoup
         # Combining all the above stundents
         from tqdm import tqdm
         # tqdm is for printing the status bar
         word_counter = []
         def filterised_text(text):
             preprocessed_text = []
             for sentance in tqdm(text):
                 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 s
                 count = len(sentance.split())
                 word_counter.append(count)
                 preprocessed_text.append(sentance.strip())
             return preprocessed_text

In [23]: preprocessed_reviews = filterised_text(final['Text'].values)
```

```
final['preprocessed_reviews']  = preprocessed_reviews
preprocessed_reviews[1822]
```

```
100%|| 87773/87773 [00:29<00:00, 2956.18it/s]
```

Out[23]: 'taste great using air popper not great little seeds fall popping'

```
In [24]: final['numbers_of_words']  = word_counter
         word_counter[1822]
```

Out[24]: 11

4.2 Preprocessing Review Summary

```
In [25]: preprocessed_summary = filterised_text(final['Summary'].values)
         final['preprocessed_summary']  = preprocessed_summary
         preprocessed_summary[1822]
```

```
100%|| 87773/87773 [00:18<00:00, 4810.09it/s]
```

Out[25]: 'pop corn'

4.2.1 Splitting data

We have considered 100 k points

```
In [26]: X = final['preprocessed_reviews']
         y = final['Score']

         # split the data set into train and test
         X_train, x_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0

         print(X_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(61441,) (26332,) (61441,) (26332,)
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [27]: ##BoW

         count_vect = CountVectorizer(ngram_range=(1,2), min_df=10) #in scikit-learn

         # train data
         X_train_bow = count_vect.fit_transform(X_train)
```

```
# test data
x_test_bow = count_vect.transform(x_test)


print('X_train_bow',X_train_bow.shape)
print('==='*10)
print('x_test_bow',x_test_bow.shape)
```

```
X_train_bow (61441, 36487)
==============================
x_test_bow (26332, 36487)
```

6 [5] Assignment 4: Apply Naive Bayes

```
In [28]: from sklearn.naive_bayes import MultinomialNB
         # importing Cross validation libs
         from sklearn.model_selection import train_test_split
         from sklearn.model_selection import cross_val_score
         from sklearn import model_selection


         # Python script for confusion matrix creation.
         from sklearn.metrics import confusion_matrix
         from sklearn.metrics import accuracy_score
         from sklearn.metrics import classification_report
         # ROC , AUC curve
         # roc curve and auc
         from sklearn.datasets import make_classification
         from sklearn.metrics import roc_curve
         from sklearn.metrics import roc_auc_score
         from matplotlib import pyplot
         from sklearn.metrics import roc_curve, auc
         # kFold
         from sklearn.model_selection import KFold

         from sklearn.model_selection import GridSearchCV

         import seaborn as sns

         from sklearn.model_selection import TimeSeriesSplit
         from sklearn.model_selection import RandomizedSearchCV
```

```
In [29]: # Common Methods

         # define the range, through which we are going to find alpha-hyperparameter
         # alpha_values = (1e-4, 1e-3,1e-2,1e-1, 1e0,1e1)
```

```
# alpha_values =  np.geomspace(1e-3, 10)

alpha_values = (1e-4, 1e-3,1e-2,0.05,1e-1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9, 1e0,3,5,7,

def finding_best_alpha(X_tr,y_tr):
    # instantiate a Multinomial Naive Bayes model
    nb = MultinomialNB()

    param_grid = dict(alpha=alpha_values)
    print(param_grid)

    #For time based splitting
    tscv = TimeSeriesSplit(n_splits=15)

    # instantiate the training grid search model
    train_grid = GridSearchCV(nb, param_grid, cv=tscv, scoring='roc_auc',n_jobs =-1,ve

    # fit the training data to train model
    train_grid.fit(X_tr, y_tr)

    return train_grid

    # plot a graph which show difference between validation error and training error

def plotAccuracyGraph(training_grid):
    alpha_range = [i for i in alpha_values]
    accuracy = [i for i in training_grid.cv_results_['mean_train_score']]
    accuracy_test = [i for i in training_grid.cv_results_['mean_test_score']]
    plt.semilogx(alpha_range, accuracy,'r',label='train_accuracy')
    plt.semilogx(alpha_range, accuracy_test,'b',label='validation_accuracy')
    plt.title('Accuracy plot')
    plt.xlabel('Alpha')
    plt.ylabel('Accuracy')
    plt.grid('on')
    plt.legend()
    plt.show()

# https://www.geeksforgeeks.org/confusion-matrix-machine-learning/
def plotConfusionMatrix(y_test,pred):
    # calculate confusion matrix
    cm =  confusion_matrix(y_test,pred)
    class_label = ['negative', 'positive']
    df_conf_matrix = pd.DataFrame(cm, index=class_label, columns=class_label)
    # heatmap --> Plot rectangular data as a color-encoded matrix.
    sns.heatmap(df_conf_matrix, annot=True, fmt='d')
    # give title to graph
    plt.title("Confusion Matrix")
    # mention axis label
```

```
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    # show the plot
    plt.show()


# https://machinelearningmastery.com/roc-curves-and-precision-recall-curves-for-class
# plot AUC curve
def plotAUC_ROC(nb_optimal,X_train, y_train, X_test, y_test):
    # predict probabilities
    test_probs = nb_optimal.predict_proba(X_test)
    train_probs = nb_optimal.predict_proba(X_train)

    # keep probabilities for the positive outcome only
    test_probs = test_probs[:, 1]
    train_probs = train_probs[:, 1]

    # calculate AUC
    test_auc = roc_auc_score(y_test, test_probs)
    train_auc = roc_auc_score(y_train, train_probs)

    # calculate roc curve
    train_fpr, train_tpr, thresholds = roc_curve(y_train, train_probs)
    test_fpr, test_tpr, thresholds2 = roc_curve(y_test, test_probs)

    # plot no skill
    pyplot.plot([0, 1], [0, 1], linestyle='--')

    # plot the roc curve for the model
    pyplot.plot(train_fpr, train_tpr, 'r',marker='.', label="train AUC ="+str(train_au
    pyplot.plot(test_fpr, test_tpr, 'b',marker='.',label="test AUC ="+str(test_auc))

    pyplot.legend()
    pyplot.xlabel("K: hyperparameter")
    pyplot.ylabel("AUC")
    pyplot.title("ERROR PLOTS")
    # show the plot
    pyplot.show()

    return train_auc, test_auc

class color:
   PURPLE = '\033[95m'
   CYAN = '\033[96m'
   DARKCYAN = '\033[36m'
   BLUE = '\033[94m'
   GREEN = '\033[92m'
   YELLOW = '\033[93m'
```

```
    RED = '\033[91m'
    BOLD = '\033[1m'
    UNDERLINE = '\033[4m'
    END = '\033[0m'



# https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-f
def important_features(feature_names,classifier,n=20):
    class_labels = classifier.classes_
    topn_class1 = sorted(zip(classifier.feature_count_[0], feature_names),reverse=Tru
    topn_class2 = sorted(zip(classifier.feature_count_[1], feature_names),reverse=Tru
    print(color.BOLD+"Important words in negative reviews"+color.END)
    print('\n'+color.BOLD+'\t Class Label '+color.END,class_labels[0])
    for coef, feat in topn_class1:
        print('{:.3f}'.format(coef), '\t'+feat)
    print("-----------------------------------------\n")
    print(color.BOLD+"Important words in positive reviews"+color.END)
    print('\n'+color.BOLD+'\t Class Label '+color.END,class_labels[1])
    for coef, feat in topn_class2:
        print('{:.3f}'.format(coef), '\t'+feat)
```

7 Applying Multinomial Naive Bayes

7.1 [5.1] Applying Naive Bayes on BOW

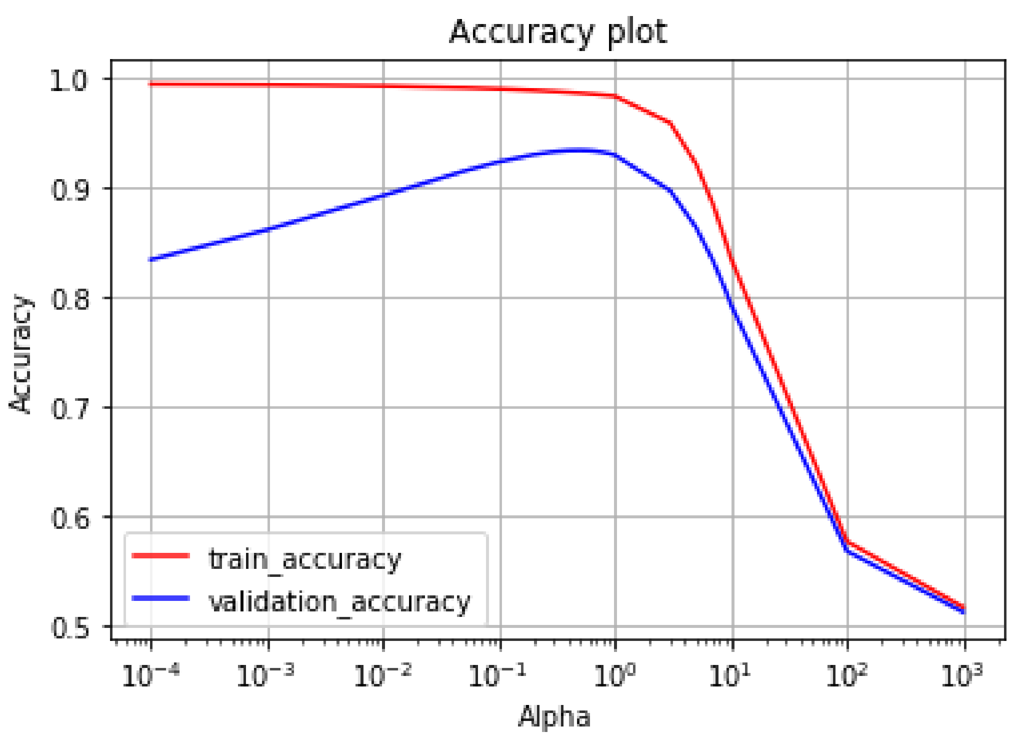
In [30]:
```
bow_train = finding_best_alpha(X_train_bow,y_train)

# view the complete results (list of named tuples)
print("=======Training========")
print (bow_train.best_score_)
print (bow_train.best_params_)
print (bow_train.best_estimator_)

plotAccuracyGraph(bow_train)
```

```
{'alpha': (0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 3, 5, 
Fitting 15 folds for each of 21 candidates, totalling 315 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    2.0s
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    2.3s
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done  53 tasks      | elapsed:    2.8s
```

```
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1969s.) Setting batch_size=2.
[Parallel(n_jobs=-1)]: Done  64 tasks      | elapsed:    3.1s
[Parallel(n_jobs=-1)]: Done  86 tasks      | elapsed:    3.8s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:    4.5s
[Parallel(n_jobs=-1)]: Done 142 tasks      | elapsed:    5.2s
[Parallel(n_jobs=-1)]: Done 172 tasks      | elapsed:    5.9s
[Parallel(n_jobs=-1)]: Done 206 tasks      | elapsed:    6.8s
[Parallel(n_jobs=-1)]: Done 240 tasks      | elapsed:    7.6s
[Parallel(n_jobs=-1)]: Done 278 tasks      | elapsed:    8.5s
[Parallel(n_jobs=-1)]: Done 308 out of 315 | elapsed:    9.3s remaining:    0.2s
[Parallel(n_jobs=-1)]: Done 315 out of 315 | elapsed:    9.5s finished
```

```
=======Training========
0.9336869731761391
{'alpha': 0.5}
MultinomialNB(alpha=0.5, class_prior=None, fit_prior=True)
```

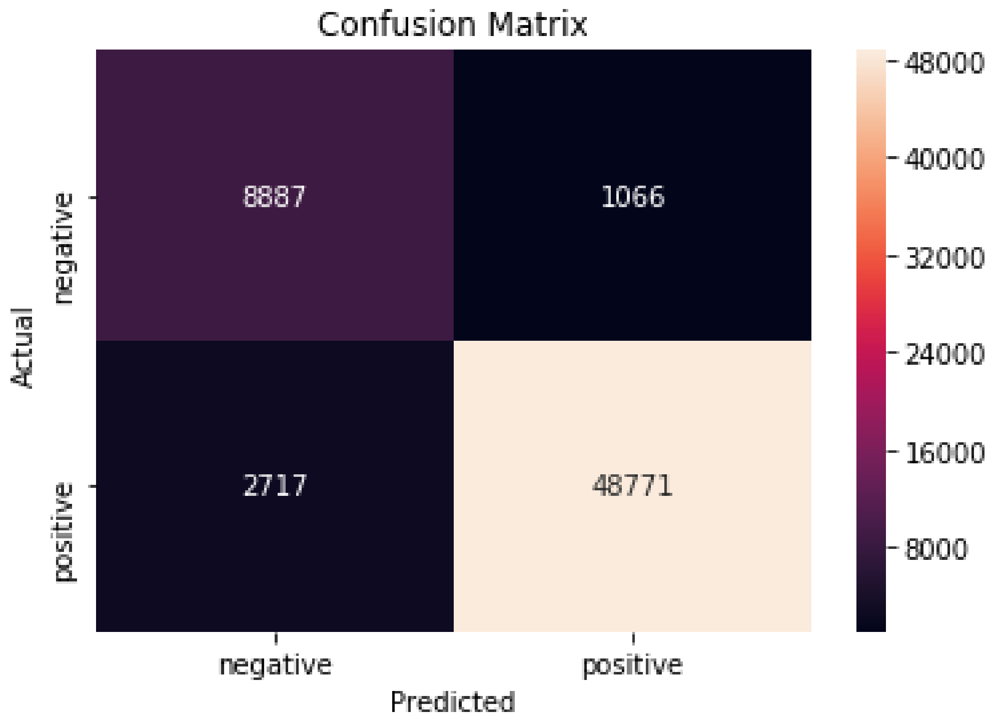
```
/home/pranay/anaconda3/lib/python3.7/site-packages/matplotlib/cbook/__init__.py:424: Matplotlil
Passing one of 'on', 'true', 'off', 'false' as a boolean is deprecated; use an actual boolean
  warn_deprecated("2.2", "Passing one of 'on', 'true', 'off', 'false' as a "
```



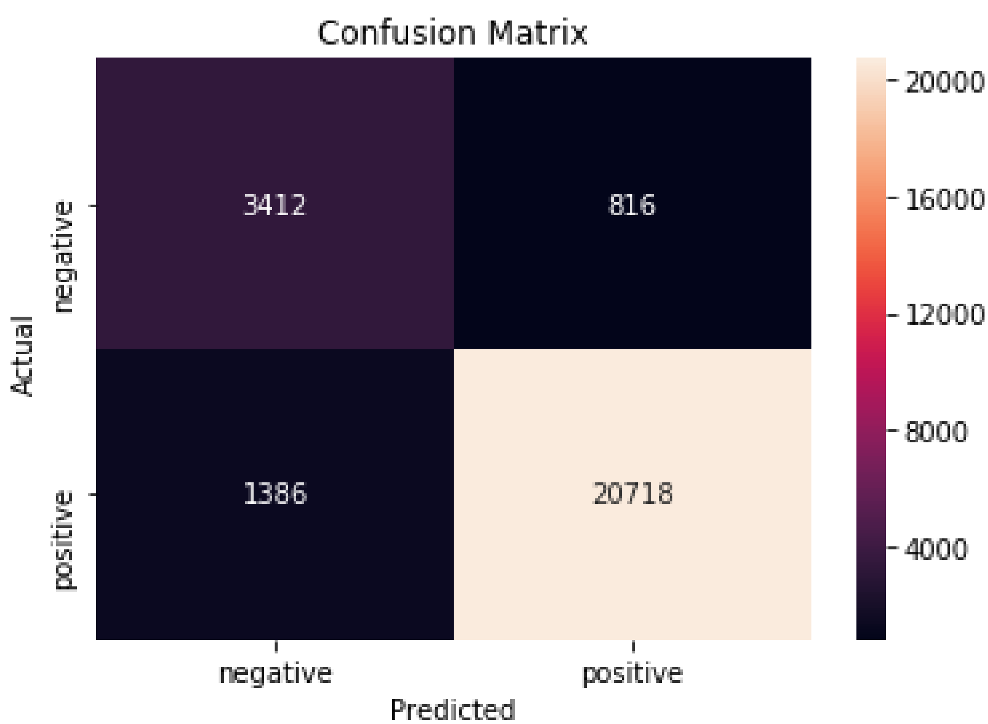
In [31]:
```
optimal_alpha = bow_train.best_params_.get('alpha')

nb_optimal= MultinomialNB(alpha=optimal_alpha, class_prior=None, fit_prior=True)

# fitting the model
nb_optimal.fit(X_train_bow,y_train)

# predict the response
test_pred = nb_optimal.predict(x_test_bow)
train_pred = nb_optimal.predict(X_train_bow)

print('\n'+color.RED+'Optimal best alpha is : '+color.END+color.BOLD+str(optimal_alpha

# plot confusion matrix

print('\n'+color.BOLD +'Confusion Matrix for Train data'+color.END)
plotConfusionMatrix(y_train,train_pred)

print('\n'+color.BOLD +'Confusion Matrix for Test data'+color.END)
plotConfusionMatrix(y_test,test_pred)

# plot AUC
train_auc,test_auc = plotAUC_ROC(nb_optimal,X_train_bow, y_train,x_test_bow, y_test )
print('\n'+color.RED+'AUC (Train): '+color.END+color.BOLD+str(train_auc)+color.END)
print('\n'+color.RED+'AUC (Test): '+color.END+color.BOLD+str(test_auc)+color.END)

# f1 score
score = f1_score(y_test,test_pred)
print('\n'+color.RED+'F1 SCORE (Train) : '+color.END+color.BOLD+str(f1_score(y_train,t
print('\n'+color.RED+'F1 SCORE (Test) : '+color.END+color.BOLD+str(score)+color.END)

# recall
recall = metrics.recall_score(y_test, test_pred)
print('\n'+color.RED+'RECALL (Train): '+color.END+color.BOLD+str(metrics.recall_score
print('\n'+color.RED+'RECALL (Test): '+color.END+color.BOLD+str(recall)+color.END)

# precision
precision = metrics.precision_score(y_test, test_pred)
print('\n'+color.RED+'PRECISION  (Train) : '+color.END+color.BOLD+str(metrics.precisio
print('\n'+color.RED+'PRECISION  (Test) : '+color.END+color.BOLD+str(precision)+color
```

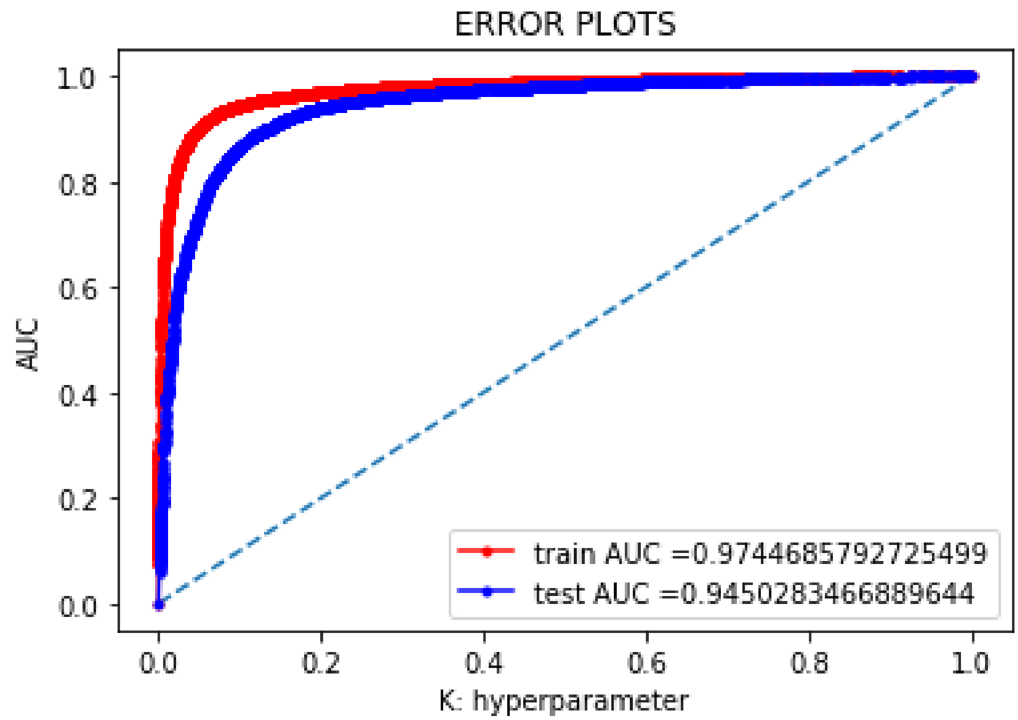
Optimal best alpha is : 0.5

Confusion Matrix for Train data



Confusion Matrix for Test data






```
AUC (Train): 0.9744685792725499

AUC (Test): 0.9450283466889644

F1 SCORE (Train) : 0.9626646928201332

F1 SCORE (Test) : 0.9495393922727898

RECALL (Train): 0.947230422622747

RECALL (Test): 0.9372964169381107

PRECISION  (Train) : 0.9786102694784999

PRECISION  (Test) : 0.9621064363332404
```

7.1.1 [5.1.1] Top 10 important features of positive class

7.1.2 [5.1.2] Top 10 important features of negative class

```
In [32]: important_features(count_vect.get_feature_names(), nb_optimal, 10)
```

```
Important words in negative reviews

         Class Label  0
16486.000         not
5374.000         like
4246.000         would
4098.000         product
4052.000         taste
3322.000         one
2651.000         coffee
2627.000         good
2498.000         flavor
2489.000         no
-----------------------------------------

Important words in positive reviews

         Class Label  1
48321.000         not
21545.000         like
18904.000         good
17323.000         great
15165.000         one
13878.000         taste
13426.000         coffee
12529.000         flavor
12454.000         love
12439.000         would
```

7.1.3 Feature Engineering

Till now we only consider Text review as feature, we are adding some extra feature like **review summary** and **number of words** in review and test our model improves efficiency or not.

We have considered on 50000 points due to memory issue.

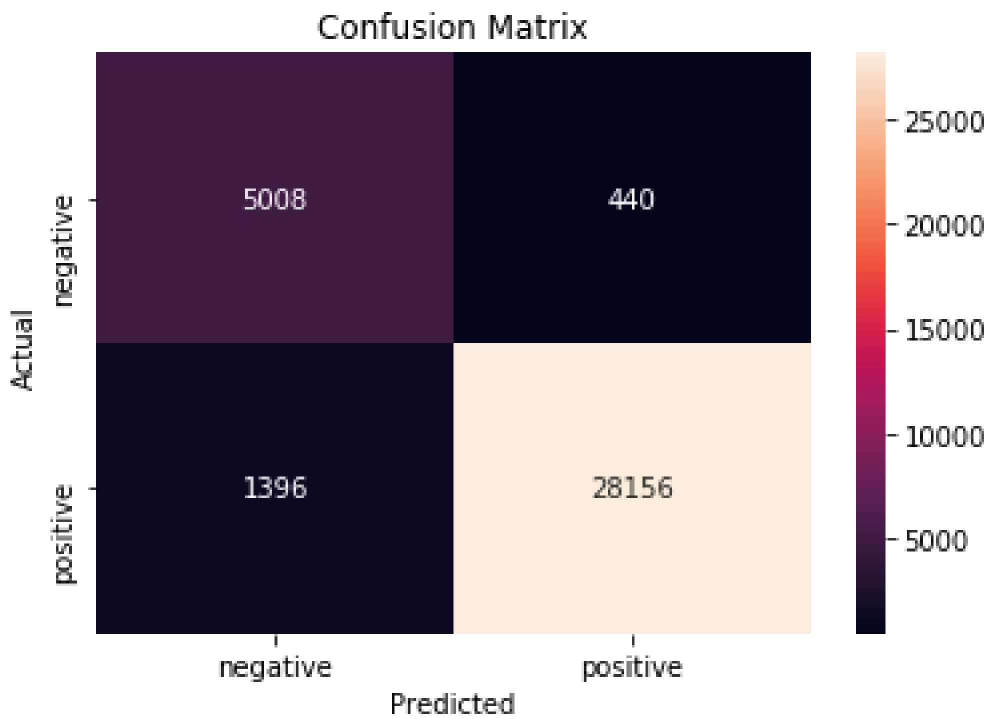
```
In [33]: # https://sondosatwi.wordpress.com/2017/08/01/using-text-data-and-dataframemapper-in-

         X = final[:50000]
         y = final['Score'][:50000]

         # split the data set into train and test
         X_train, x_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0
```

```
print(X_train.shape, x_test.shape, y_train.shape, y_test.shape)

mapper = DataFrameMapper([
     ('preprocessed_reviews', CountVectorizer(ngram_range=(1,3), min_df=10)),
     ('preprocessed_summary', CountVectorizer(ngram_range=(1,3), min_df=10)),
     ('numbers_of_words', None),
 ])

train_features = mapper.fit_transform(X_train)
test_features = mapper.transform(x_test)

optimal_alpha = bow_train.best_params_.get('alpha')

nb_optimal= MultinomialNB(alpha=optimal_alpha, class_prior=None, fit_prior=True)

# fitting the model
nb_optimal.fit(train_features,y_train)

# predict the response
test_pred = nb_optimal.predict(test_features)
train_pred = nb_optimal.predict(train_features)

# plot confusion matrix

print('\n'+color.BOLD +'Confusion Matrix for Train data'+color.END)
plotConfusionMatrix(y_train,train_pred)

print('\n'+color.BOLD +'Confusion Matrix for Test data'+color.END)
plotConfusionMatrix(y_test,test_pred)

# plot AUC
train_auc,test_auc = plotAUC_ROC(nb_optimal,train_features, y_train,test_features, y_
print('\n'+color.RED+'AUC (Train): '+color.END+color.BOLD+str(train_auc)+color.END)
print('\n'+color.RED+'AUC (Test): '+color.END+color.BOLD+str(test_auc)+color.END)

# f1 score
score = f1_score(y_test,test_pred)
print('\n'+color.RED+'F1 SCORE (Train) : '+color.END+color.BOLD+str(f1_score(y_train,
print('\n'+color.RED+'F1 SCORE (Test) : '+color.END+color.BOLD+str(score)+color.END)

# recall
recall = metrics.recall_score(y_test, test_pred)
print('\n'+color.RED+'RECALL (Train): '+color.END+color.BOLD+str(metrics.recall_score
print('\n'+color.RED+'RECALL (Test): '+color.END+color.BOLD+str(recall)+color.END)

# precision
precision = metrics.precision_score(y_test, test_pred)
```

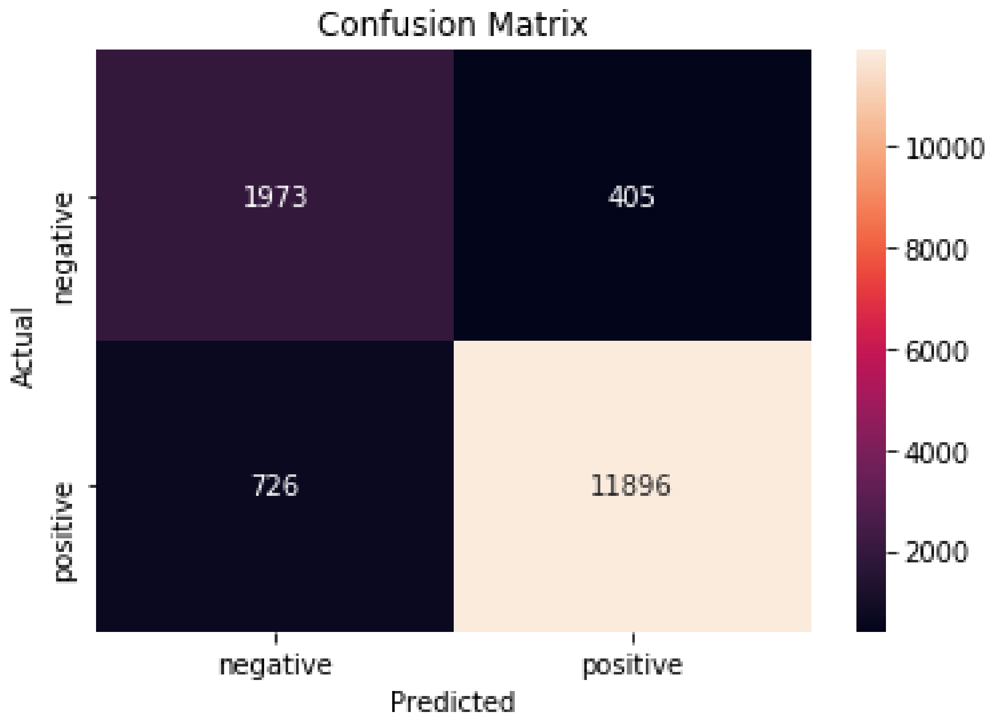
```
        print('\n'+color.RED+'PRECISION  (Train) : '+color.END+color.BOLD+str(metrics.precisi
        print('\n'+color.RED+'PRECISION  (Test) : '+color.END+color.BOLD+str(precision)+color
```

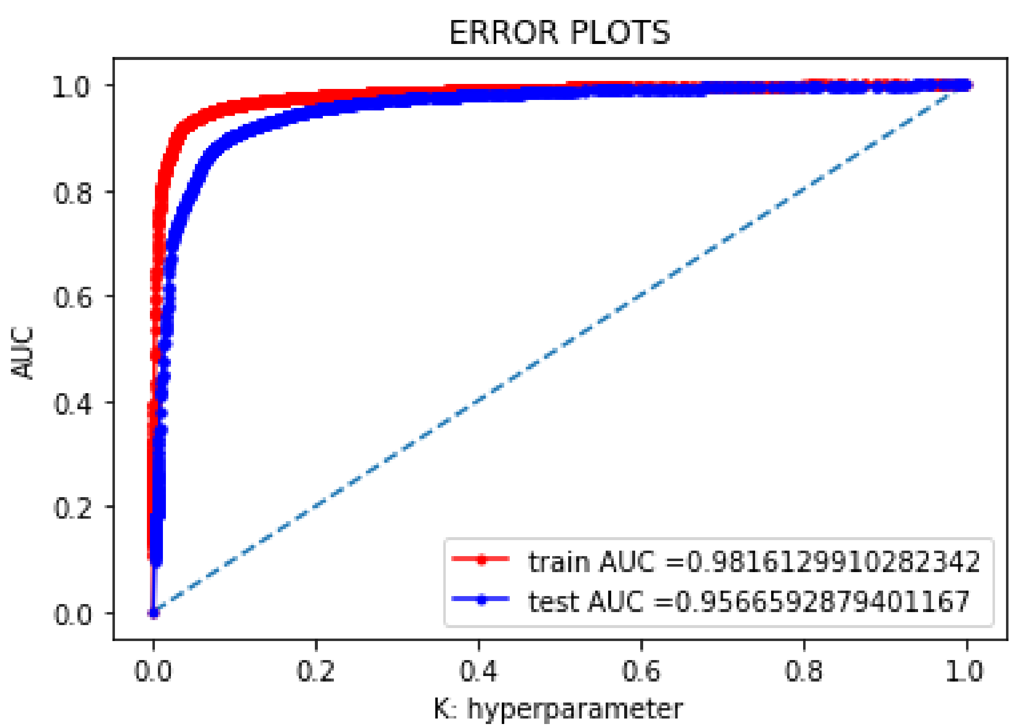
(35000, 13) (15000, 13) (35000,) (15000,)

Confusion Matrix for Train data



Confusion Matrix for Test data


Confusion Matrix
1973
405
726
11896
negative
positive
Actual
negative
positive
Predicted
10000
8000
6000
4000
2000


ERROR PLOTS
train AUC =0.9816129910282342
test AUC =0.9566592879401167
AUC
K: hyperparameter
0.0
0.2
0.4
0.6
0.8
1.0

```
AUC (Train): 0.9816129910282342

AUC (Test): 0.9566592879401167

F1 SCORE (Train) : 0.9684253972621587

F1 SCORE (Test) : 0.9546202303093528

RECALL (Train): 0.9527612344342177

RECALL (Test): 0.9424813817144668

PRECISION  (Train) : 0.9846132326199468

PRECISION  (Test) : 0.9670758474920739
```

7.1.4 [5.1.1] Top 10 important features of positive class

7.1.5 [5.1.2] Top 10 important features of negative class

```
In [34]: merged_features_vectorizer = mapper.features[0][1].get_feature_names() + mapper.featu
         important_features(merged_features_vectorizer, nb_optimal, 10)
```

```
Important words in negative reviews

         Class Label  0
8654.000         not
2765.000         like
2208.000         product
2190.000         would
2009.000         taste
1808.000         one
1421.000         good
1379.000         no
1379.000         food
1330.000         not
-----------------------------------------

Important words in positive reviews

         Class Label  1
26431.000         not
11388.000         like
10595.000         good
9743.000         great
8923.000         tea
8144.000         one
```

```
7372.000         taste
6762.000         love
6690.000         flavor
6674.000         product
```

As we can see that by consider 'review text', 'summary text' and 'number of words' in review text all together, **AUC value is changed from 0.94502 to 0.95665**

7.2 [4.2] TF-IDF

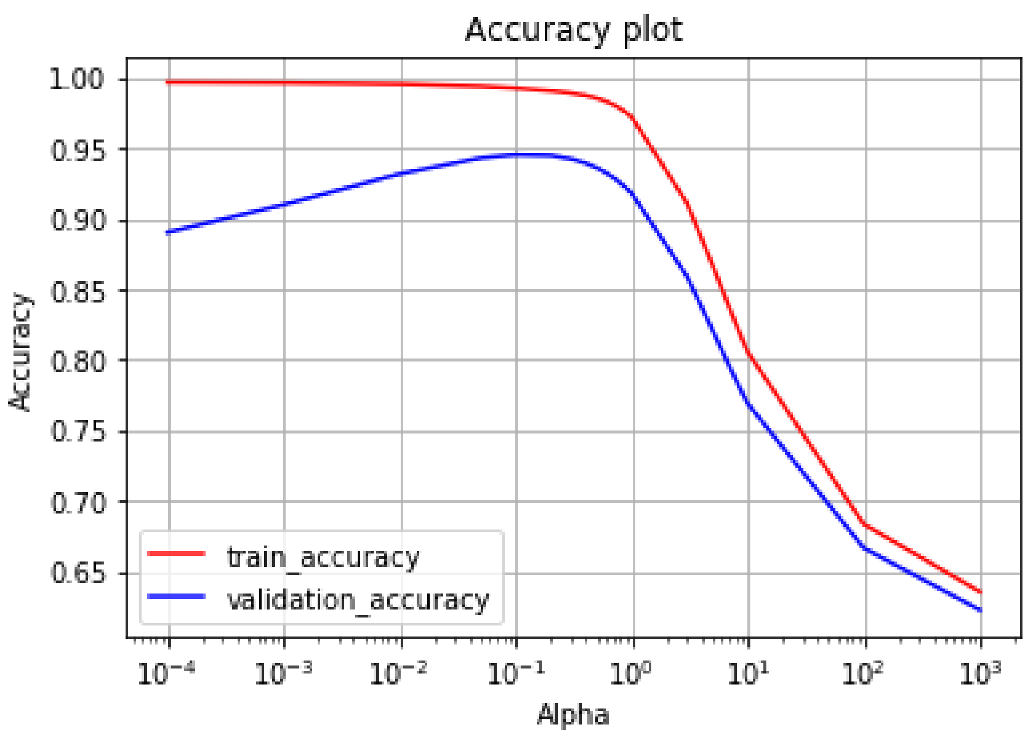
```
In [35]: X = final['preprocessed_reviews']
         y = final['Score']

         # split the data set into train and test
         X_train, x_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0

         print(X_train.shape, x_test.shape, y_train.shape, y_test.shape)

         tf_idf_vect = TfidfVectorizer(ngram_range=(1,3), min_df=10) #in scikit-learn

         # train data
         X_train_tfidf = tf_idf_vect.fit_transform(X_train)

         # test data
         x_test_tfidf = tf_idf_vect.transform(x_test)

         print('X_train_tfidf', X_train_tfidf.shape)
         print('==='*10)
         print('x_test_tfidf', x_test_tfidf.shape)
```

```
(61441,) (26332,) (61441,) (26332,)
X_train_tfidf (61441, 40217)
==============================
x_test_tfidf (26332, 40217)
```

7.3 [5.2] Applying Naive Bayes on TFIDF

```
In [36]: tfidf_train = finding_best_alpha(X_train_tfidf,y_train)

         # view the complete results (list of named tuples)
         print("=======Training========")
         print (tfidf_train.best_score_)
         print (tfidf_train.best_params_)
         print (tfidf_train.best_estimator_)

         plotAccuracyGraph(tfidf_train)
```

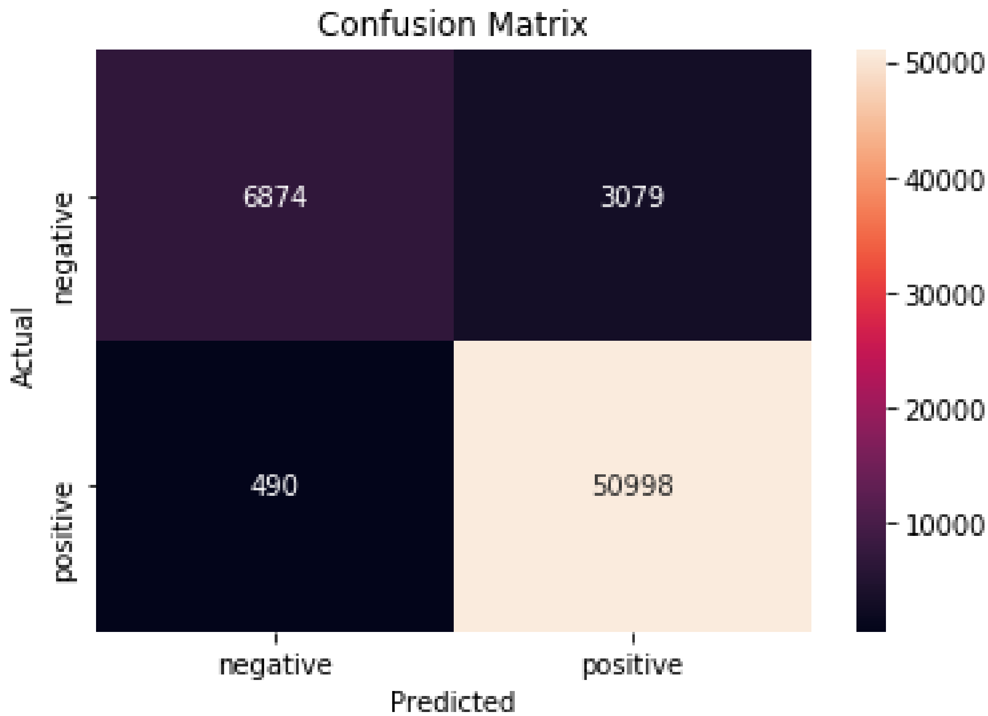
```
{'alpha': (0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 3, 5, 7
Fitting 15 folds for each of 21 candidates, totalling 315 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Batch computation too fast (0.0550s.) Setting batch_size=6.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done  20 tasks      | elapsed:    0.7s
[Parallel(n_jobs=-1)]: Done  62 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done 104 tasks      | elapsed:    2.9s
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:    4.1s
[Parallel(n_jobs=-1)]: Done 212 tasks      | elapsed:    5.3s
[Parallel(n_jobs=-1)]: Done 278 tasks      | elapsed:    7.0s
[Parallel(n_jobs=-1)]: Done 315 out of 315 | elapsed:    7.9s finished
/home/pranay/anaconda3/lib/python3.7/site-packages/matplotlib/cbook/__init__.py:424: Matplotlib
Passing one of 'on', 'true', 'off', 'false' as a boolean is deprecated; use an actual boolean
  warn_deprecated("2.2", "Passing one of 'on', 'true', 'off', 'false' as a "


=======Training========
0.945188332274678
{'alpha': 0.1}
MultinomialNB(alpha=0.1, class_prior=None, fit_prior=True)
```



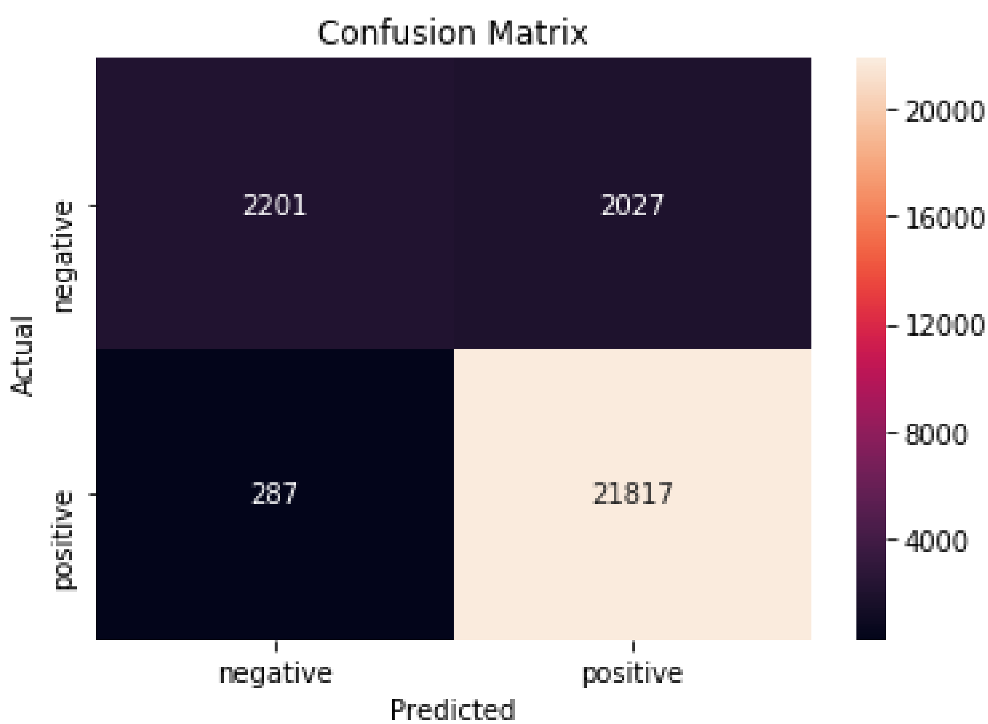
In [37]:
```
optimal_alpha = tfidf_train.best_params_.get('alpha')

print('\n'+color.RED+'Optimal best alpha is : '+color.END+color.BOLD+str(optimal_alpha

nb_optimal= MultinomialNB(alpha=optimal_alpha, class_prior=None, fit_prior=True)

# fitting the model
nb_optimal.fit(X_train_tfidf,y_train)

# predict the response
test_pred = nb_optimal.predict(x_test_tfidf)
train_pred = nb_optimal.predict(X_train_tfidf)

# plot confusion matrix

print('\n'+color.BOLD +'Confusion Matrix for Train data'+color.END)
plotConfusionMatrix(y_train,train_pred)

print('\n'+color.BOLD +'Confusion Matrix for Test data'+color.END)
plotConfusionMatrix(y_test,test_pred)

# plot AUC
train_auc,test_auc = plotAUC_ROC(nb_optimal,X_train_tfidf, y_train,x_test_tfidf, y_tes
print('\n'+color.RED+'AUC (Train): '+color.END+color.BOLD+str(train_auc)+color.END)
print('\n'+color.RED+'AUC (Test): '+color.END+color.BOLD+str(test_auc)+color.END)

# f1 score
score = f1_score(y_test,test_pred)
print('\n'+color.RED+'F1 SCORE (Train) : '+color.END+color.BOLD+str(f1_score(y_train,t
print('\n'+color.RED+'F1 SCORE (Test) : '+color.END+color.BOLD+str(score)+color.END)

# recall
recall = metrics.recall_score(y_test, test_pred)
print('\n'+color.RED+'RECALL (Train): '+color.END+color.BOLD+str(metrics.recall_score
print('\n'+color.RED+'RECALL (Test): '+color.END+color.BOLD+str(recall)+color.END)

# precision
precision = metrics.precision_score(y_test, test_pred)
print('\n'+color.RED+'PRECISION  (Train) : '+color.END+color.BOLD+str(metrics.precisio
print('\n'+color.RED+'PRECISION  (Test) : '+color.END+color.BOLD+str(precision)+color
```

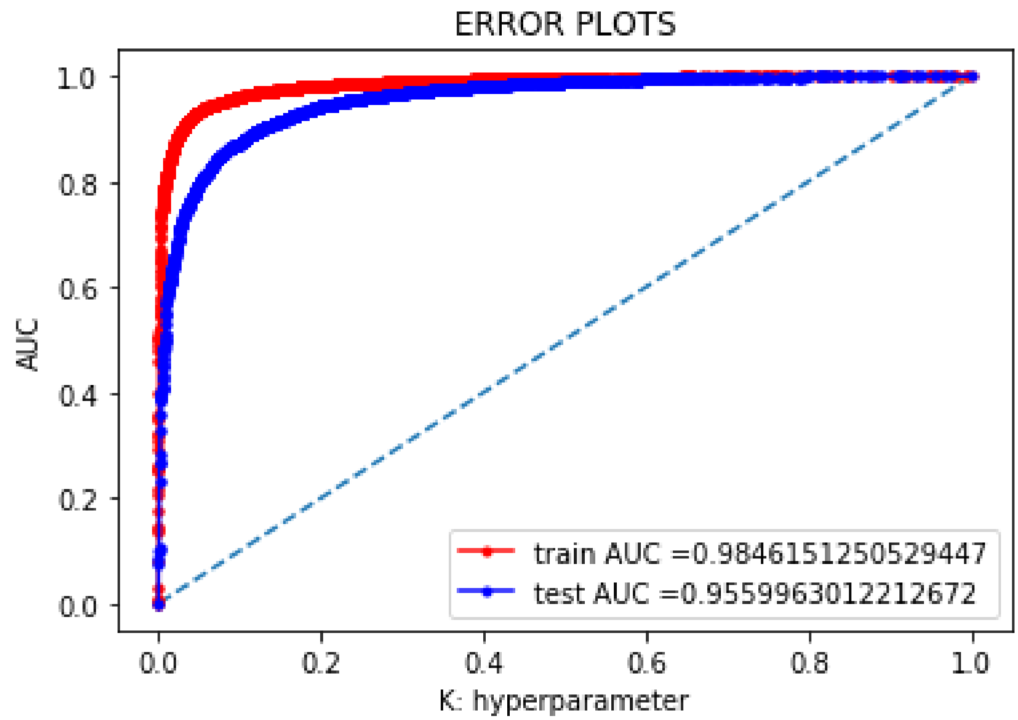
```
Optimal best alpha is : 0.1
```

Confusion Matrix for Train data



Confusion Matrix for Test data





AUC (Train): 0.9846151250529447

AUC (Test): 0.9559963012212672

F1 SCORE (Train) : 0.9661914460285133

F1 SCORE (Test) : 0.9496387220336033

RECALL (Train): 0.9904832193909261

RECALL (Test): 0.9870159247195078

PRECISION (Train) : 0.9430626698966289

PRECISION (Test) : 0.9149890957892971

7.3.1 [5.2.1] Top 10 important features of positive class

7.3.2 [5.2.2] Top 10 important features of negative class

```
In [38]: important_features(tf_idf_vect.get_feature_names(), nb_optimal, 10)
```

```
Important words in negative reviews

         Class Label  0
519.547        not
228.356        like
212.892        product
203.388        would
202.627        taste
162.527        coffee
150.752        one
132.950        flavor
130.494        no
117.575        good
-----------------------------------------

Important words in positive reviews

         Class Label  1
1456.513        not
1030.260        great
972.931        good
923.692        like
882.647        coffee
817.438        love
808.220        tea
729.114        one
719.204        taste
712.064        product
```

7.3.3 Feature Engineering

Till now we only consider Text review as feature, we are adding some extra feature like **review summary** and **number of words** in review and test our model improves efficiency or not.

We have considered on 50000 points due to memory issue.

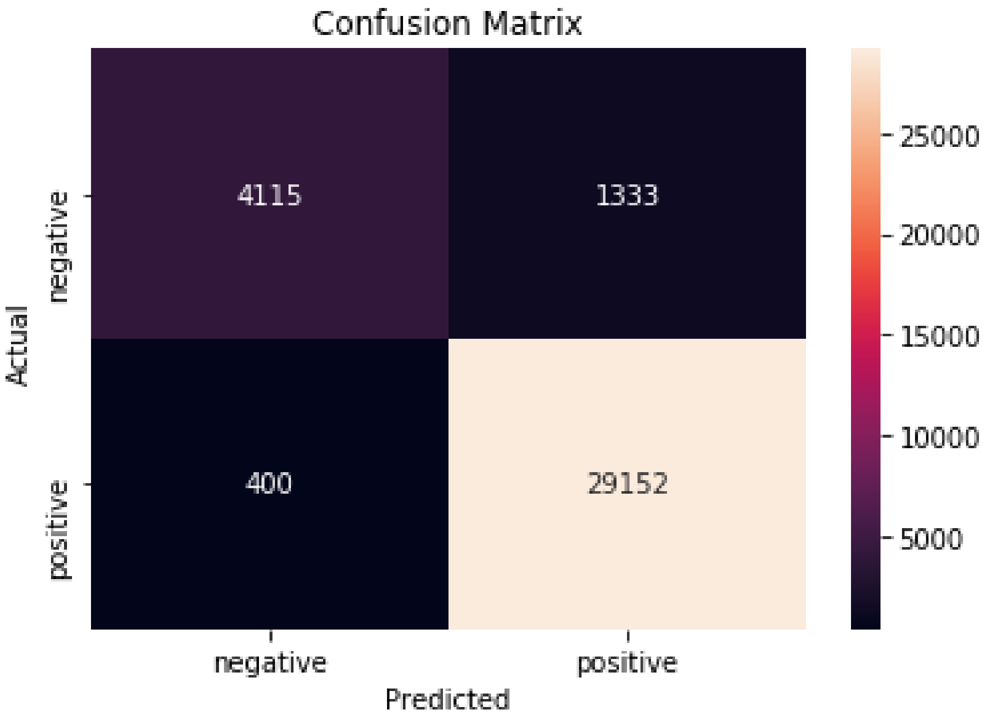
```
In [41]: # https://sondosatwi.wordpress.com/2017/08/01/using-text-data-and-dataframemapper-in-p

         X = final[:50000]
         y = final['Score'][:50000]

         # split the data set into train and test
         X_train, x_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0
```

```python
print(X_train.shape, x_test.shape, y_train.shape, y_test.shape)

mapper = DataFrameMapper([
     ('preprocessed_reviews', TfidfVectorizer(ngram_range=(1,2), min_df=10)),
     ('preprocessed_summary', TfidfVectorizer(ngram_range=(1,2), min_df=10)),
     ('numbers_of_words', None),
 ])

train_features = mapper.fit_transform(X_train)
test_features = mapper.transform(x_test)

optimal_alpha = bow_train.best_params_.get('alpha')

optimal_alpha

nb_optimal= MultinomialNB(alpha=optimal_alpha, class_prior=None, fit_prior=True)

# fitting the model
nb_optimal.fit(train_features,y_train)

# predict the response
test_pred = nb_optimal.predict(test_features)
train_pred = nb_optimal.predict(train_features)

# plot confusion matrix

print('\n'+color.BOLD +'Confusion Matrix for Train data'+color.END)
plotConfusionMatrix(y_train,train_pred)

print('\n'+color.BOLD +'Confusion Matrix for Test data'+color.END)
plotConfusionMatrix(y_test,test_pred)

# plot AUC
train_auc,test_auc = plotAUC_ROC(nb_optimal,train_features, y_train,test_features, y_
print('\n'+color.RED+'AUC (Train): '+color.END+color.BOLD+str(train_auc)+color.END)
print('\n'+color.RED+'AUC (Test): '+color.END+color.BOLD+str(test_auc)+color.END)

# f1 score
score = f1_score(y_test,test_pred)
print('\n'+color.RED+'F1 SCORE (Train) : '+color.END+color.BOLD+str(f1_score(y_train,
print('\n'+color.RED+'F1 SCORE (Test) : '+color.END+color.BOLD+str(score)+color.END)

# recall
recall = metrics.recall_score(y_test, test_pred)
print('\n'+color.RED+'RECALL (Train): '+color.END+color.BOLD+str(metrics.recall_score
print('\n'+color.RED+'RECALL (Test): '+color.END+color.BOLD+str(recall)+color.END)
```

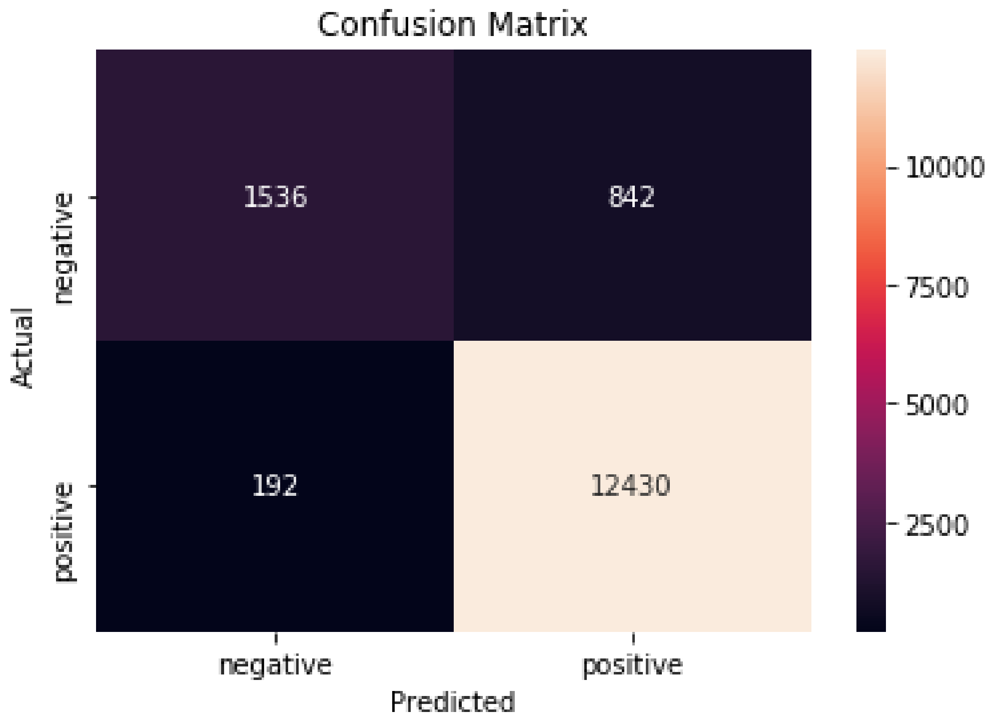
```
# precision
precision = metrics.precision_score(y_test, test_pred)
print('\n'+color.RED+'PRECISION  (Train) : '+color.END+color.BOLD+str(metrics.precisio
print('\n'+color.RED+'PRECISION  (Test) : '+color.END+color.BOLD+str(precision)+color
```

```
(35000, 13) (15000, 13) (35000,) (15000,)
```

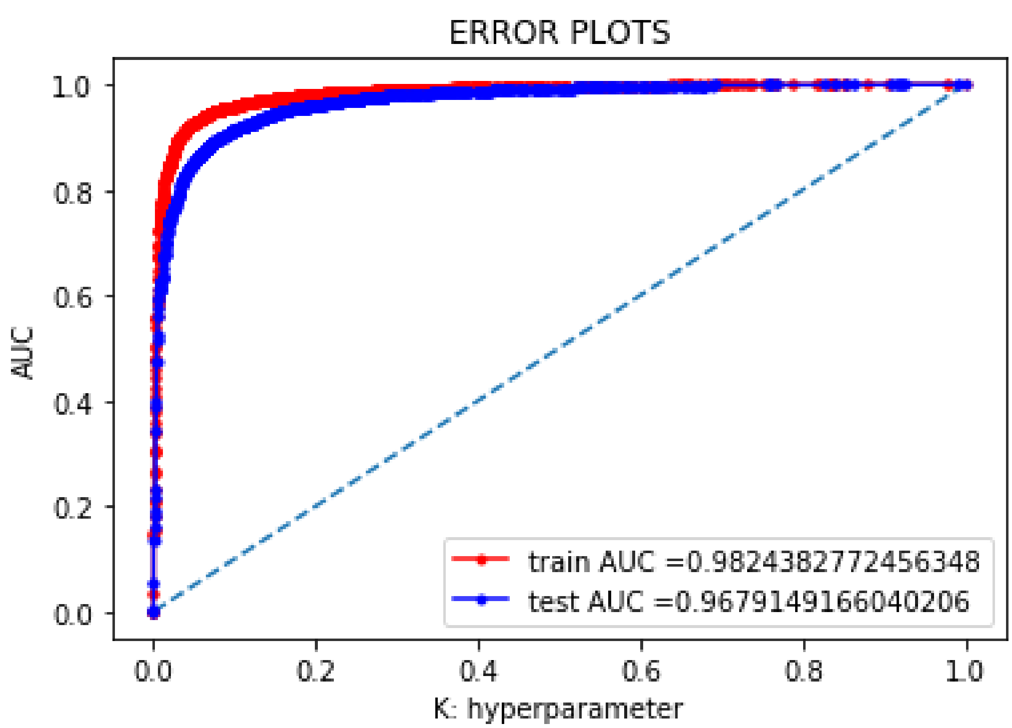
Confusion Matrix for Train data



Confusion Matrix for Test data



Confusion Matrix
1536
842
192
12430
10000
7500
5000
2500
negative
positive
Actual
negative
positive
Predicted



ERROR PLOTS
1.0
0.8
0.6
0.4
0.2
0.0
AUC
train AUC =0.9824382772456348
test AUC =0.9679149166040206
0.0
0.2
0.4
0.6
0.8
1.0
K: hyperparameter

```
AUC (Train): 0.9824382772456348

AUC (Test): 0.9679149166040206

F1 SCORE (Train) : 0.9711344670786349

F1 SCORE (Test) : 0.9600679694137637

RECALL (Train): 0.9864645370871684

RECALL (Test): 0.9847884645856441

PRECISION  (Train) : 0.9562735771690996

PRECISION  (Test) : 0.9365581675708258
```

```
In [42]: merged_features_vectorizer = mapper.features[0][1].get_feature_names() + mapper.featu
         important_features(merged_features_vectorizer, nb_optimal, 10)
```

```
Important words in negative reviews

         Class Label  0
466.440        not
306.290        not
134.836        like
126.875        product
121.272        would
115.669        taste
109.655        taste
94.308        disappointed
92.847        one
86.631        like
-----------------------------------------

Important words in positive reviews

         Class Label  1
1496.994        great
1066.364        good
907.671        not
845.669        love
845.563        best
803.768        delicious
661.154        tea
644.066        great
621.736        tea
```

```
614.086          good
```

As we can see that by consider 'review text', 'summary text' and 'number of words' in review text all together, **AUC value is changed from 0.9560 to 0.96933**

8 [6] Conclusions

```
In [63]: import pandas as pd
         from prettytable import PrettyTable

         print(color.BOLD+'\t\t\t\t Naive Bayes  '+color.END)
         print('\n')

         print(color.BOLD+'For BOW and TFIDF, We have considered 100k points'+color.END)
         print(color.BOLD+'For BOW- Additional Feature and TFIDF- Additional Feature, We have c


         x = PrettyTable()
         x.field_names =  ['Metric','BOW','BOW-Additional Feature', 'TFIDF', 'TFIDF- Additional

         x.add_row(["Alpha Value ", 0.5,0.5,0.1,0.1])

         x.add_row(["AUC Train ", 0.97446,0.98161,0.98461,0.98243])
         x.add_row(["AUC Test ", 0.94502,0.95665,0.9560,0.96791])

         x.add_row(["F1 SCORE Train ", 0.96266,0.96842,0.96619,0.97113])
         x.add_row(["F1 SCORE Test ", 0.94953,0.95462,0.949638,0.96006])

         x.add_row(["RECALL Train ",0.94723,0.95276,0.99048,0.9864])
         x.add_row(["RECALL Test ", 0.97729,0.942481,0.9870,0.98478])

         x.add_row(["PRECISION Train ", 0.97861,0.98461,0.94306,0.95627])
         x.add_row(["PRECISION Test ",0.96210,0.96707,0.91498,0.93655])


         print('\n')
         print(x)
```

```
                                Naive Bayes


For BOW and TFIDF, We have considered 100k points
For BOW- Additional Feature and TFIDF- Additional Feature, We have considered 50k points


+-------------------+---------+------------------------+----------+---------------------------
|      Metric       |   BOW   | BOW-Additional Feature |  TFIDF   | TFIDF- Additional Features
```

Alpha Value	0.5	0.5	0.1	0.1
AUC Train	0.97446	0.98161	0.98461	0.98243
AUC Test	0.94502	0.95665	0.956	0.96791
F1 SCORE Train	0.96266	0.96842	0.96619	0.97113
F1 SCORE Test	0.94953	0.95462	0.949638	0.96006
RECALL Train	0.94723	0.95276	0.99048	0.9864
RECALL Test	0.97729	0.942481	0.987	0.98478
PRECISION Train	0.97861	0.98461	0.94306	0.95627
PRECISION Test	0.9621	0.96707	0.91498	0.93655