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 the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

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 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 id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [102]:

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

import os
import re
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sb
import pickle
```

```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer


from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve,auc

from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.stem import PorterStemmer

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

from sklearn.preprocessing import StandardScaler
#TSNE
from sklearn.manifold import TSNE
from bs4 import BeautifulSoup
```

In [103]:

```
# Temporarily Suppressing Warnings
def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()
```

[1]. Reading Data

In [104]:

```
# using the SQLite Table to read data.
# con = sqlite3.connect('./amazon-fine-food-reviews/database.sqlite')

con = sqlite3.connect('C:/Users/Saraswathi/Music/Appliedai/Data/amazon-fine-food-
reviews/database.sqlite')

#filetering only positve and negative reviews
#reviews not taking in to consideration with score = 3

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 200000""", co
n)
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)


# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating.
def partition( x ):
    if x > 3:
        return 1 #positive
#          return 1
    else:
        return 0 #negative

#changing reviews with score less than 3 to be positive and vice versa
actual_score = filtered_data['Score']
positivenegative = actual_score.map(partition)
filtered_data['Score']=positivenegative
print('Number of data point in our data',filtered_data.shape)
filtered_data.head(5)
```

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

Out[104]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	0	1307923200	Cough Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	1	1350777600	Great taffy

Exploratory Data Analysis

[2] 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 [105]:

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

In [106]:

```
display.head()
```

Out[106]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summ
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANII WAFE
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANII WAFE
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANII WAFE
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANII WAFE

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summ
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANI WAFE

As can be seen above the same user has multiple reviews of the with the 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 [107]:

```
#Sorting data according to ProductId in ascending order
sorted_data = filtered_data.sort_values('ProductId',axis=0,ascending= True, inplace=False, kind ='q
uicksort',na_position='last')
```

In [108]:

```
#Duplication of entries
final = sorted_data.drop_duplicates(subset={'UserId','ProfileName','Time','Text'}, keep = 'first' ,
inplace= False)
final.shape
```

Out[108]:

```
(364173, 10)
```

In [109]:

```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[109]:

```
69.25890143662969
```

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 [110]:

```
display = pd.read_sql_query("""
SELECt *
FROM Reviews
WHERE Score !=3 AND Id=44737 OR Id=64422
ORDER BY ProductId
""",con)
display.head()
```

Out[110]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892800	Bought This for My Son at College

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside

In [111]:

```
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]
```

In [112]:

```
final.shape
final['Score'].value_counts()
```

Out[112]:

```
1    307061
0     57110
Name: Score, dtype: int64
```

[3] Text Preprocessing.

[3.1]. Preprocessing Review Text

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

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

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

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

In [113]:

```
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 [114]:

```
stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "y
ou're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
```

```
'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having',
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', '
while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during',
'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under'
, 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'e
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll'
, 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "do
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [115]:

```
# 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):
for sentance in 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)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

In [116]:

```
preprocessed_reviews[100]
```

Out[116]:

```
'pros dog anything treat not smell bad many treats easy break smaller pieces nothing artificial ea
sy digestion cons costly dog treats overall great product expensive dog anything treat several pho
bias including getting car walking doorways ignores fears get treat'
```

[3.2]. Preprocessing Summary

In [117]:

```
##preprocessing for review summary also.

# Combining all the above stundents
from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
# for sentance in tqdm(final['Summary'].values):
for sentance in (final['Summary'].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)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwords)
    preprocessed_summary.append(sentance.strip())
```

In [118]:

```
preprocessed_summary[100]
```

```
preprocessed_summary[100]
```

Out[118]:

```
'awesome'
```

[5] Apply Naive Bayes

1. **Apply Multinomial NaiveBayes on these feature sets**
    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

2. **The hyper paramter tuning(find best Alpha)**
    - Find the best hyper parameter which will give the maximum [AUC]() value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Feature importance**
    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using values of `feature_log_prob_` parameter of [MultinomialNB]() and print their corresponding feature names

4. **Feature engineering**
    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

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

6. **[Conclusion]()**
    - [You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link]()

Note: Data Leakage

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

Applying Multinomial Naive Bayes

In [119]:

```
final['cleaned_text'] = preprocessed_reviews
final['cleaned_summary'] = preprocessed_summary
final.head()
```

Out[119]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Su

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Su
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	1	939340800	edu
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	1	1194739200	L boo t
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	1	1191456000	sc
138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1	1	1076025600	rhy
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	4	1	1018396800	le

As data is time series data. So, first sort the data based on time

In [120]:

```
final_sort_data = final.sort_values('Time',axis = 0, ascending= True, inplace= False, kind= 'quicks
ort',na_position='last')
```

In [121]:

```
#Train,CV,test split
final_train_cv_data = final_sort_data[:int((final_sort_data.shape[0]*70)/100)] # slice first 70% po
ints in training set and rest 30% points in test set.
final_sort_test_data = final_sort_data[int((final_sort_data.shape[0]*70)/100)+1:]
final_sort_train_data = final_train_cv_data[:int((final_train_cv_data.shape[0]*70)/100)] # slice fi
rst 70% points in training set and rest 30% points in test
final_sort_cv_data = final_train_cv_data[int((final_train_cv_data.shape[0]*70)/100)+1:]

# print(final_train_cv_data.shape)
print(final_sort_test_data.shape)
print(final_sort_cv_data.shape)
print(final_sort_train_data.shape)
# print(final_sort_train_data.columns)

x_train = final_sort_train_data['cleaned_text']
y_train = np.array(final_sort_train_data['Score'])
x_cv = final_sort_cv_data['cleaned_text']
y_cv = np.array(final_sort_cv_data['Score'])
x_test = final_sort_test_data['cleaned_text']
y_test = np.array(final_sort_test_data['Score'])

x_train[100]
```

```
(109251, 12)
(76475, 12)
(178443, 12)
```

Out[121]:

'diappointed flavor texture mix usually like low carb things tried diappointed specific one'

[5.1] Applying Naive Bayes on BOW

In [122]:

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score,auc
```

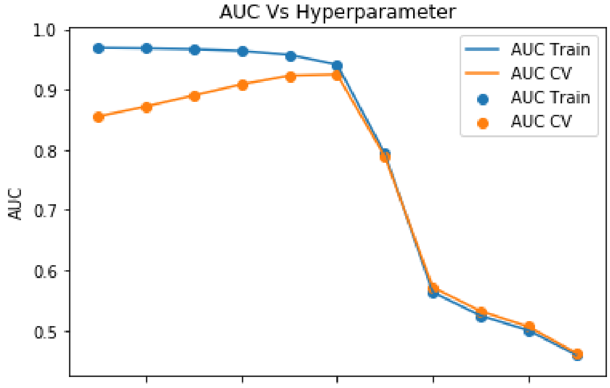
In [123]:

```
cou_vec = CountVectorizer()
final_x_train = cou_vec.fit_transform(x_train)
final_x_cv = cou_vec.transform(x_cv)
final_x_test = cou_vec.transform(x_test)

auc_train = []
auc_cv = []

print(final_x_cv.shape)
```

```
(76475, 79848)
```

In [124]:

```
import math
alpha_values = [10**-5,10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4,10**5]

for i in alpha_values:
    naive = MultinomialNB(alpha = i,class_prior = [0.5,0.5])
    naive.fit(final_x_train, y_train)

    y_train_pred_prob = naive.predict_proba(final_x_train)[:,1]
    y_cv_pred_prob = naive.predict_proba(final_x_cv)[:,1]

    auc_train.append(roc_auc_score(y_train,y_train_pred_prob))
    auc_cv.append(roc_auc_score(y_cv,y_cv_pred_prob))

optimal_alpha = alpha_values[auc_cv.index(max(auc_cv))]
alpha_values = [np.log10(x) for x in alpha_values]

plt.plot(alpha_values, auc_train, label='AUC Train')
plt.scatter(alpha_values, auc_train, label='AUC Train')
plt.plot(alpha_values,auc_cv,label = 'AUC CV')
plt.scatter(alpha_values,auc_cv,label = 'AUC CV')

plt.title('AUC Vs Hyperparameter')
plt.xlabel('log(alpha)')
plt.ylabel('AUC')
plt.legend()
plt.show()

print('Optimal alpha for which AUC is maximum :',optimal_alpha)
```

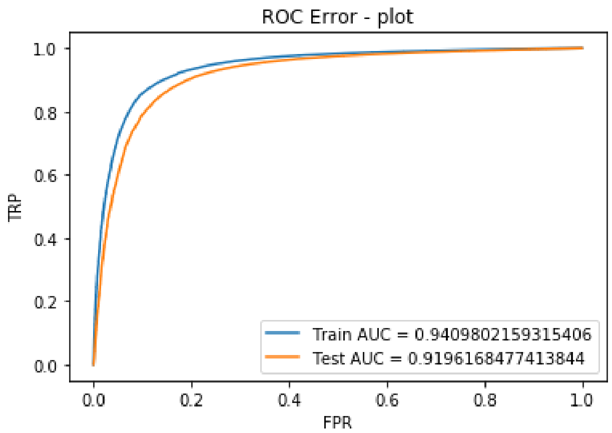



```
Optimal alpha for which AUC is maximum : 1
```

Testing with Test data

In [125]:

```
#Roc for alpha = 1
naive = MultinomialNB(alpha= optimal_alpha)
naive.fit(final_x_train,y_train)

train_prob = naive.predict_proba(final_x_train)[:,1]
test_prob = naive.predict_proba(final_x_test)[:,1]


train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_prob )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

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.xlabel('FPR')
plt.ylabel('TRP')
plt.title('ROC Error - plot')
plt.legend()
plt.show()
```



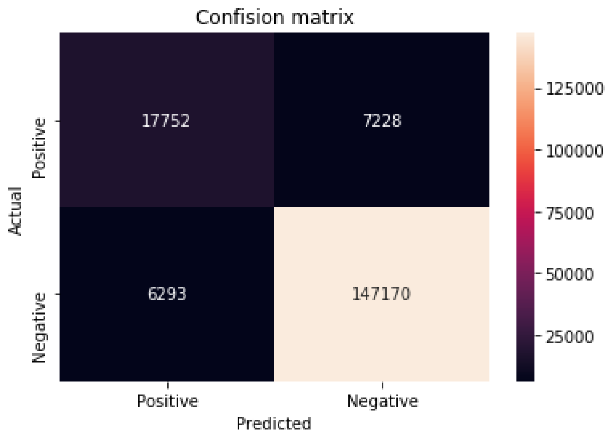
Confusion Matrix

In [126]:

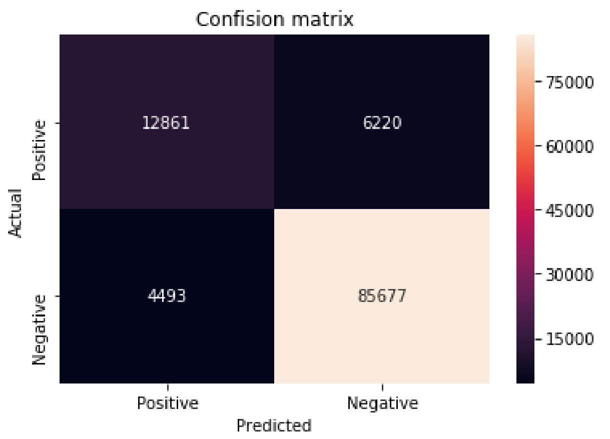
```
#confusion matrix using heatmap for train data
print('Confusion Matrix for train data')
conf_matr = confusion_matrix(y_train, naive.predict(final_x_train))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
#confusion matrix using heatmap for test data

print('Confusion matrix for test data')
conf_matr = confusion_matrix(y_test, naive.predict(final_x_test))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Confusion Matrix for train data
```

Confusion matrix for train data



Confusion matrix for test data



[5.1.1] Top 10 important features of positive class

In [127]:

```
naive = MultinomialNB(alpha = optimal_alpha)
naive.fit(final_x_train,y_train)

features = naive.feature_log_prob_ #log probability of features given a class
feature_names = cou_vec.get_feature_names()
positive_features = np.argsort(features[1])[::-1] # a[::-1] all items in the array, reversed
negative_features = np.argsort(features[0])[::-1] # Returns the indices that would sort an array
print("Top 10 important features of positive class from BOW")

# for i in list(positive_features[0:10]):
for i in list(positive_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of positive class from BOW
not
like
good
great
one
tea
taste
flavor
love
product
```

[5.1.2] Top 10 important features of negative class

In [128]:

```
print("Top 10 important features of negative class from BOW")
```

```
print('Top 10 important features of negative class from BOW')
for i in list(negative_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of negative class from BOW
not
like
would
product
taste
one
good
no
flavor
coffee
```

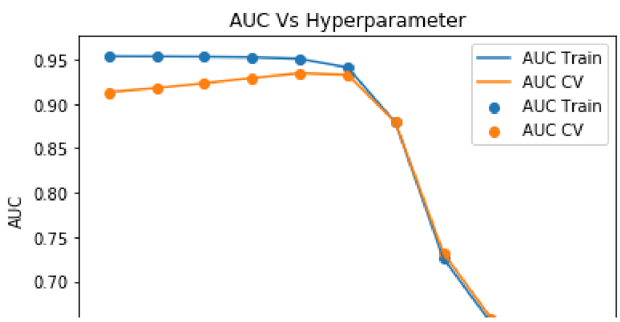
[5.2] Applying Naive Bayes on TFIDF

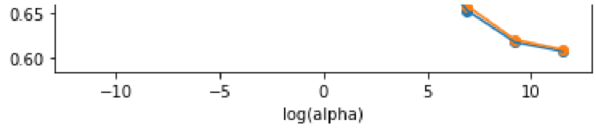
In [129]:

```
tf_idf_vect = TfidfVectorizer(min_df= 10)
final_x_train = tf_idf_vect.fit_transform(x_train)
final_x_cv = tf_idf_vect.transform(x_cv)
final_x_test = tf_idf_vect.transform(x_test)

auc_train = []
auc_cv = []
```

In [130]:

```
import math
alpha_values = [10**-5,10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4,10**5]

for i in alpha_values:
    naive = MultinomialNB(alpha = i,class_prior = [0.5,0.5])
    naive.fit(final_x_train, y_train)

    y_train_pred_prob = naive.predict_proba(final_x_train)[:,1]
    y_cv_pred_prob = naive.predict_proba(final_x_cv)[:,1]

    auc_train.append(roc_auc_score(y_train,y_train_pred_prob))
    auc_cv.append(roc_auc_score(y_cv,y_cv_pred_prob))



optimal_alpha = alpha_values[auc_cv.index(max(auc_cv))]
alpha_values = [np.log(x) for x in alpha_values]

plt.plot(alpha_values, auc_train, label='AUC Train')
plt.scatter(alpha_values, auc_train, label='AUC Train')
plt.plot(alpha_values,auc_cv,label = 'AUC CV')
plt.scatter(alpha_values,auc_cv,label = 'AUC CV')

plt.title('AUC Vs Hyperparameter')
plt.xlabel('log(alpha)')
plt.ylabel('AUC')
plt.legend()
plt.show()

print('Optimal alpha for which AUC is maximum :',optimal_alpha)
```



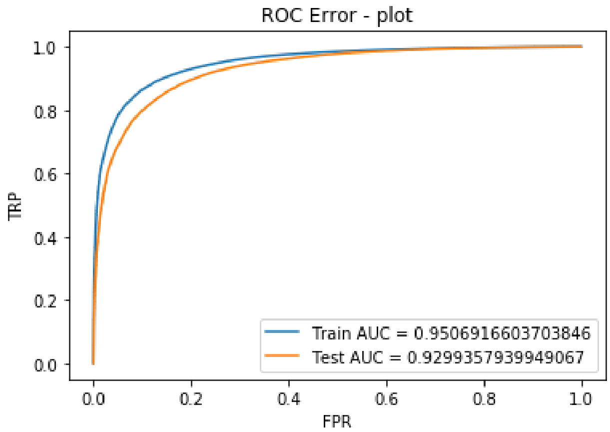



```
Optimal alpha for which AUC is maximum : 0.1
```

Testing with Test data

In [131]:

```
#Roc for alpha = 1
naive = MultinomialNB(alpha= optimal_alpha)
naive.fit(final_x_train,y_train)

train_prob = naive.predict_proba(final_x_train)[:,1]
test_prob = naive.predict_proba(final_x_test)[:,1]


train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_prob )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

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.xlabel('FPR')
plt.ylabel('TRP')
plt.title('ROC Error - plot')
plt.legend()
plt.show()
```



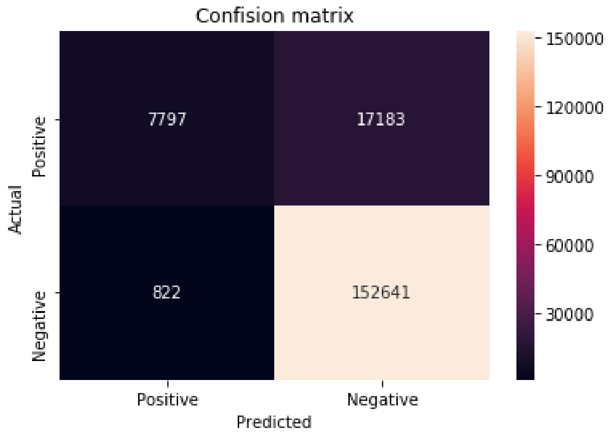
Confusion Matrix

In [132]:

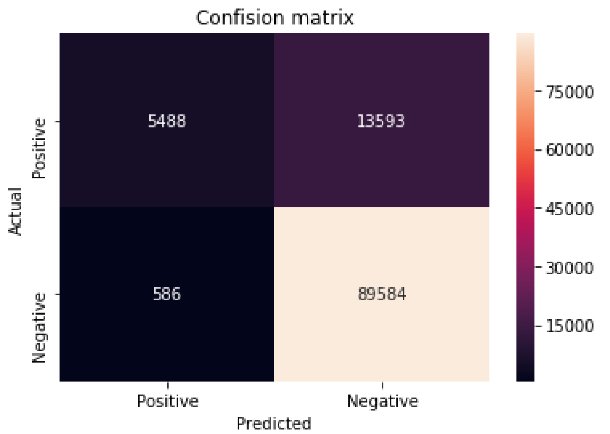
```
#confusion matrix using heatmap for train data
print('Confusion Matrix for train data')
conf_matr = confusion_matrix(y_train, naive.predict(final_x_train))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
#confusion matrix using heatmap for test data

print('Confusion matrix for test data')
conf_matr = confusion_matrix(y_test, naive.predict(final_x_test))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
plt.show()
```

```
Confusion Matrix for train data
```




```
Confusion matrix for test data
```



[5.2.1] Top 10 important features of positive class

In [133]:

```
naive = MultinomialNB(alpha = optimal_alpha)
naive.fit(final_x_train,y_train)

features = naive.feature_log_prob_ #log probability of features given a class
feature_names = tf_idf_vect.get_feature_names()
positive_features = np.argsort(features[1])[::-1] # a[::-1] all items in the array, reversed
negative_features = np.argsort(features[0])[::-1] # Returns the indices that would sort an array
print("Top 10 important features of positive class from BOW")

# for i in list(positive_features[0:10]):
for i in list(positive_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of positive class from BOW
not
great
good
tea
like
coffee
love
product
taste
one
```

[5.2.2] Top 10 important features of negative class from

In [134]:

```
print("Top 10 important features of negative class from BOW")
for i in list(negative_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of negative class from BOW
not
like
taste
product
would
coffee
one
flavor
no
good
```

[5.3] Feature engineering

In [135]:

```
#Adding preprocessed summary and review length to preprocessed summary
# for i in range(len(preprocessed_reviews)):
#     preprocessed_reviews[i] += ' '+preprocessed_summary[i]+ ' ' + str(len(final.Text.iloc[i]))

# preprocessed_reviews[100]
# print(final['cleaned_text'][100])

final['cleaned_text'] = final['cleaned_text'] + ' ' + final['cleaned_summary'] + ' ' + str(len(fina
l['cleaned_text']))

print(final['cleaned_text'][100])
```

```
diappointed flavor texture mix usually like low carb things tried diappointed specific one low car
b angel food puffs 364171
```

[5.4] Applying Naive Bayes on BOW

In [136]:

```
final.head()
```

Out[136]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Su
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	1	939340800	edu
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	1	1194739200	L boo t
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	1	1191456000	sc
				Catherine					

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Su
138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg "(Kate)"	1	1	1	1076025600	Su
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	4	1	1018396800	le

As data is time series data. So, first sort the data based on time

In [137]:

```
final_sort_data = final.sort_values('Time',axis = 0, ascending= True, inplace= False, kind= 'quicks
ort',na_position='last')
```

In [138]:

```
#Train,CV,test split
final_train_cv_data = final_sort_data[:int((final_sort_data.shape[0]*70)/100)] # slice first 70% po
ints in training set and rest 30% points in test set.
final_sort_test_data = final_sort_data[int((final_sort_data.shape[0]*70)/100)+1:]
final_sort_train_data = final_train_cv_data[:int((final_train_cv_data.shape[0]*70)/100)] # slice fi
rst 70% points in training set and rest 30% points in test
final_sort_cv_data = final_train_cv_data[int((final_train_cv_data.shape[0]*70)/100)+1:]

# print(final_train_cv_data.shape)
print(final_sort_test_data.shape)
print(final_sort_cv_data.shape)
print(final_sort_train_data.shape)
# print(final_sort_train_data.columns)

x_train = final_sort_train_data['cleaned_text']
y_train = np.array(final_sort_train_data['Score'])
x_cv = final_sort_cv_data['cleaned_text']
y_cv = np.array(final_sort_cv_data['Score'])
x_test = final_sort_test_data['cleaned_text']
y_test = np.array(final_sort_test_data['Score'])

x_train[100]
```

```
(109251, 12)
(76475, 12)
(178443, 12)
```

Out[138]:

```
'diappointed flavor texture mix usually like low carb things tried diappointed specific one low ca
rb angel food puffs 364171'
```

In [139]:

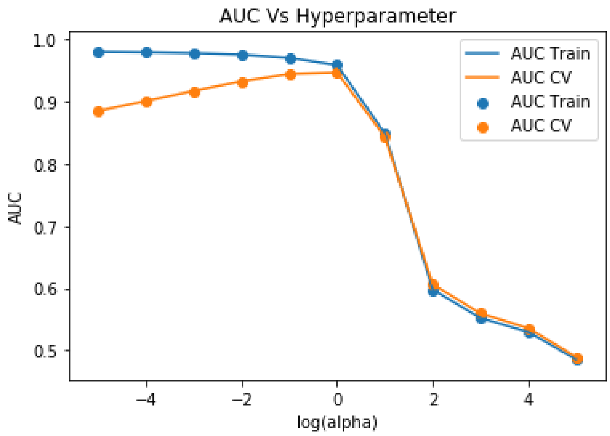
```
cou_vec = CountVectorizer()
final_x_train = cou_vec.fit_transform(x_train)
final_x_cv = cou_vec.transform(x_cv)
final_x_test = cou_vec.transform(x_test)

auc_train = []
auc_cv = []

print(final_x_cv.shape)
```

```
(76475, 83285)
```

In [140]:

```
import math
```

```
alpha_values = [10**-5,10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4,10**5]

for i in alpha_values:
    naive = MultinomialNB(alpha = i,class_prior = [0.5,0.5])
    naive.fit(final_x_train, y_train)

    y_train_pred_prob = naive.predict_proba(final_x_train)[:,1]
    y_cv_pred_prob = naive.predict_proba(final_x_cv)[:,1]

    auc_train.append(roc_auc_score(y_train,y_train_pred_prob))
    auc_cv.append(roc_auc_score(y_cv,y_cv_pred_prob))

optimal_alpha = alpha_values[auc_cv.index(max(auc_cv))]
alpha_values = [np.log10(x) for x in alpha_values]

plt.plot(alpha_values, auc_train, label='AUC Train')
plt.scatter(alpha_values, auc_train, label='AUC Train')
plt.plot(alpha_values,auc_cv,label = 'AUC CV')
plt.scatter(alpha_values,auc_cv,label = 'AUC CV')

plt.title('AUC Vs Hyperparameter')
plt.xlabel('log(alpha)')
plt.ylabel('AUC')
plt.legend()
plt.show()

print('Optimal alpha for which AUC is maximum :',optimal_alpha)
```

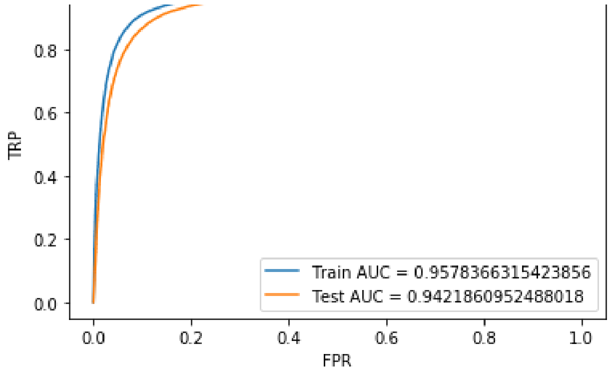



```
Optimal alpha for which AUC is maximum : 1
```

Testing with Test data

In [141]:

```
#Roc for alpha = 1
naive = MultinomialNB(alpha= optimal_alpha)
naive.fit(final_x_train,y_train)

train_prob = naive.predict_proba(final_x_train)[:,1]
test_prob = naive.predict_proba(final_x_test)[:,1]


train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_prob )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

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.xlabel('FPR')
plt.ylabel('TRP')
plt.title('ROC Error - plot')
plt.legend()
plt.show()
```

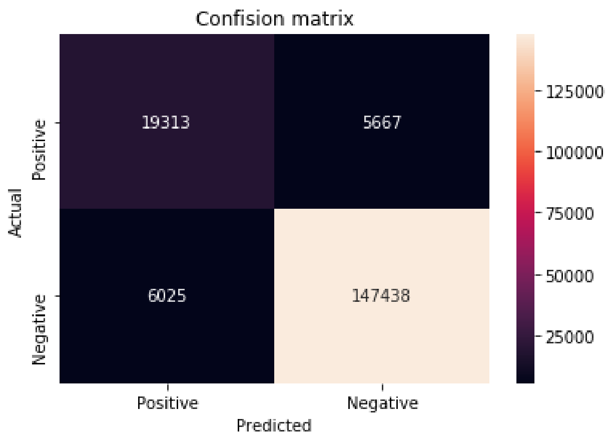


Confusion Matrix

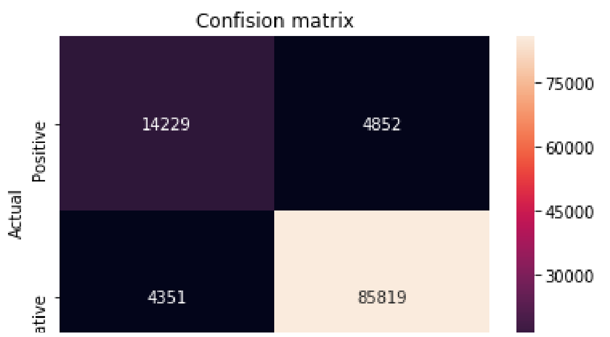
In [142]:

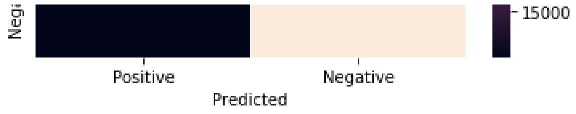
```
#confusion matrix using heatmap for train data
print('Confusion Matrix for train data')
conf_matr = confusion_matrix(y_train, naive.predict(final_x_train))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
#confusion matrix using heatmap for test data

print('Confusion matrix for test data')
conf_matr = confusion_matrix(y_test, naive.predict(final_x_test))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Confusion Matrix for train data
```




```
Confusion matrix for test data
```





[5.4.1] Top 10 important features of positive class

In [143]:

```
naive = MultinomialNB(alpha = optimal_alpha)
naive.fit(final_x_train,y_train)

features = naive.feature_log_prob_ #log probability of features given a class
feature_names = cou_vec.get_feature_names()
positive_features = np.argsort(features[1])[::-1] # a[::-1] all items in the array, reversed
negative_features = np.argsort(features[0])[::-1] # Returns the indices that would sort an array
print("Top 10 important features of positive class from BOW")

# for i in list(positive_features[0:10]):
for i in list(positive_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of positive class from BOW
364171
not
great
good
like
tea
one
taste
love
product
```

[5.4.2] Top 10 important features of negative class

In [144]:

```
print("Top 10 important features of negative class from BOW")
for i in list(negative_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of negative class from BOW
not
364171
like
taste
product
would
one
good
no
flavor
```

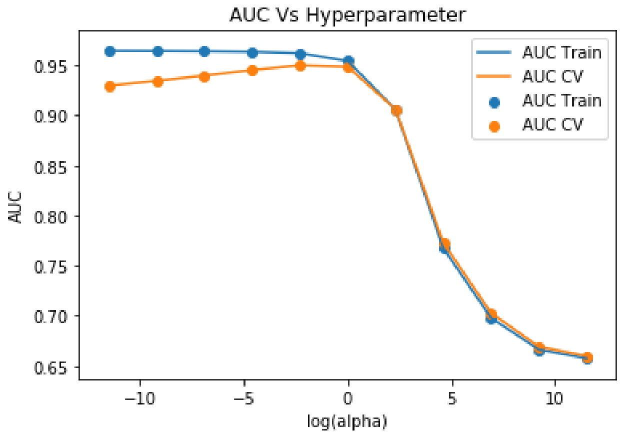
[5.5] Applying Naive Bayes on TFIDF

In [145]:

```
tf_idf_vect = TfidfVectorizer(min_df= 10)
final_x_train = tf_idf_vect.fit_transform(x_train)
final_x_cv = tf_idf_vect.transform(x_cv)
final_x_test = tf_idf_vect.transform(x_test)

auc_train = []
auc_cv = []
```

In [146]:

```
import math
alpha_values = [10**-5,10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4,10**5]

for i in alpha_values:
    naive = MultinomialNB(alpha = i,class_prior = [0.5,0.5])
    naive.fit(final_x_train, y_train)

    y_train_pred_prob = naive.predict_proba(final_x_train)[:,1]
    y_cv_pred_prob = naive.predict_proba(final_x_cv)[:,1]

    auc_train.append(roc_auc_score(y_train,y_train_pred_prob))
    auc_cv.append(roc_auc_score(y_cv,y_cv_pred_prob))



optimal_alpha = alpha_values[auc_cv.index(max(auc_cv))]
alpha_values = [np.log(x) for x in alpha_values]

plt.plot(alpha_values, auc_train, label='AUC Train')
plt.scatter(alpha_values, auc_train, label='AUC Train')
plt.plot(alpha_values,auc_cv,label = 'AUC CV')
plt.scatter(alpha_values,auc_cv,label = 'AUC CV')

plt.title('AUC Vs Hyperparameter')
plt.xlabel('log(alpha)')
plt.ylabel('AUC')
plt.legend()
plt.show()

print('Optimal alpha for which AUC is maximum :',optimal_alpha)
```

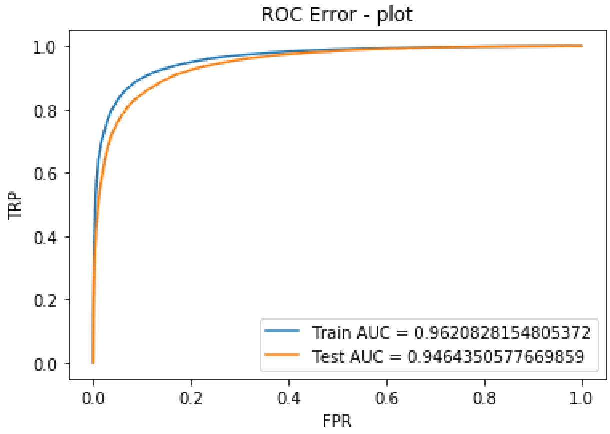



```
Optimal alpha for which AUC is maximum : 0.1
```

Testing with Test data

In [147]:

```
#Roc for alpha = 1
naive = MultinomialNB(alpha= optimal_alpha)
naive.fit(final_x_train,y_train)

train_prob = naive.predict_proba(final_x_train)[:,1]
test_prob = naive.predict_proba(final_x_test)[:,1]


train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_prob )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

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.xlabel('FPR')
plt.ylabel('TRP')
plt.title('ROC Error - plot')
plt.legend()
plt.show()
```

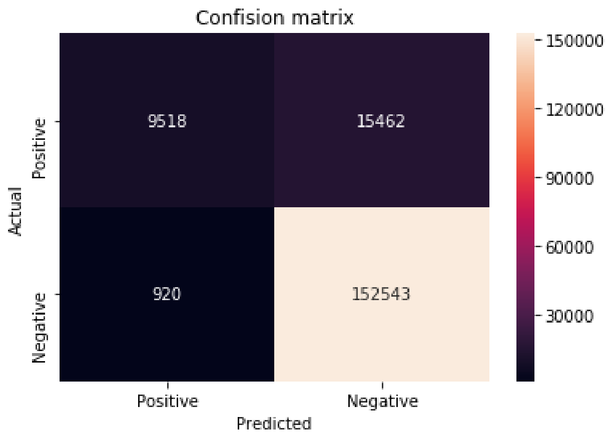


Confusion Matrix

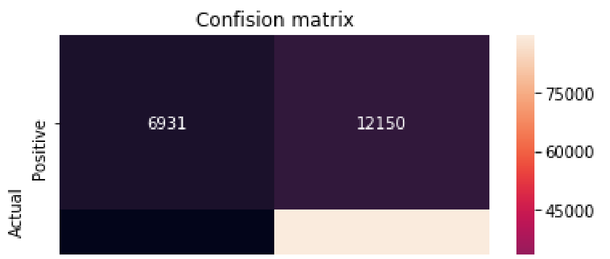
In [148]:

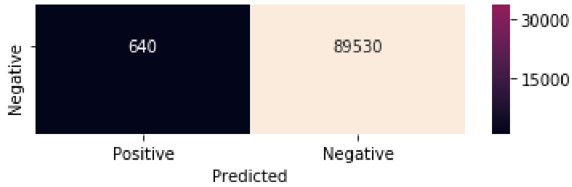
```
#confusion matrix using heatmap for train data
print('Confusion Matrix for train data')
conf_matr = confusion_matrix(y_train, naive.predict(final_x_train))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
#confusion matrix using heatmap for test data

print('Confusion matrix for test data')
conf_matr = confusion_matrix(y_test, naive.predict(final_x_test))
class_labes = ['Positive','Negative']
df = pd.DataFrame(conf_matr, index= class_labes, columns=class_labes)
sb.heatmap(df, annot= True ,fmt = 'd')
plt.title('Confision matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Confusion Matrix for train data
```




```
Confusion matrix for test data
```





[5.5.1] Top 10 important features of positive class

In [149]:

```
naive = MultinomialNB(alpha = optimal_alpha)
naive.fit(final_x_train,y_train)

features = naive.feature_log_prob_ #log probability of features given a class
feature_names = tf_idf_vect.get_feature_names()
positive_features = np.argsort(features[1])[::-1] # a[::-1] all items in the array, reversed
negative_features = np.argsort(features[0])[::-1] # Returns the indices that would sort an array
print("Top 10 important features of positive class from BOW")

# for i in list(positive_features[0:10]):
for i in list(positive_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of positive class from BOW
not
great
364171
good
tea
coffee
love
like
best
product
```

[5.5.2] Top 10 important features of negative class from

In [150]:

```
print("Top 10 important features of negative class from BOW")
for i in list(negative_features[0:10]):
    print(feature_names[i])
```

```
Top 10 important features of negative class from BOW
not
like
364171
taste
product
would
coffee
one
flavor
no
```

[6] Conclusions

In [152]:

```
# compare all your models
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ['Vectorizer','Feature Engineering','Hyperameter(Alpha)','AUC']
x.add_row(['BOW','Not featured ',1,0.91])
x.add_row(['TFIDF','Not featured ',0.1,0.92])
x.add_row(['BOW','featured',1,0.94])
x.add_row(['TFIDF','featured',0.1,0.94])
```

```
print(x)
```

```
+------------+---------------------+--------------------+------+
| Vectorizer | Feature Engineering | Hyperameter(Alpha) | AUC  |
+------------+---------------------+--------------------+------+
|    BOW     |     Not featured    |         1          | 0.91 |
|   TFIDF    |     Not featured    |        0.1         | 0.92 |
|    BOW     |       featured      |         1          | 0.94 |
|   TFIDF    |       featured      |        0.1         | 0.94 |
+------------+---------------------+--------------------+------+
```

[7] Observations

- > when summary of every product is added to the actual reviews then it gives better performance as compared to the model which takes only the text of the reviews in both bow and tfidf vectorization

- > tfidf is haviing little edge as compared to Bow vectorizer[TEXT] vectorizer as it gives better stats

- > Naive bayes is the simplest algorithm and it takes very much less time then KNN.

- > for feature engineering and found that after feature engineering our auc increased