Amazon_Fine_Food_Reviews_Analysis_NaiveBayes

March 23, 2019

1 Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective: Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative? [Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 [1]. Reading Data

2.1 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

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


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

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

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

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

        from tqdm import tqdm
        import os
```

```
In [2]: # using SQLite Table to read data.
        con = sqlite3.connect('database.sqlite')

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

        # filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5
```

```
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)

# 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 (525814, 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  B0070SBE1U   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  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

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

In [6]:
```python
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]:
```python
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]: (364173, 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]: 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 [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()
```

```
(364171, 10)
```

```
Out[13]: 1    307061
         0     57110
         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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pref
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only th
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of this
==================================================
```

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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
```

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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pref
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only th
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of this
```

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)
```

```
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
```

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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alo
```

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

```
Great ingredients although chicken should have been 1st rather than chicken broth the only thi
```

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]:
```
# 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%|| 364171/364171 [03:13<00:00, 1884.65it/s]
```

In [23]:
```
preprocessed_reviews[1500]
```

Out[23]:
```
'great ingredients although chicken rather chicken broth thing not think belongs canol
```

[3.2] Preprocessing Review Summary

In [24]:
```
preprocessed_summary = []
# tqdm is for printing the status bar
for sentance in tqdm(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)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwo
    preprocessed_summary.append(sentance.strip())
```

```
100%|| 364171/364171 [02:12<00:00, 2747.27it/s]
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

In [25]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaa', 'aaaaaaaaaaa', 'aaaaaaaaaaaa', 'aa
==================================================
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (364171, 116756)
the number of unique words  116756
```

5.2 [4.2] Bi-Grams and n-Grams.

In [26]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/stable/mod

# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_bigram_
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (364171, 5000)
the number of unique words including both unigrams and bigrams  5000
```

5.3 [4.3] TF-IDF

In [27]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_name
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_tf_idf
```

```
some sample features(unique words in the corpus) ['aa', 'aaa', 'aaaaa', 'aaah', 'aafco', 'ab',
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (364171, 203034)
the number of unique words including both unigrams and bigrams  203034
```

5.4 [4.4] Word2Vec

In [28]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
```

```
    for sentance in preprocessed_reviews:
        list_of_sentance.append(sentance.split())
```

In [29]:
```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bi
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v = True, t
```

```
[('terrific', 0.8946336507797241), ('fantastic', 0.8892163634300232), ('awesome', 0.8583937888
==================================================
[('nastiest', 0.8621901869773865), ('greatest', 0.7646499872207642), ('disgusting', 0.75236147
```

In [30]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  33573
sample words  ['witty', 'little', 'book', 'makes', 'son', 'laugh', 'loud', 'recite', 'car', 'd
```

5.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [0]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need to
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|| 4986/4986 [00:03<00:00, 1330.47it/s]


4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [28]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [0]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this li
row=0;
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
```

```
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
```

100%|| 4986/4986 [00:20<00:00, 245.63it/s]

In [25]:
```
# Function to plot confusion matrix
def confusion_matrix_plot(test_y, predict_y):
    # C stores the confusion matrix
    C = confusion_matrix(test_y, predict_y)


    # Class labels
    labels_x = ["Predicted No","Predicted Yes"]
    labels_y = ["Original No","Original Yes"]

    cmap=sns.light_palette("orange")
    print("Confusion matrix")
    plt.figure(figsize=(4,4))
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels_x, yticklabels
    plt.show()
```

In [26]:
```
# Function to plot roc curve

def plot_roc_curve(Y_test,predict_y_test,Y_train,predict_y_train):
    fpr1,tpr1,threshold1 = roc_curve(Y_test,predict_y_test) # For test dataset
    fpr2,tpr2,threshold2 = roc_curve(Y_train,predict_y_train) # For train dataset

    plt.plot([0,1],[0,1])
    plt.plot(fpr1,tpr1,label="Test AUC")
    plt.plot(fpr2,tpr2,label="Train AUC")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend()
    plt.show()
```

In [34]:
```
import math
# Plotting graph of auc and parameter for training and cross validation error
alpha1 = [0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
alpha2 = [math.log10(i) for i in alpha1]
def plot_train_vs_auc(train_auc_list,cv_auc_list):
```

```python
plt.plot(alpha2,train_auc_list,label="Train AUC")
plt.xlabel("Hyper-parameter alpha")
plt.ylabel("Area Under Curve")
plt.plot(alpha2,cv_auc_list,label="Validation AUC")
plt.legend()
plt.show()
```

6 [5] Assignment 4: Apply Naive Bayes

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)
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

```
</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 
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature engin
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
<img src='confusion_matrix.png' width=300px></li>
    </ul>
```

```
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

Note: Data Leakage

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

7 Applying Multinomial Naive Bayes

7.1 [5.1] Applying Naive Bayes on BOW, SET 1

On Uni-grams

In [214]:
```
# Initializing BagOfWords
bow_vect = CountVectorizer()

# Spplitting data into train and test
from sklearn.cross_validation import train_test_split
from sklearn.model_selection import TimeSeriesSplit

X = preprocessed_reviews
Y = final['Score']

X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,random_state=42)
print(len(X_train),len(X_test))
```

```
254919 109252
```

In [36]:
```
# Vectorizing the reviews
train_vect = bow_vect.fit_transform(X_train)
test_vect = bow_vect.transform(X_test)

print(train_vect.shape)
```

```
(254919, 96683)
```

```
In [37]: # Creating a list of alpha values to calculate best alpha
         alpha = [0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]

In [38]: from sklearn.naive_bayes import MultinomialNB
         from sklearn.metrics import roc_auc_score
         from tqdm import tqdm  # this module is used to check the progress of loops
         # In this section we will train naive bayes model and find training error for various

         train_auc_list = [] # Stores area under curve for each alpha value

         for k  in tqdm(alpha):
             clf = MultinomialNB(alpha=k)

             # Trainig our model
             clf.fit(train_vect,Y_train)

             predict_probab = clf.predict_log_proba(train_vect)[:,1] # Returns probability for

             auc = roc_auc_score(Y_train,predict_probab)
             train_auc_list.append(auc)
```

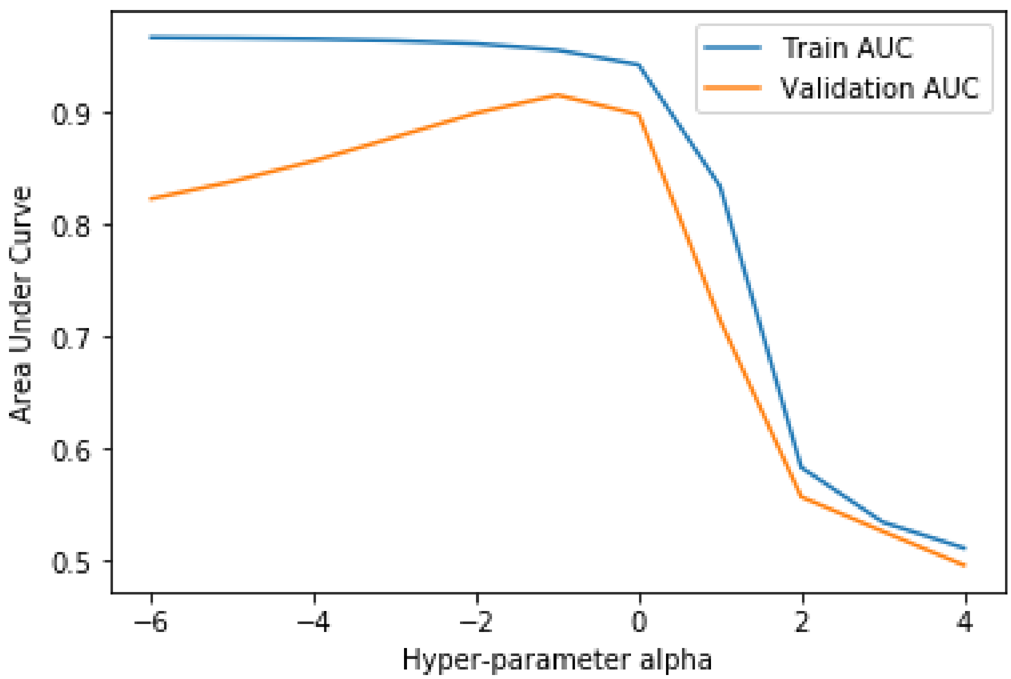
```
100%|| 11/11 [00:05<00:00,  2.28it/s]
```

```
In [39]: # We will do time based splitting and do 10 fold cross validation
         # This is done as reviews keeps changing with time and hence time based splitting is

         from sklearn.model_selection import TimeSeriesSplit
         # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         cv_auc_list = [] # will contain cross validation AUC corresponding to each k

         for k in tqdm(alpha):
             # Naive bayes classifier
             clf = MultinomialNB(alpha=k)
             i=0
             auc=0.0
             for train_index,test_index in tscv.split(train_vect):
                 x_train = train_vect[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 x_test = train_vect[train_index[-1]:test_index[-1]][:] # row from train_index
                 y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to

                 clf.fit(x_train,y_train)

                 predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for pos
```

```
        i += 1
        auc += roc_auc_score(y_test,predict_probab)

    cv_auc_list.append(auc/i) # Storing AUC value
```

```
100%|| 11/11 [00:42<00:00,  3.85s/it]
```

In [40]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

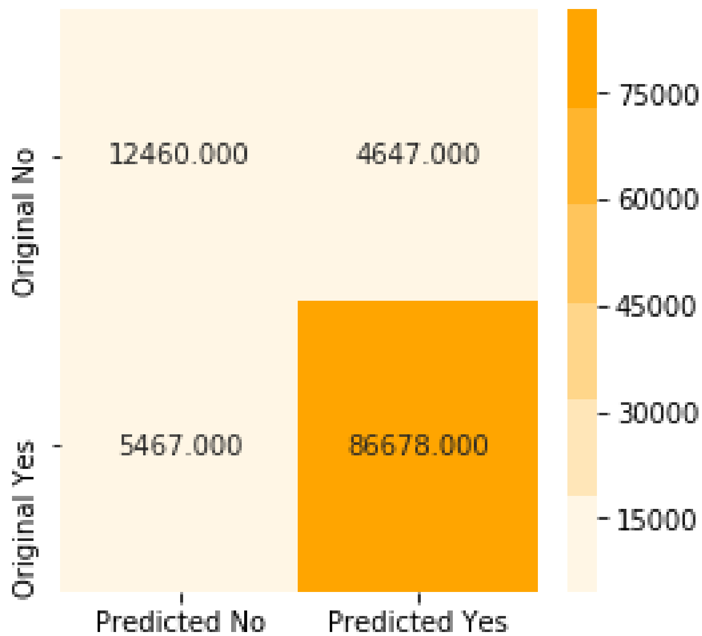


In [41]:
```
# Here best validation and train AUC occurs at -1 which means at alpha 0.1 as we took
# Initializing model
final_clf = MultinomialNB(alpha=0.1)

# Training final model
final_clf.fit(train_vect,Y_train)

predict_y = final_clf.predict(test_vect)
predict_probab = final_clf.predict_log_proba(test_vect)[:,1] # Returns probabality fo
predict_y_train = final_clf.predict(train_vect)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for BoW Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for BoW Naive Bayes is 0.925
```

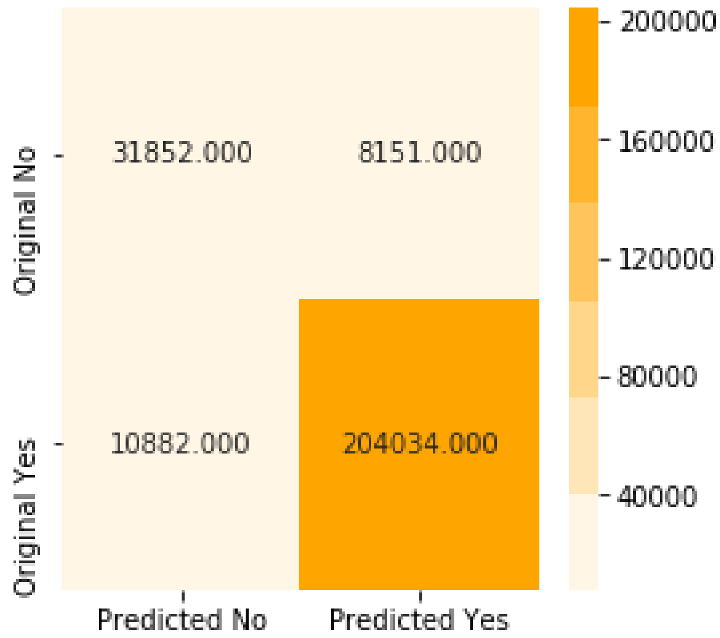
```
In [43]: # Plotting confusion matrix for train
         print("For test datset")
         confusion_matrix_plot(Y_test,predict_y)
```

```
For test datset
Confusion matrix
```

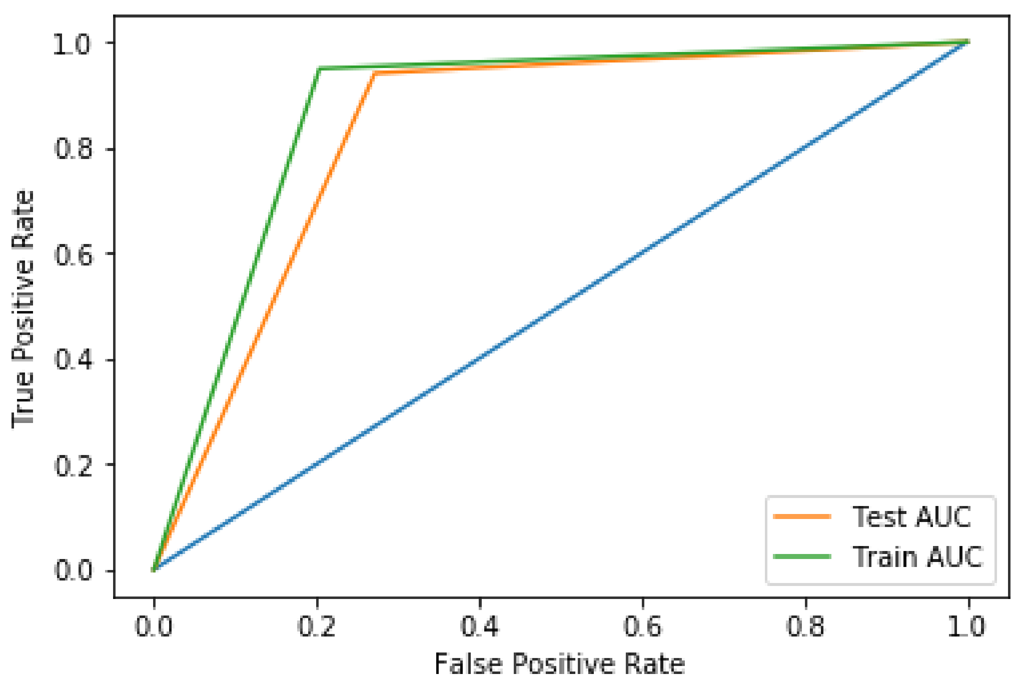



```
In [44]: # Plotting confusion matrix for test
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```




```
In [45]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyperparameter tuning using GridSearch CV

In [46]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer

# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = MultinomialNB()


# Dictionary of parameters to be searched on
parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

# Value on which model will be evaluated
auc_score = make_scorer(roc_auc_score)

# Calling GridSearchCV .
grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,scor

# Training the gridsearchcv instance
grid_model.fit(train_vect,Y_train)

# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_

predict_probab = optimized_clf.predict_log_proba(test_vect)[:,1] # returns probabilit
predict_y = optimized_clf.predict(test_vect)
predict_y_train = optimized_clf.predict(train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

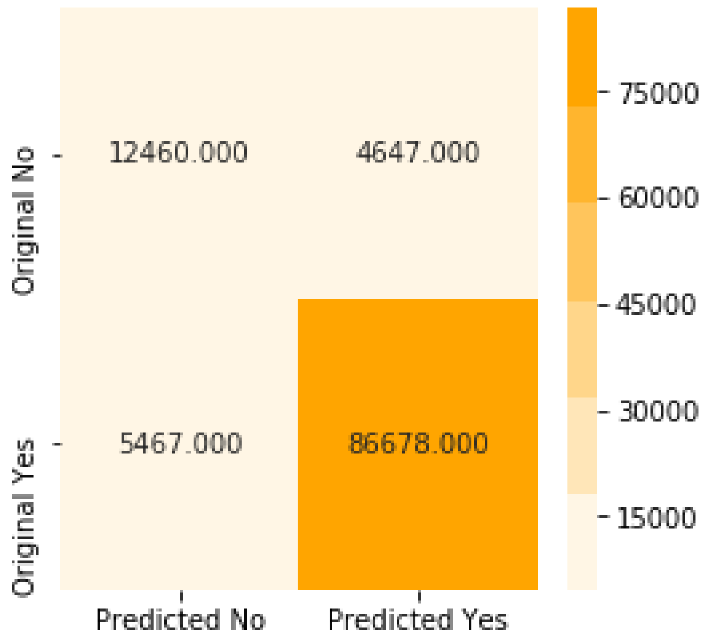
```
AUC is 0.925
```

In [47]:
```
print(grid_model.best_params_)
```

```
{'alpha': 0.1}
```

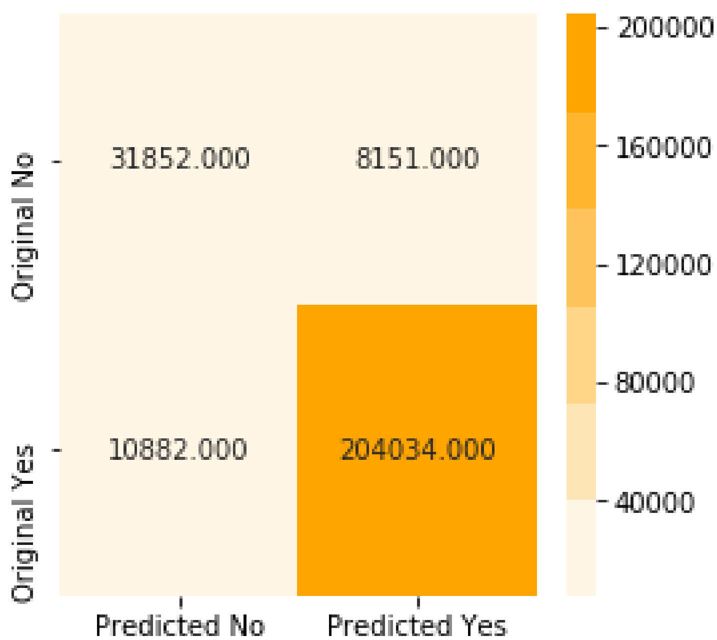
In [48]:
```
# Plotting confusion matrix for train
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

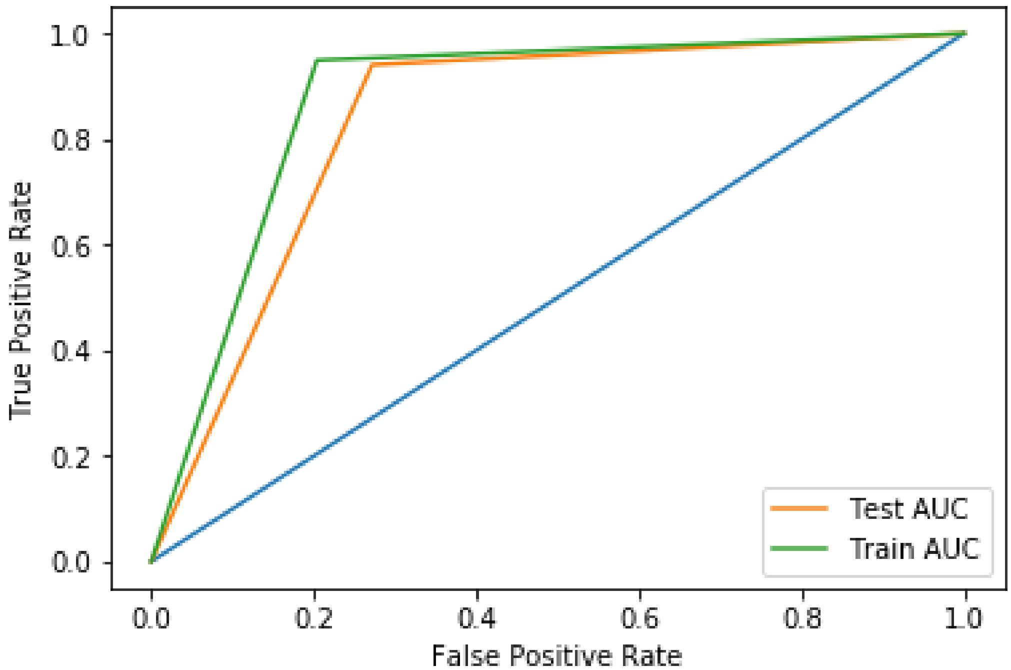



```
In [49]: # Plotting confusion matrix for test
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



In [47]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Observation

1. The AUC score improves by 1 percent when hyper-parameter tuning is done using grid-search

7.1.1 [5.1.1] Top 10 important features of positive class from SET 1

In [50]:
```
import numpy as np
# Top 10 features log probability

# Sorting all probability in ascending and getting their index
positive_top10 = final_clf.feature_log_prob_[1,:].argsort()

# Getting last 10 features as they have largest prob value
top10_features = [bow_vect.get_feature_names()[i] for i in positive_top10[-10:]]

print("Top 10 feature for positive class are ::",top10_features)
```

```
Top 10 feature for positive class are :: ['love', 'coffee', 'tea', 'product', 'taste', 'one',
```

7.1.2 [5.1.2] Top 10 important features of negative class from SET 1

```
In [51]: # Top 10 features for negative class

         # Sorting all probability in ascending and getting their index
         negative_top10 = optimized_clf.feature_log_prob_[0,:].argsort()

         # Getting last 10 features as they have largest prob value
         top10_features = [bow_vect.get_feature_names()[i] for i in negative_top10[-10:]]

         print("Top 10 feature for negative class are ::",top10_features)
```

```
Top 10 feature for negative class are :: ['flavor', 'coffee', 'no', 'good', 'one', 'taste', 'wo
```

On bigrams

```
In [52]: # Initializing BagOfWords
         bow_vect = CountVectorizer(ngram_range=(2,2))

         # Spplitting data into train and test
         from sklearn.cross_validation import train_test_split
         from sklearn.model_selection import TimeSeriesSplit

         X = preprocessed_reviews
         Y = final['Score']

         X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,random_state=42)
         print(len(X_train),len(X_test))
```

```
254919 109252
```

```
In [53]: # Vectorizing the reviews
         train_vect = bow_vect.fit_transform(X_train)
         test_vect = bow_vect.transform(X_test)
         print(train_vect.shape)
```

```
(254919, 2973643)
```

```
In [54]: # In this section we will train naive bayes model and find training error for various

         train_auc_list = [] # Stores area under curve for each alpha value

         for k  in tqdm(alpha):
             clf = MultinomialNB(alpha=k)

             # Trainig our model
```

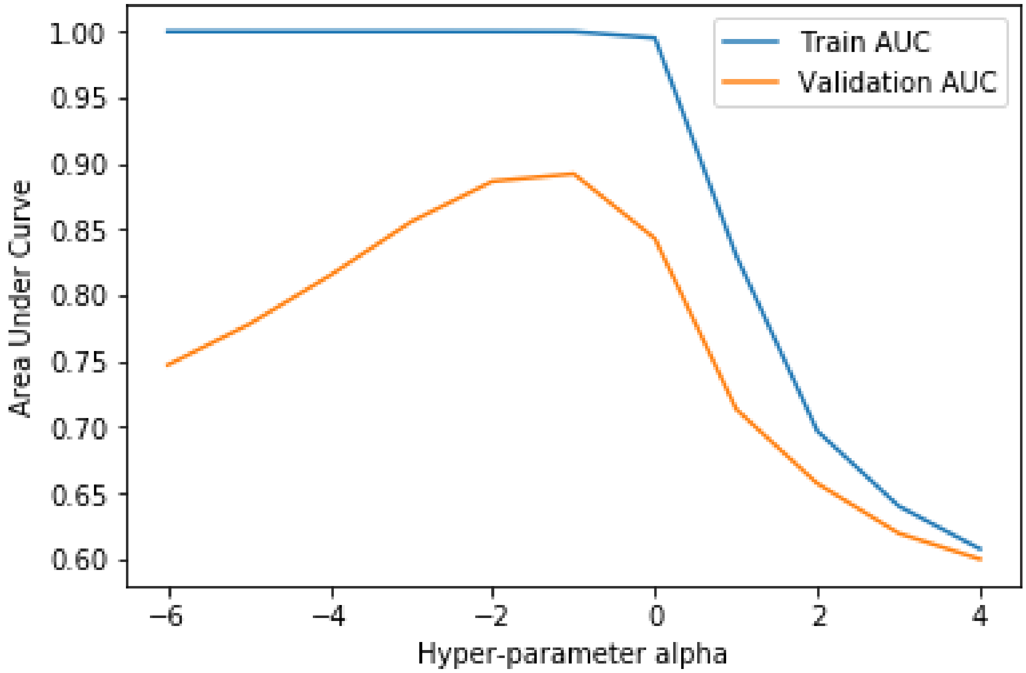
```
            clf.fit(train_vect,Y_train)

            predict_probab = clf.predict_log_proba(train_vect)[:,1] # Returns probability for

            auc = roc_auc_score(Y_train,predict_probab)
            train_auc_list.append(auc)
```

```
100%|| 11/11 [00:11<00:00,  1.01s/it]
```

```
In [55]: # We will do time based splitting and do 10 fold cross validation
         # This is done as reviews keeps changing with time and hence time based splitting is

         from sklearn.model_selection import TimeSeriesSplit
         # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         cv_auc_list = [] # will contain cross validation AUC corresponding to each k

         for k in tqdm(alpha):
             # Naive bayes classifier
             clf = MultinomialNB(alpha=k)
             i=0
             auc=0.0
             for train_index,test_index in tscv.split(train_vect):
                 x_train = train_vect[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 x_test = train_vect[train_index[-1]:test_index[-1]][:] # row from train_index
                 y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to

                 clf.fit(x_train,y_train)

                 predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for pos
                 i += 1
                 auc += roc_auc_score(y_test,predict_probab)

             cv_auc_list.append(auc/i) # Storing AUC value
```

```
100%|| 11/11 [01:29<00:00,  8.19s/it]
```

```
In [56]: # Plotitng paramter vs auc curve

         plot_train_vs_auc(train_auc_list,cv_auc_list)
```

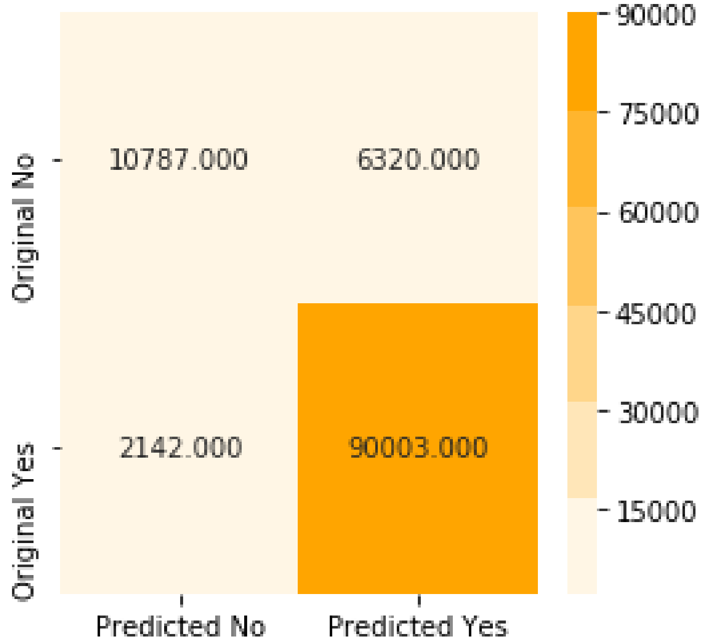



```
In [57]: # Taking best value of alpha = 0.1 an trainig final model
         # Initializing model
         final_clf = MultinomialNB(alpha=0.1)

         # Training final model
         final_clf.fit(train_vect,Y_train)

         predict_y = final_clf.predict(test_vect)
         predict_probab = final_clf.predict_log_proba(test_vect)[:,1] # Returns probabality fo
         predict_y_train = final_clf.predict(train_vect)
         auc = roc_auc_score(Y_test,predict_probab)
         print("Final AUC for BoW Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for BoW Naive Bayes is 0.921
```

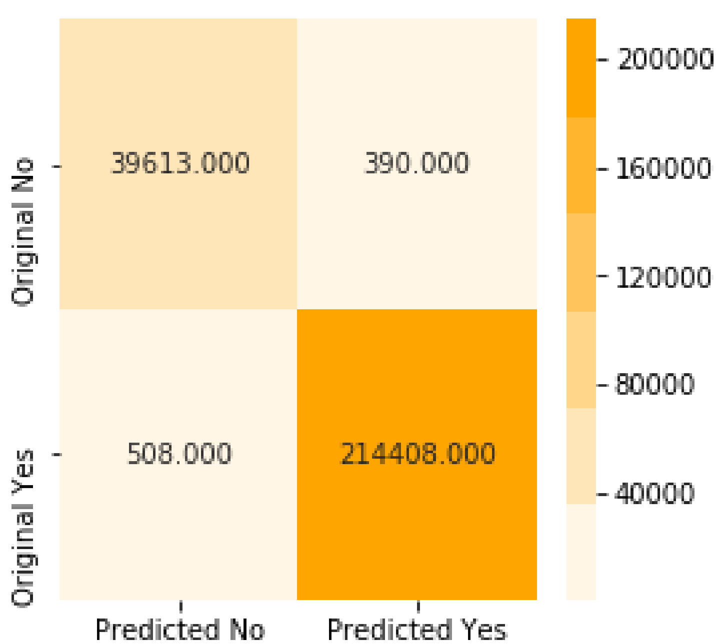
```
In [58]: # Plotting confusion matrix
         print("For test dataset")
         confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

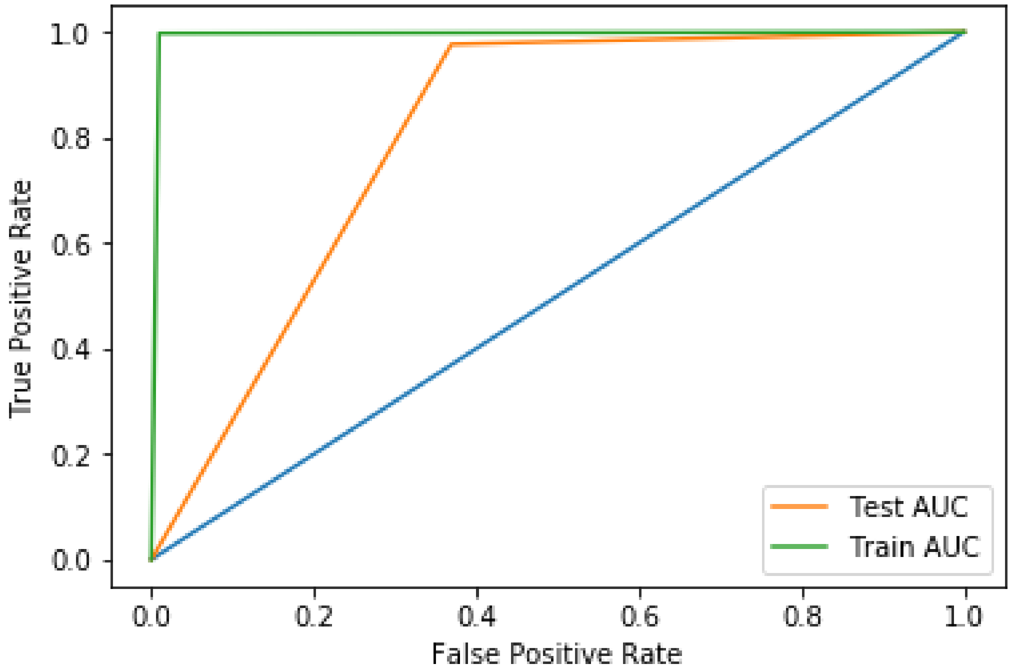



```
In [59]: # Plotting confusion matrix
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



```
In [60]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyper parameter tunning using GridSearchCV

```
In [187]: from sklearn.model_selection import GridSearchCV
          from sklearn.metrics import make_scorer

          # Selecting the estimator . Estimator is the model that you will use to train your m
          # We will pass this instance to GridSearchCV
          clf = MultinomialNB()

          # Dictionary of parameters to be searched on
          parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

          # Value on which model will be evaluated
          auc_score = make_scorer(roc_auc_score)

          # Calling GridSearchCV .
          grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,sco

          # Training the gridsearchcv instance
          grid_model.fit(train_vect,Y_train)
```

```
# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_

predict_probab = optimized_clf.predict_log_proba(test_vect)[:,1] # returns probabili
predict_y = optimized_clf.predict(test_vect)
predict_y_train = optimized_clf.predict(train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

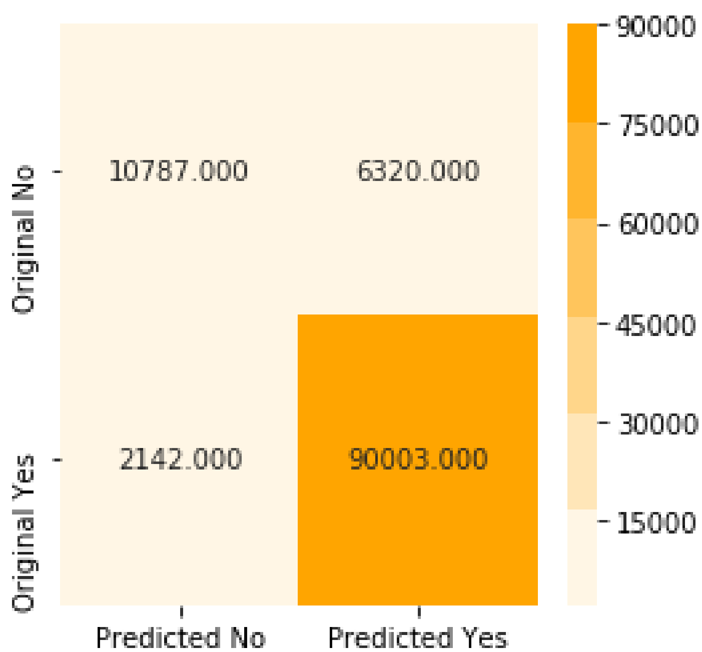
```
AUC is 0.928
```

```
In [188]: # Printing best parameter selected by grid search
          print(grid_model.best_params_)
```

```
{'alpha': 0.1}
```

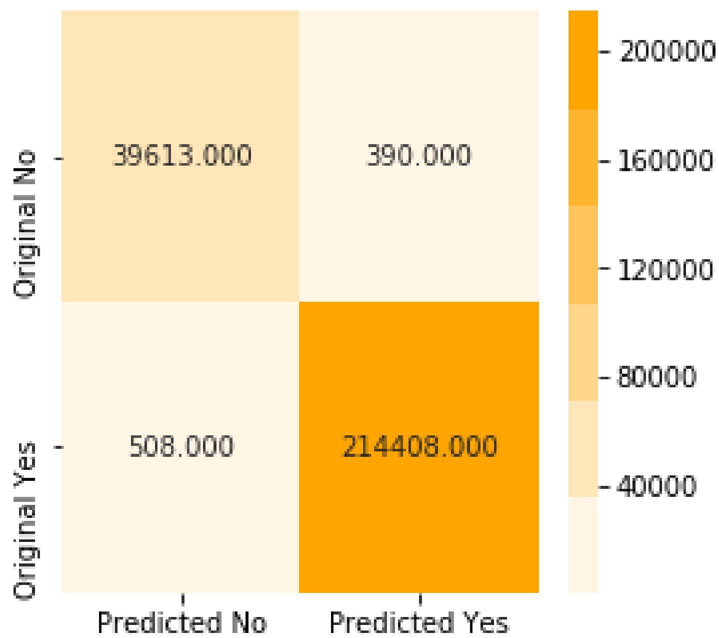
```
In [62]: # Plotting confusion matrix
         print("For test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
For test data
Confusion matrix
```

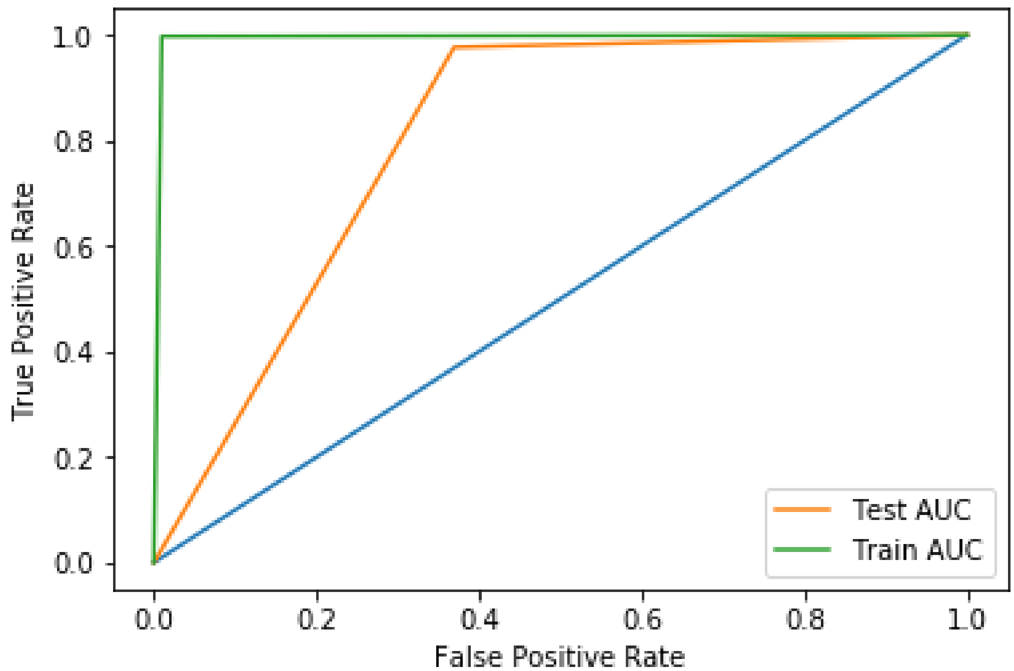


```
In [63]: # Plotting confusion matrix
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```




```
In [64]: #Plotting ROC Curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```




```
In [65]: # Top 10 features log probability
         positive_top10 = optimized_clf.feature_log_prob_[1,:].argsort()

         top10_features = [bow_vect.get_feature_names()[i] for i in positive_top10[-10:]]

         print("Top 10 feature for positive class are ::",top10_features)
```

```
Top 10 feature for positive class are :: ['much better', 'taste like', 'would not', 'green tea
```

```
In [66]: # Top 10 features for negative class
         negative_top10 = optimized_clf.feature_log_prob_[0,:].argsort()

         top10_features = [bow_vect.get_feature_names()[i] for i in negative_top10[-10:]]

         print("Top 10 feature for negative class are ::",top10_features)
```

```
Top 10 feature for negative class are :: ['not know', 'tastes like', 'not good', 'not taste',
```

7.2 [5.2] Applying Naive Bayes on TFIDF, SET 2

On Uni-grams

```
In [67]: # Initializing Tfidf model
         tfidf_vect = TfidfVectorizer()
```

```
X = preprocessed_reviews
Y = final['Score']

X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,random_state=42)
print(len(X_train),len(X_test))
```

```
254919 109252
```

```
In [68]: # Vectorizing the reviews
         train_vect = tfidf_vect.fit_transform(X_train)
         test_vect = tfidf_vect.transform(X_test)
         print(train_vect.shape)
```

```
(254919, 96683)
```

```
In [69]: # In this section we will train naive bayes model and find training error for various
         train_auc_list = [] # Stores area under curve for each alpha value

         for k in tqdm(alpha):
             clf = MultinomialNB(alpha=k)

             # Trainig our model
             clf.fit(train_vect,Y_train)

             predict_probab = clf.predict_log_proba(train_vect)[:,1] # Returns probability for

             auc = roc_auc_score(Y_train,predict_probab)
             train_auc_list.append(auc)
```

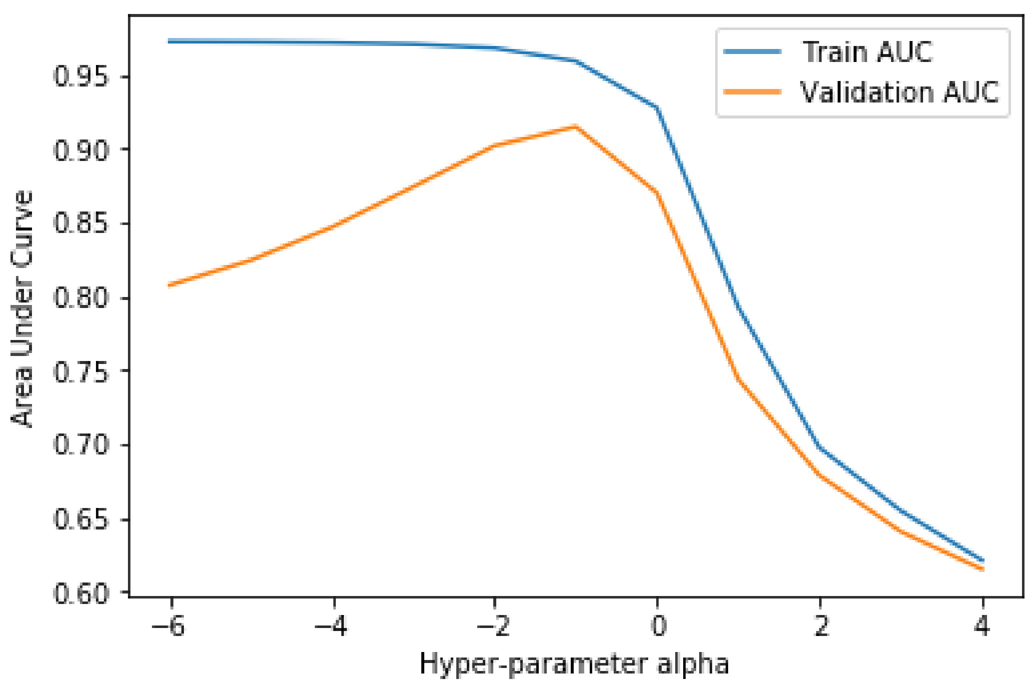
```
100%|| 11/11 [00:04<00:00,  2.76it/s]
```

```
In [70]: # We will do time based splitting and do 10 fold cross validation
         # This is done as reviews keeps changing with time and hence time based splitting is

         from sklearn.model_selection import TimeSeriesSplit
         # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         cv_auc_list = [] # will contain cross validation AUC corresponding to each k

         for k in tqdm(alpha):
             # Naive bayes classifier
             clf = MultinomialNB(alpha=k)
             i=0
             auc=0.0
```

```
        for train_index,test_index in tscv.split(train_vect):
            x_train = train_vect[0:train_index[-1]][:] # row 0 to train_index(excluding)
            y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
            x_test = train_vect[train_index[-1]:test_index[-1]][:] # row from train_index
            y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to

            clf.fit(x_train,y_train)

            predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for pos
            i += 1
            auc += roc_auc_score(y_test,predict_probab)

        cv_auc_list.append(auc/i) # Storing AUC value
```

```
100%|| 11/11 [00:39<00:00,  3.61s/it]
```

```
In [71]: # Plotting graph of auc and parameter for training and cross validation error
         plot_train_vs_auc(train_auc_list,cv_auc_list)
```



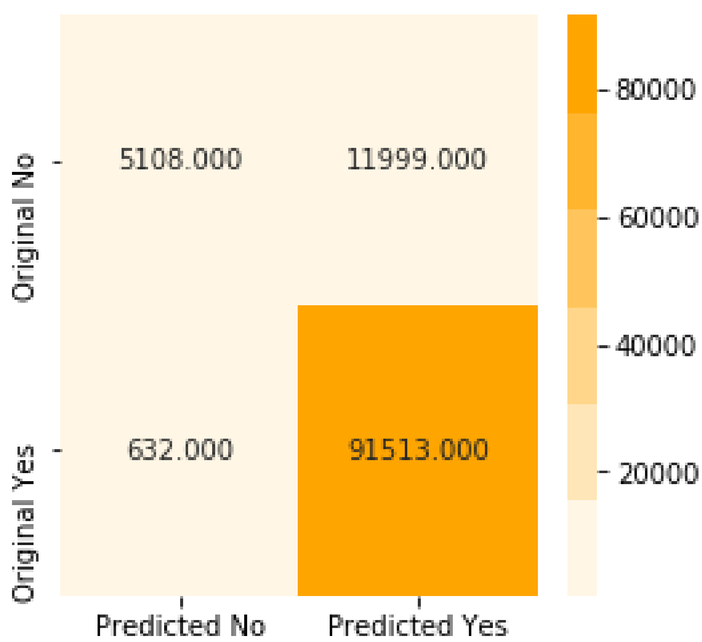

```
In [72]: # Taking best value of alpha = 0.1 an trainig final model
         # Initializing model
         final_clf = MultinomialNB(alpha=0.1)
```

```
# Training final model
final_clf.fit(train_vect,Y_train)

predict_y = final_clf.predict(test_vect)
predict_probab = final_clf.predict_log_proba(test_vect)[:,1] # Returns probabality fo
predict_y_train = final_clf.predict(train_vect)

auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for Tfidf Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Naive Bayes is 0.932
```

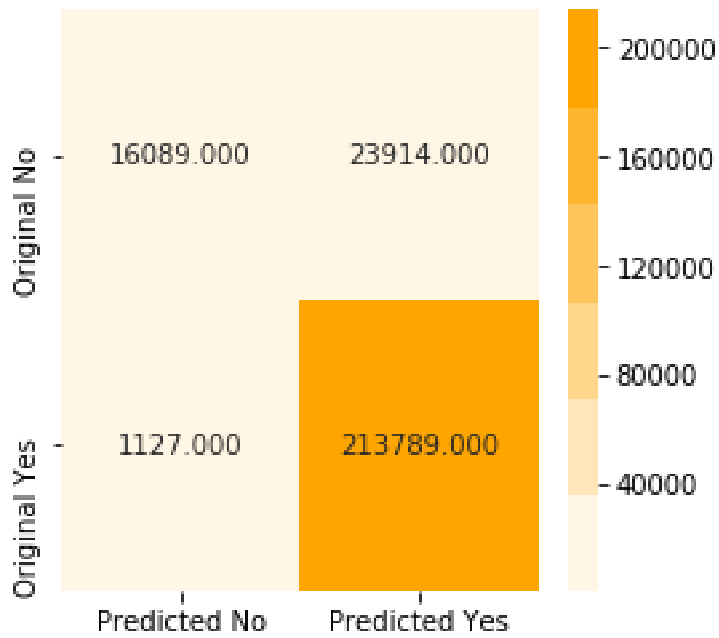
```
In [73]: # Plotting confusion matrix
         print("For test dataset")
         confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

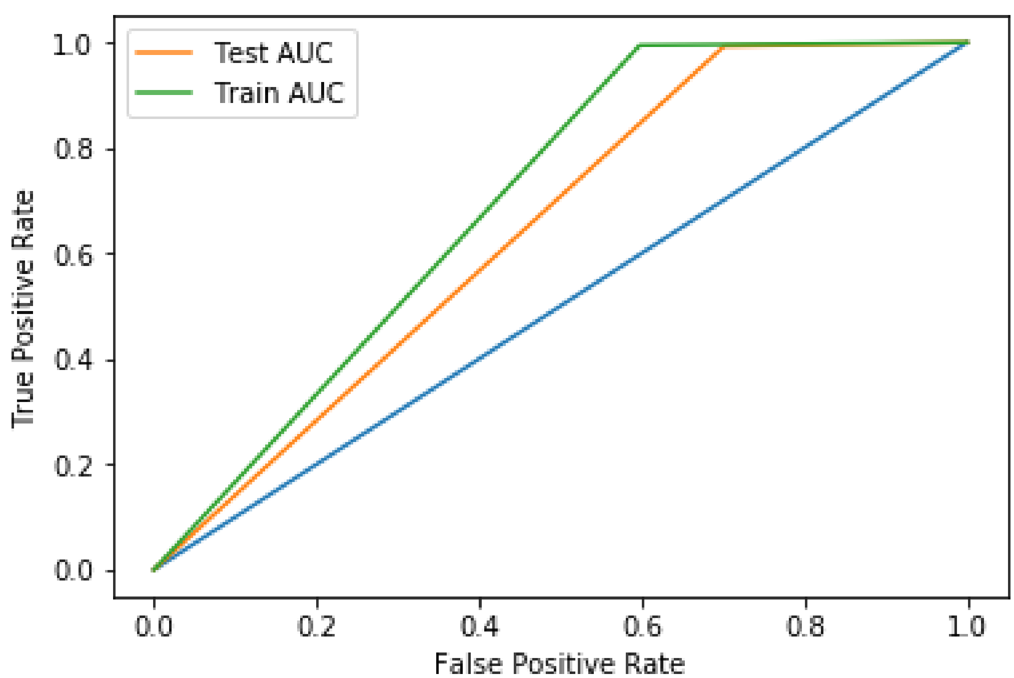



```
In [74]: # Plotting confusion matrix
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```




```
In [75]: #Plotting ROC Curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyper-parameter tunning using GridSearchCV

In [76]:
```
# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = MultinomialNB()

# Dictionary of parameters to be searched on
parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

# Value on which model will be evaluated
auc_score = make_scorer(roc_auc_score)

# Calling GridSearchCV .
grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,scor

# Training the gridsearchcv instance
grid_model.fit(train_vect,Y_train)

# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_

predict_probab = optimized_clf.predict_log_proba(test_vect)[:,1] # returns probabilit
predict_y = optimized_clf.predict(test_vect)
predict_y_train = optimized_clf.predict(train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

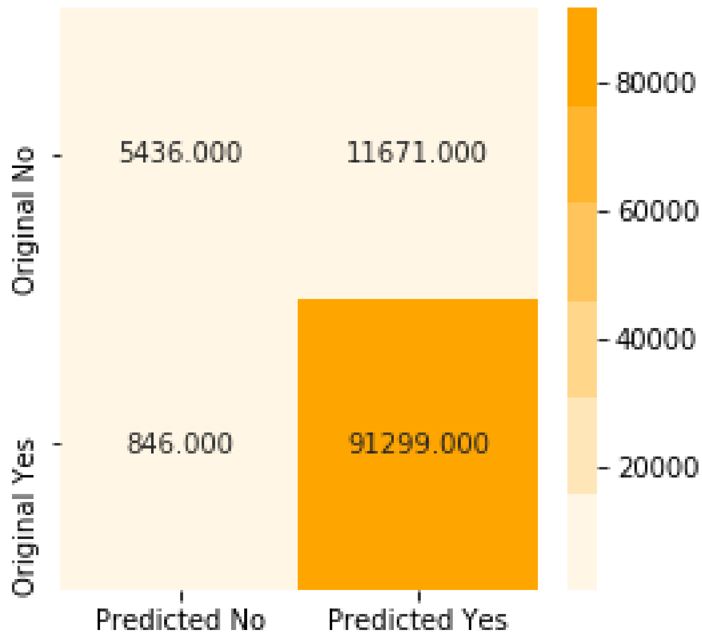
```
AUC is 0.919
```

In [77]:
```
print(grid_model.best_params_)
```

```
{'alpha': 0.01}
```

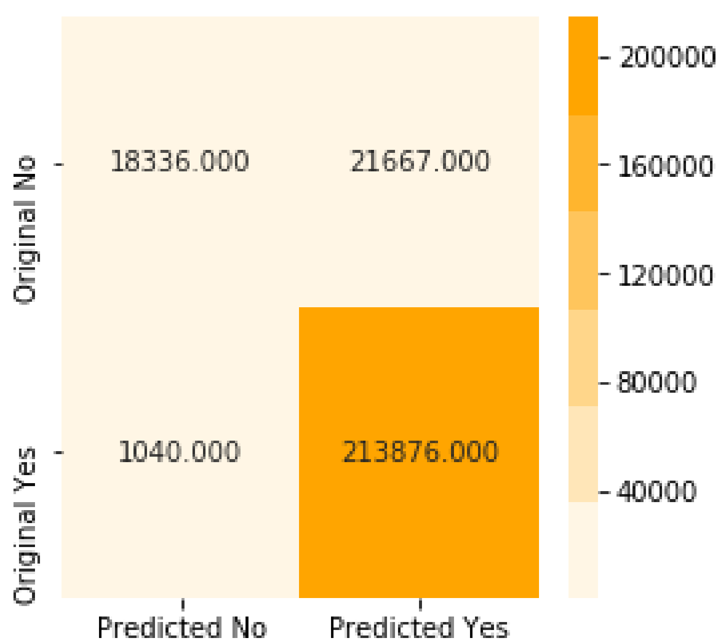
In [78]:
```
# Plotting confusion matrix
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

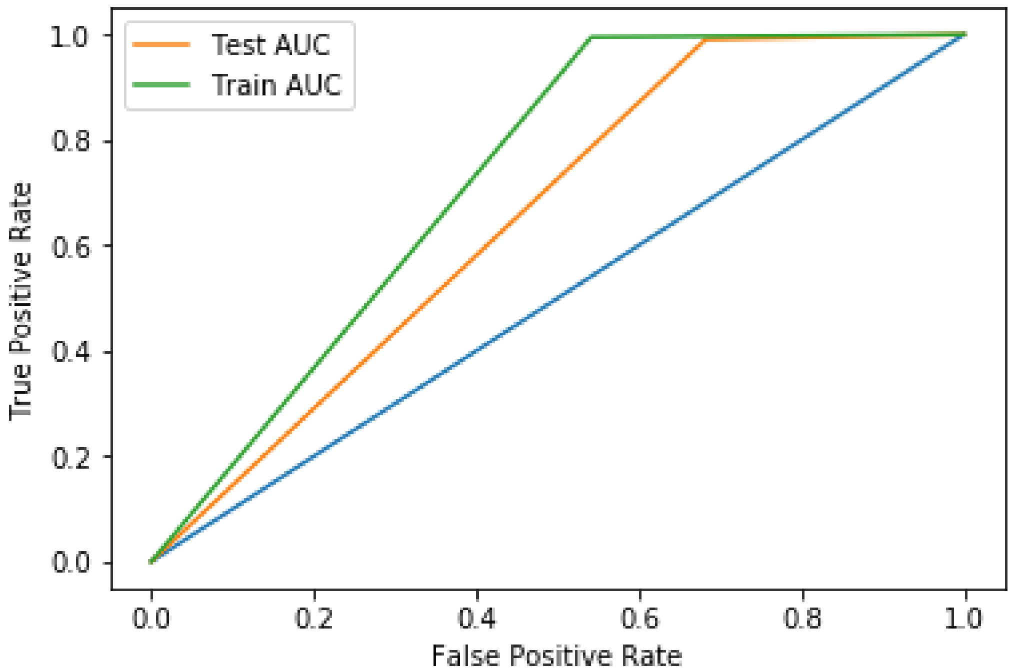



```
In [79]: # Plotting confusion matrix
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



```
In [80]: #Plotting ROC Curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



7.2.1 [5.2.1] Top 10 important features of positive class from SET 2

```
In [81]: # Top 10 features log probability
         positive_top10 = optimized_clf.feature_log_prob_[1,:].argsort() # Sorts all the proba

         top10_features = [tfidf_vect.get_feature_names()[i] for i in positive_top10[-10:]]# T
         print("Top 10 feature for positive class are ::",top10_features)
```

```
Top 10 feature for positive class are :: ['one', 'taste', 'product', 'love', 'tea', 'coffee',
```

7.2.2 [5.2.2] Top 10 important features of negative class from SET 2

```
In [82]: # Top 10 features for negative class
         negative_top10 = optimized_clf.feature_log_prob_[0,:].argsort()

         top10_features = [tfidf_vect.get_feature_names()[i] for i in negative_top10[-10:]]
         print("Top 10 feature for negative class are ::",top10_features)
```

```
Top 10 feature for negative class are :: ['good', 'no', 'flavor', 'one', 'coffee', 'would', 'ta
```

On Bigrams

```
In [83]: # Initializing Tfidf model
         tfidf_vect = TfidfVectorizer(ngram_range=(2,2))

         # Vectorizing the reviews
         train_vect = tfidf_vect.fit_transform(X_train)
         test_vect = tfidf_vect.transform(X_test)
         print(train_vect.shape)
```

```
(254919, 2973643)
```

```
In [84]: # In this section we will train naive bayes model and find training error for various

         train_auc_list = [] # Stores area under curve for each alpha value

         for k  in tqdm(alpha):
             clf = MultinomialNB(alpha=k)

             # Trainig our model
             clf.fit(train_vect,Y_train)

             predict_probab = clf.predict_log_proba(train_vect)[:,1] # Returns probability for

             auc = roc_auc_score(Y_train,predict_probab)
             train_auc_list.append(auc)
```

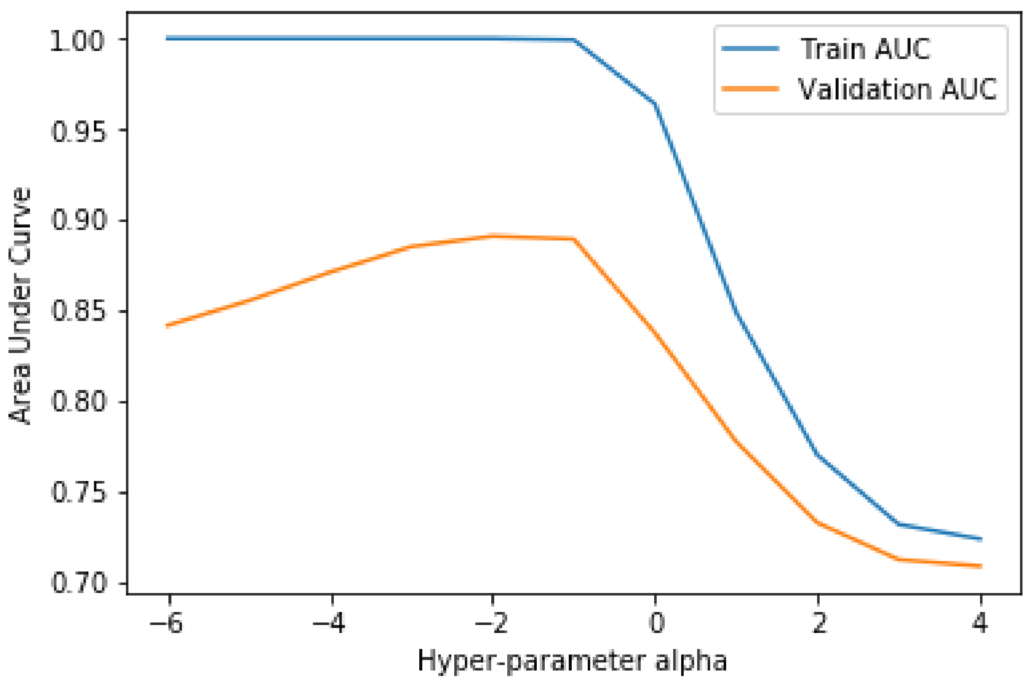
```
100%|| 11/11 [00:10<00:00,  1.05it/s]
```

```
In [85]: # We will do time based splitting and do 10 fold cross validation
         # This is done as reviews keeps changing with time and hence time based splitting is

         from sklearn.model_selection import TimeSeriesSplit
         # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         cv_auc_list = [] # will contain cross validation AUC corresponding to each k

         for k in tqdm(alpha):
             # Naive bayes classifier
             clf = MultinomialNB(alpha=k)
             i=0
             auc=0.0
             for train_index,test_index in tscv.split(train_vect):
```

```
            x_train = train_vect[0:train_index[-1]][:] # row 0 to train_index(excluding)
            y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
            x_test = train_vect[train_index[-1]:test_index[-1]][:] # row from train_index
            y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index to

            clf.fit(x_train,y_train)

            predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for pos
            i += 1
            auc += roc_auc_score(y_test,predict_probab)

        cv_auc_list.append(auc/i) # Storing AUC value
```

```
100%|| 11/11 [01:27<00:00,  7.81s/it]
```

In [86]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```



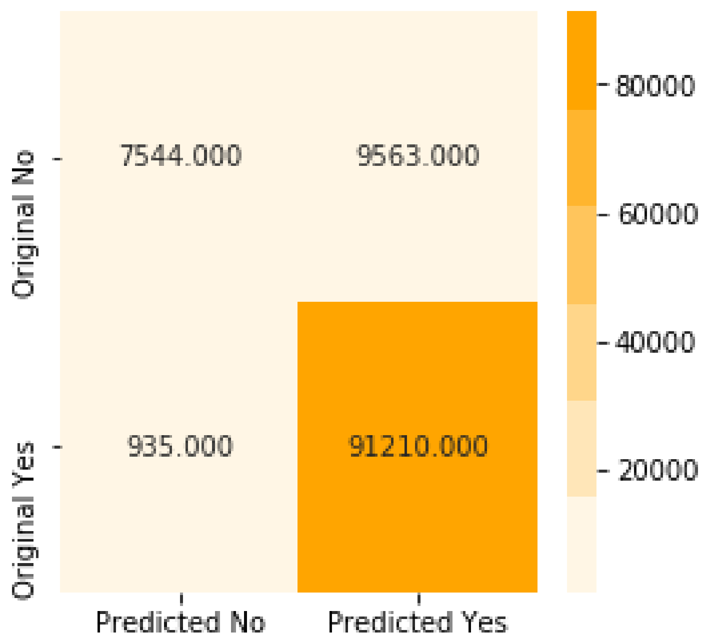
In [87]:
```
# Taking best value of alpha = 0.01 an trainig final model
# Initializing model
final_clf = MultinomialNB(alpha=0.01)
```

```
# Training final model
final_clf.fit(train_vect,Y_train)

predict_y = final_clf.predict(test_vect)
predict_probab = final_clf.predict_log_proba(test_vect)[:,1] # Returns probabality fo
predict_y_train = final_clf.predict(train_vect)

auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for BoW Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for BoW Naive Bayes is 0.936
```

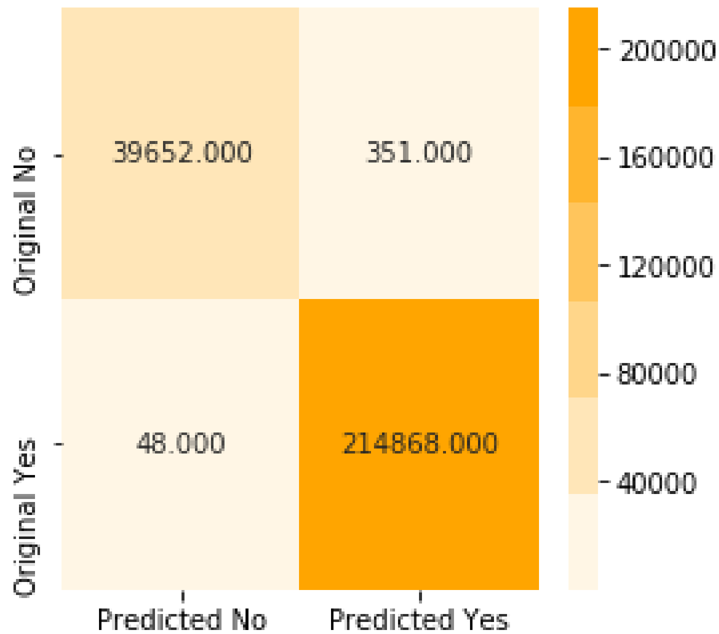
In [75]:
```
# Plotting confusion matrix
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion matrix
```

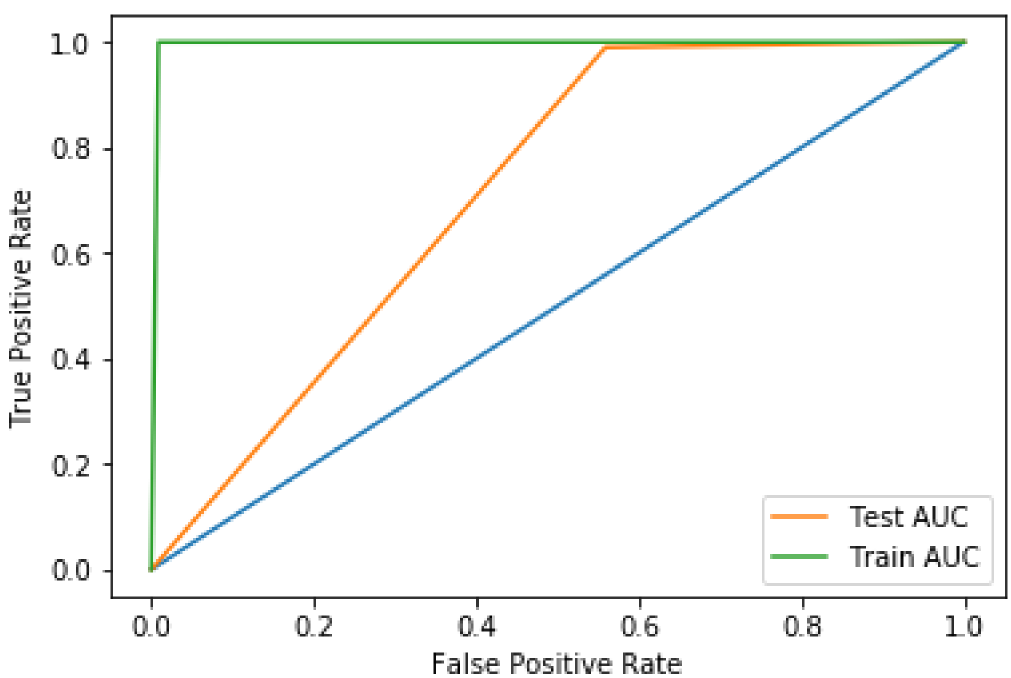


In [88]:
```
# Plotting confusion matrix
print("For train dataset")
confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```




```
In [89]: #Plotting ROC Curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Tunning hyper parameter using GridSearchCV

```
In [77]: # Selecting the estimator . Estimator is the model that you will use to train your mo
         # We will pass this instance to GridSearchCV
         clf = MultinomialNB()

         # Dictionary of parameters to be searched on
         parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

         # Value on which model will be evaluated
         auc_score = make_scorer(roc_auc_score)

         # Calling GridSearchCV .
         grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,scor

         # Training the gridsearchcv instance
         grid_model.fit(train_vect,Y_train)

         # this gives the best model with best hyper parameter
         optimized_clf = grid_model.best_estimator_

         predict_probab = optimized_clf.predict_log_proba(test_vect)[:,1] # returns probabilit
         predict_y = optimized_clf.predict(test_vect)
         predict_y_train = optimized_clf.predict(train_vect)

         print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

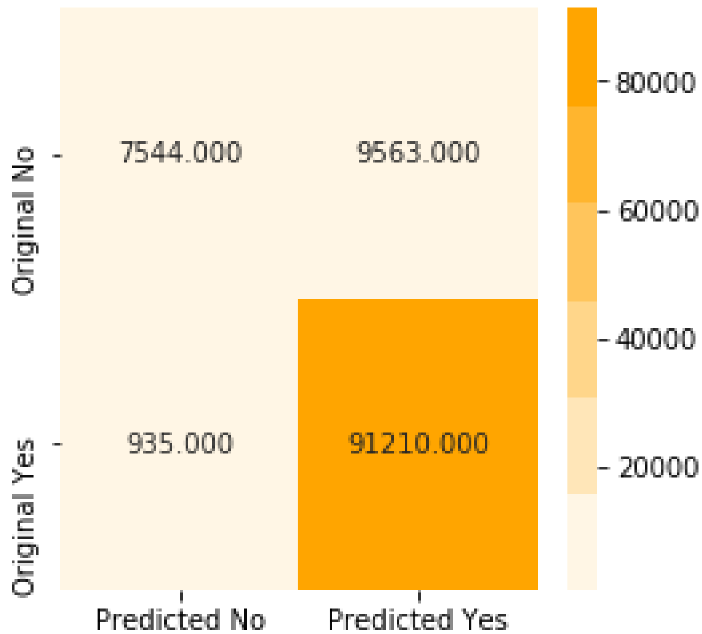
```
AUC is 0.936
```

```
In [90]: # Printing best classifier choosen by GridSearchCV
         print(grid_model.best_params_)
```

```
{'alpha': 0.01}
```

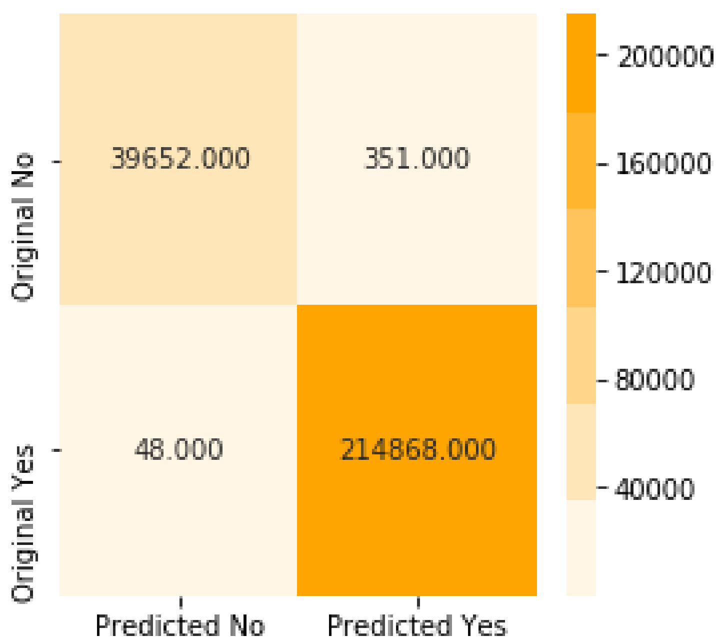
```
In [91]: # Plotting confusion matrix
         print("For test dataset")
         confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

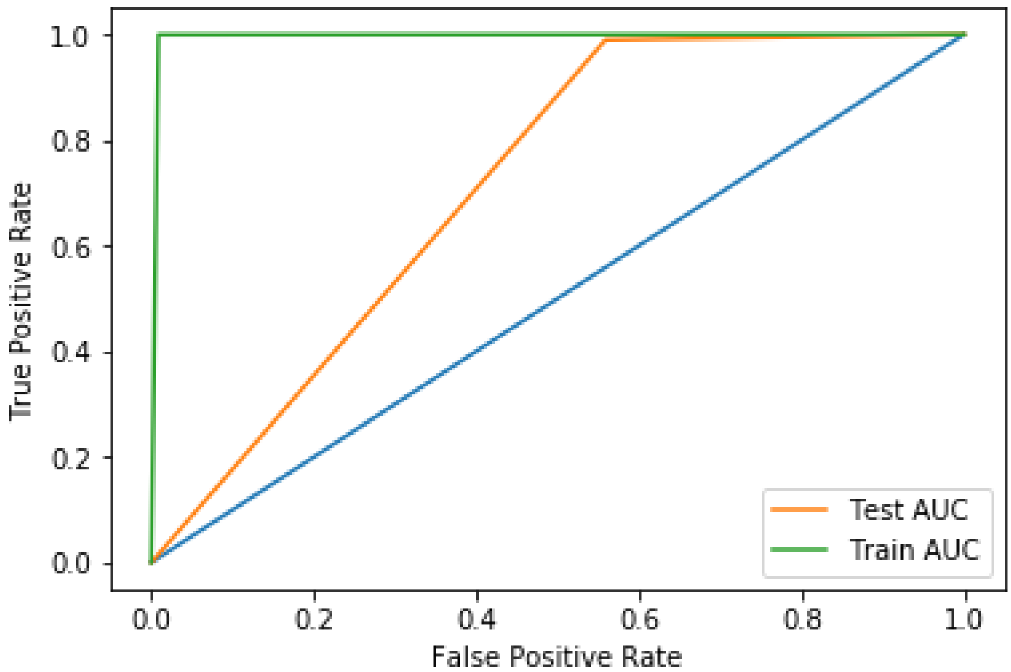



```
In [92]: # Plotting confusion matrix
         print("For train dataset")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



In [93]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



In [94]:
```
# Top 10 features log probability
# This contains index of most important positive features in ascending order.
positive_top10 = optimized_clf.feature_log_prob_[1,:].argsort()

# we will take fetaures corresponding to the last 10 index in positive_top10
top10_features = [tfidf_vect.get_feature_names()[i] for i in positive_top10[-10:]]
print("Top 10 feature for positive class are ::",top10_features)
```

```
Top 10 feature for positive class are :: ['almost haribo', 'amd chili', 'also diabetes', 'alask
```

In [95]:
```
# Top 10 features for negative class
# This contains index of most important negative features in ascending order.
negative_top10 = optimized_clf.feature_log_prob_[0,:].argsort()

# we will take fetaures corresponding to the last 10 index in negative_top10
top10_features = [tfidf_vect.get_feature_names()[i] for i in negative_top10[-10:]]
print("Top 10 feature for negative class are ::",top10_features)
```

```
Top 10 feature for negative class are :: ['affected flavor', 'almond bad', 'adult made', 'almos
```

Using review length as a feature

```
In [96]: # Calculating and storing length of each review in train data set, in an numpy array

         train_review_len = np.zeros(len(X_train))
         i=0
         for sent in X_train:
             train_review_len[i] = len(sent)
             i += 1

         print(train_review_len.shape)
```

```
(254919,)
```

```
In [97]: # Calculating and storing length of each review in train data set, in an numpy array

         test_review_len = np.zeros(len(X_test))
         i=0
         for sent in X_test:
             test_review_len[i] = len(sent)
             i += 1

         print(test_review_len.shape)
```

```
(109252,)
```

Using bow for vectorization

```
In [115]: # vectorizing train and test dataset using bow
          bow_train_vect = bow_vect.fit_transform(X_train)
          bow_test_vect = bow_vect.transform(X_test)
```

```
In [116]: print(bow_train_vect.shape)
```

```
(254919, 2973643)
```

```
In [117]: from scipy.sparse import hstack
          from scipy.sparse import coo_matrix
          from scipy.sparse import csr_matrix

          # now we will add review length as a new feature to train  data set
          # The shape of train_review_len is 254919 and hstack takes compatible matrices only
          # Making the train_review_len to bow_train_vect
```

```
A = coo_matrix([train_review_len]).T

bow_train_vect = hstack([bow_train_vect,A])
print(bow_train_vect.shape)
```

```
(254919, 2973644)
```

```
In [118]: # now we will add review length as a new feature to train  data set
          # Since hstack takes compatible matrices only
          # Making the test_review_len to bow_test_vect
          B = coo_matrix([test_review_len]).T
          bow_test_vect = hstack([bow_test_vect,B])
          print(bow_test_vect.shape)
```

```
(109252, 2973644)
```

```
In [123]: from scipy import sparse
          # Converting bow_train_vect from scipy.sparse.coo.coo_matrix to scipy.sparse.csr.csr
          # scipy.sparse.coo.coo_matrix are not subscriptable

          bow_train_vect = sparse.csr_matrix(bow_train_vect)
          print(type(bow_train_vect))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

```
In [127]: # Doing same as above for test dataset
          bow_test_vect = sparse.csr_matrix(bow_test_vect)
          print(type(bow_test_vect))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

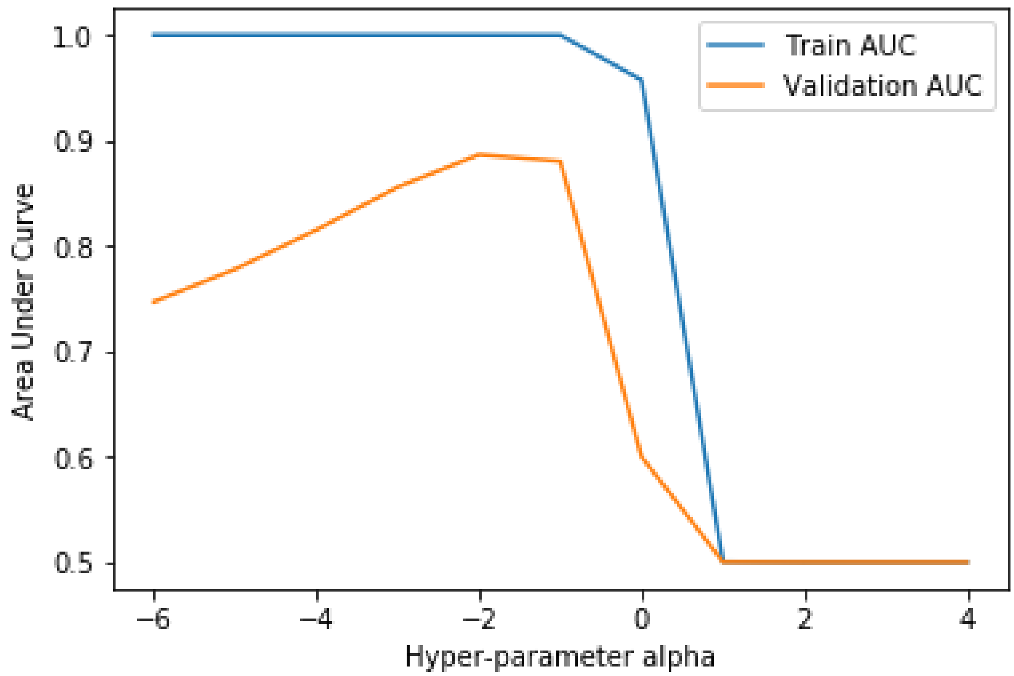
```
In [124]: # In this section we will train naive bayes model and find training error for variou

          train_auc_list = [] # Stores area under curve for each alpha value

          for k  in tqdm(alpha):
              clf = MultinomialNB(alpha=k)

              # Trainig our model
              clf.fit(bow_train_vect,Y_train)

              predict_probab = clf.predict_log_proba(bow_train_vect)[:,1] # Returns probabilit

              auc = roc_auc_score(Y_train,predict_probab)
              train_auc_list.append(auc)
```

100%|| 11/11 [00:09<00:00, 1.14it/s]

In [125]:
```
# We will do time based splitting and do 10 fold cross validation
# This is done as reviews keeps changing with time and hence time based splitting is

from sklearn.model_selection import TimeSeriesSplit
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

cv_auc_list = [] # will contain cross validation AUC corresponding to each k

for k in tqdm(alpha):
    # Naive bayes classifier
    clf = MultinomialNB(alpha=k)
    i=0
    auc=0.0
    for train_index,test_index in tscv.split(bow_train_vect):
        x_train = bow_train_vect[0:train_index[-1]][:] # row 0 to train_index(exclud
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = bow_train_vect[train_index[-1]:test_index[-1]][:] # row from train_
        y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t

        clf.fit(x_train,y_train)

        predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for po
        i += 1
        auc += roc_auc_score(y_test,predict_probab)

    cv_auc_list.append(auc/i) # Storing AUC value
```

100%|| 11/11 [01:29<00:00, 7.90s/it]

In [128]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

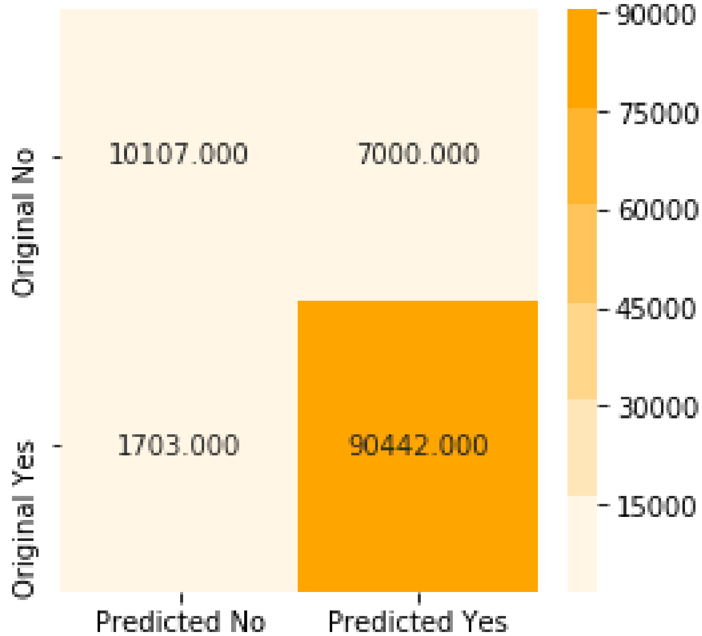


In [133]:
```
# Taking best value of alpha = 0.1 an trainig final model
# 0.1 was selected instead of 0.01 because at 0.1 training AUC is less compared to A
# Initializing model
final_clf = MultinomialNB(alpha=0.1)

# Training final model
final_clf.fit(bow_train_vect,Y_train)

predict_y = final_clf.predict(bow_test_vect)
predict_probab = final_clf.predict_log_proba(bow_test_vect)[:,1] # Returns probabali
predict_y_train = final_clf.predict(bow_train_vect)

auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for BoW Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for BoW Naive Bayes is 0.915
```

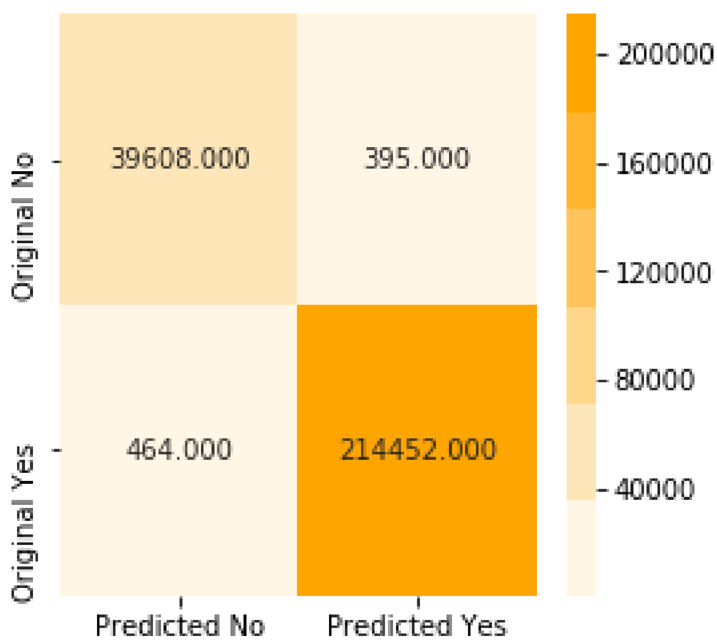
In [134]:
```
# Plotting confusion matrix
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

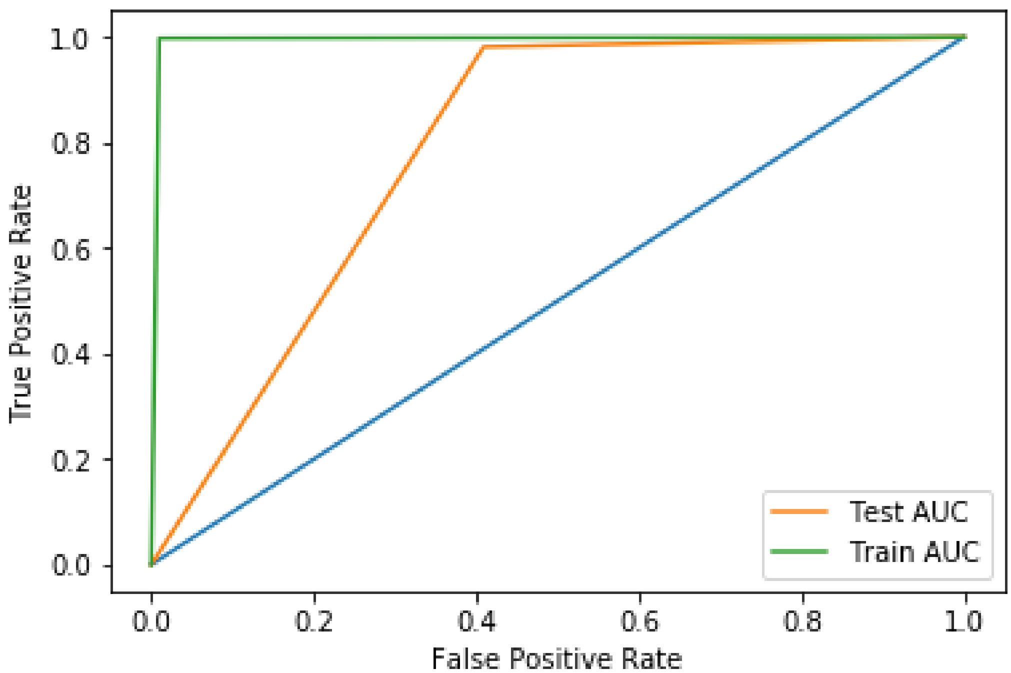



```
In [135]: # Plotting confusion matrix
          print("For train dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



In [136]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Performing hyper parameter tunning using GridSearchCV

In [137]:
```
# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = MultinomialNB()

# Dictionary of parameters to be searched on
parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

# Value on which model will be evaluated
auc_score = make_scorer(roc_auc_score)

# Calling GridSearchCV .
grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,scor

# Training the gridsearchcv instance
grid_model.fit(bow_train_vect,Y_train)

# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_
```

```
predict_probab = optimized_clf.predict_log_proba(bow_test_vect)[:,1] # returns proba
predict_y = optimized_clf.predict(bow_test_vect)
predict_y_train = optimized_clf.predict(bow_train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

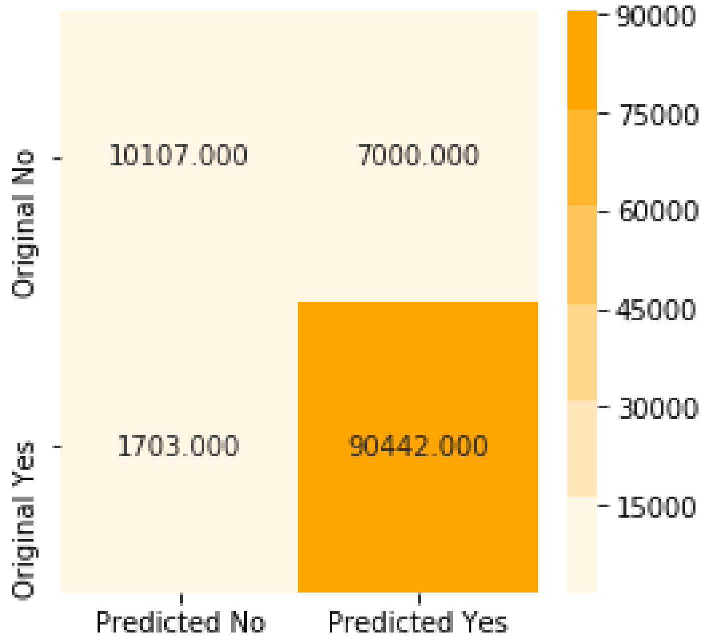
```
AUC is 0.915
```

In [138]:
```
# Prints best alpha selected by GridSearchCV
print(grid_model.best_params_)
```

```
{'alpha': 0.1}
```

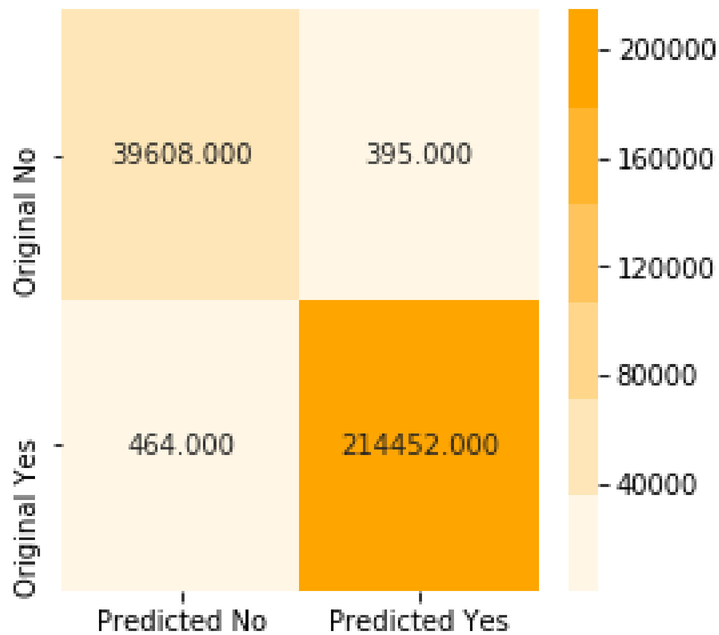
In [139]:
```
# Plotting confusion matrix
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

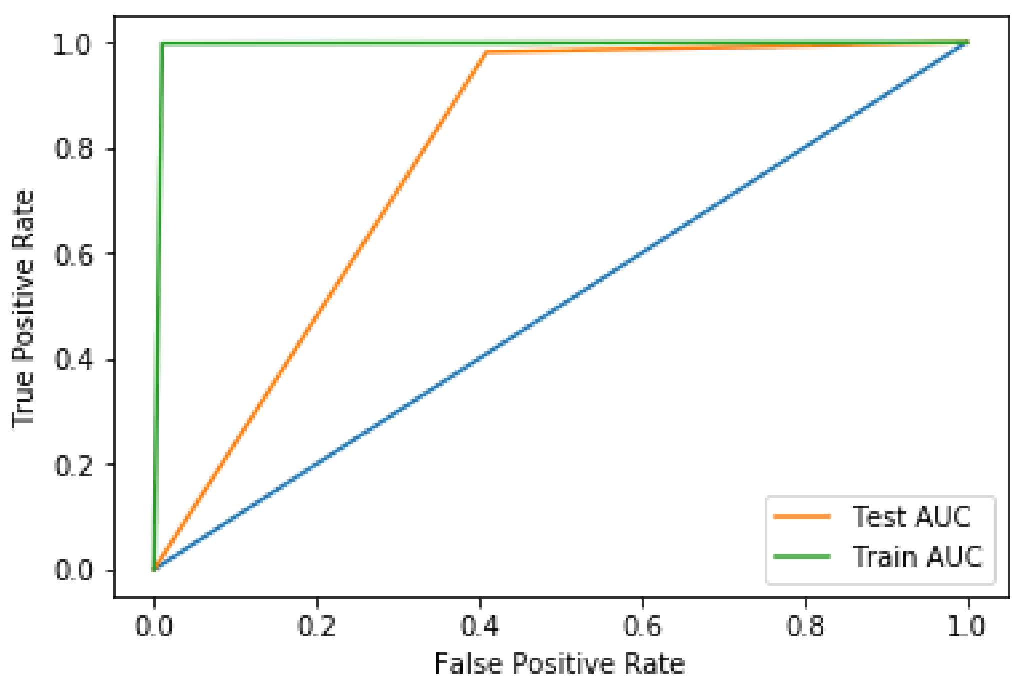


In [140]:
```
# Plotting confusion matrix
print("For train dataset")
confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```




```
In [141]: #Plotting ROC Curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Using Tfidf for vectorization

```
In [142]: # vectorizing train and test dataset using bow
          tfidf_vect = TfidfVectorizer()
          tfidf_train_vect = tfidf_vect.fit_transform(X_train)
          tfidf_test_vect = tfidf_vect.transform(X_test)
```

```
In [143]: # now we will add review length as a new feature to train  data set
          # The shape of train_review_len is 254919 and hstack takes compatible matrices only
          # Making the train_review_len to bow_train_vect
          tfidf_train_vect = hstack([tfidf_train_vect,A])
          print(tfidf_train_vect.shape)
```

```
(254919, 96684)
```

```
In [144]: # now we will add review length as a new feature to test data set
          # The shape of train_review_len is 254919 and hstack takes compatible matrices only
          # Making the train_review_len to bow_train_vect
          tfidf_test_vect = hstack([tfidf_test_vect,B])
          print(tfidf_test_vect.shape)
```

```
(109252, 96684)
```

```
In [145]: # Converting tfidf_train_vect and tfidf_test_vect from scipy.sparse.coo.coo_matrix t
          # scipy.sparse.coo.coo_matrix are not subscriptable

          tfidf_train_vect = sparse.csr_matrix(tfidf_train_vect)
          tfidf_test_vect = sparse.csr_matrix(tfidf_test_vect)
          print(type(tfidf_train_vect))
          print(type(tfidf_test_vect))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
```

```
In [146]: # In this section we will train naive bayes model and find training error for variou

          train_auc_list = [] # Stores area under curve for each alpha value

          for k  in tqdm(alpha):
              clf = MultinomialNB(alpha=k)

              # Trainig our model
              clf.fit(tfidf_train_vect,Y_train)
```

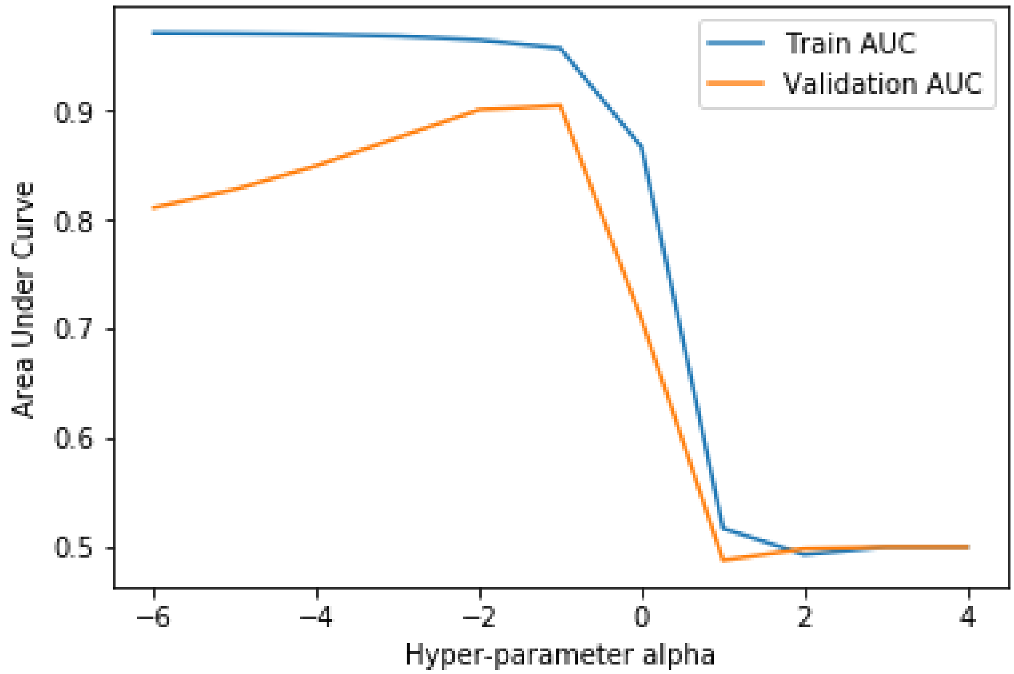
```
            predict_probab = clf.predict_log_proba(tfidf_train_vect)[:,1] # Returns probabil

            auc = roc_auc_score(Y_train,predict_probab)
            train_auc_list.append(auc)
```

100%|| 11/11 [00:03<00:00, 2.84it/s]

In [147]:
```
# We will do time based splitting and do 10 fold cross validation
# This is done as reviews keeps changing with time and hence time based splitting is

# Time series object
tscv = TimeSeriesSplit(n_splits=10)

cv_auc_list = [] # will contain cross validation AUC corresponding to each k

for k in tqdm(alpha):
    # Naive bayes classifier
    clf = MultinomialNB(alpha=k)
    i=0
    auc=0.0
    for train_index,test_index in tscv.split(tfidf_train_vect):
        x_train = tfidf_train_vect[0:train_index[-1]][:] # row 0 to train_index(excl
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = tfidf_train_vect[train_index[-1]:test_index[-1]][:] # row from trai
        y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t

        clf.fit(x_train,y_train)

        predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for po
        i += 1
        auc += roc_auc_score(y_test,predict_probab)

    cv_auc_list.append(auc/i) # Storing AUC value
```

100%|| 11/11 [00:40<00:00, 3.63s/it]

In [148]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

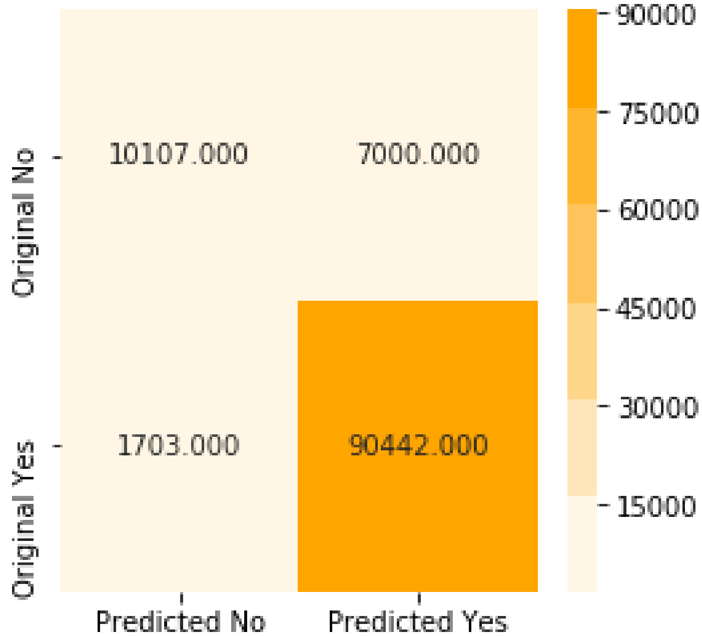



```
In [149]: # Taking best value of alpha = 0.1 an trainig final model
          # Initializing model
          final_clf = MultinomialNB(alpha=0.1)

          # Training final model
          final_clf.fit(bow_train_vect,Y_train)

          predict_y = final_clf.predict(bow_test_vect)
          predict_probab = final_clf.predict_log_proba(bow_test_vect)[:,1] # Returns probabali
          predict_y_train = final_clf.predict(bow_train_vect)

          auc = roc_auc_score(Y_test,predict_probab)
          print("Final AUC for Tfidf Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Naive Bayes is 0.915
```

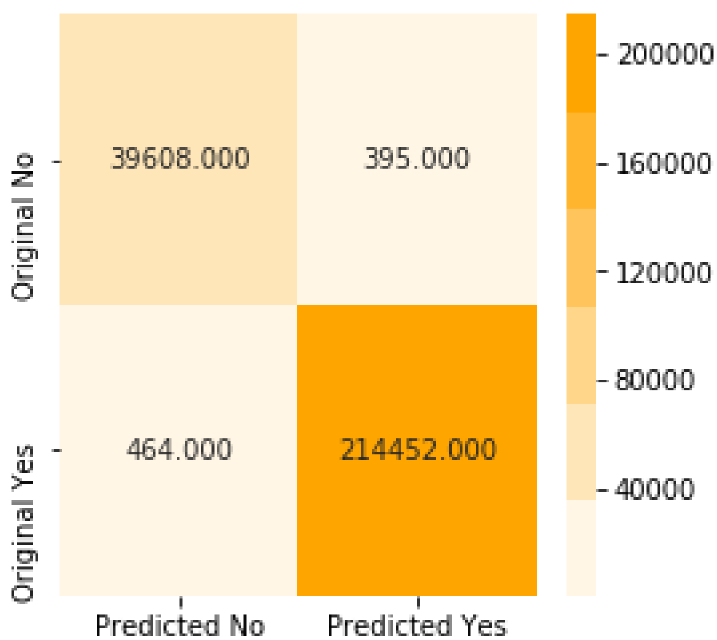
```
In [150]: # Plotting confusion matrix
          print("For test dataset")
          confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

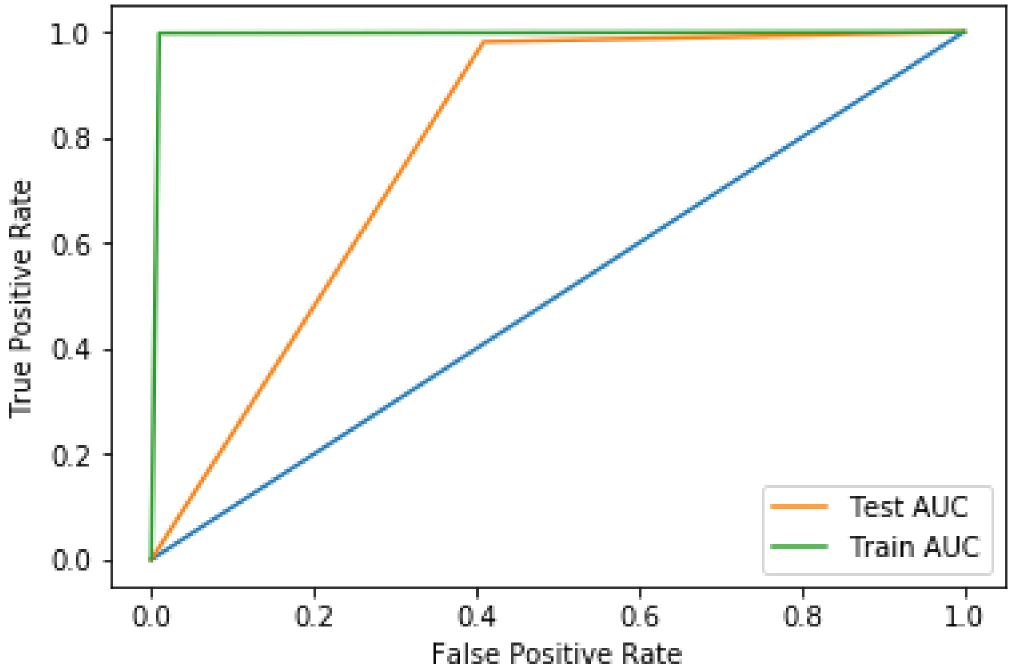



```
In [151]: # Plotting confusion matrix
          print("For train dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



In [152]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Performing hyper parameter tunning using GridSearchCV

In [153]:
```
# Selecting the estimator . Estimator is the model that you will use to train your m
# We will pass this instance to GridSearchCV
clf = MultinomialNB()

# Dictionary of parameters to be searched on
parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

# Value on which model will be evaluated
auc_score = make_scorer(roc_auc_score)

# Calling GridSearchCV .
grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,scor

# Training the gridsearchcv instance
grid_model.fit(tfidf_train_vect,Y_train)

# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_
```

```
predict_probab = optimized_clf.predict_log_proba(tfidf_test_vect)[:,1] # returns pro
predict_y = optimized_clf.predict(tfidf_test_vect)
predict_y_train = optimized_clf.predict(tfidf_train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

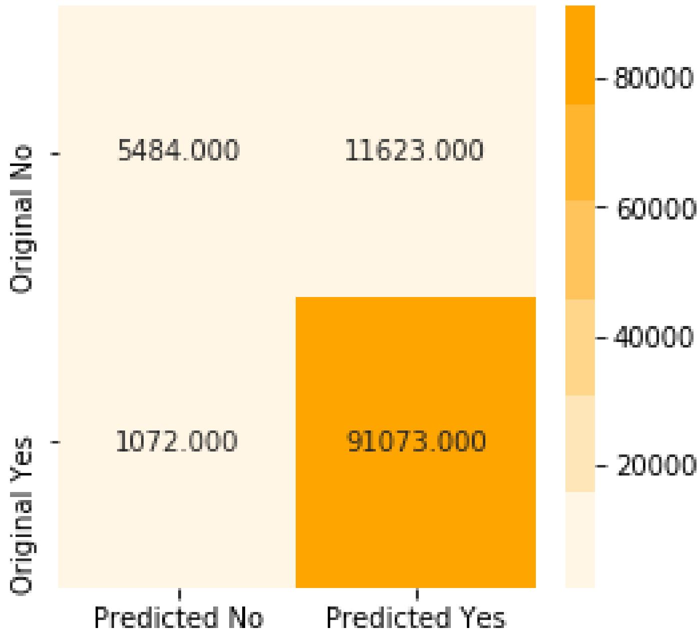
```
AUC is 0.917
```

```
In [154]: # Printing best alpha selected by GriddSearch
          print(grid_model.best_params_)
```

```
{'alpha': 0.01}
```

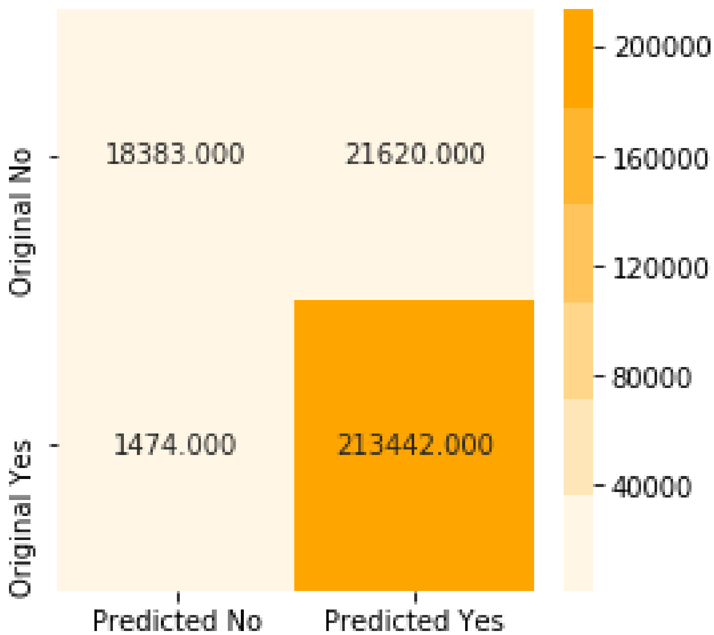
```
In [155]: # Plotting confusion matrix
          print("For test dataset")
          confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

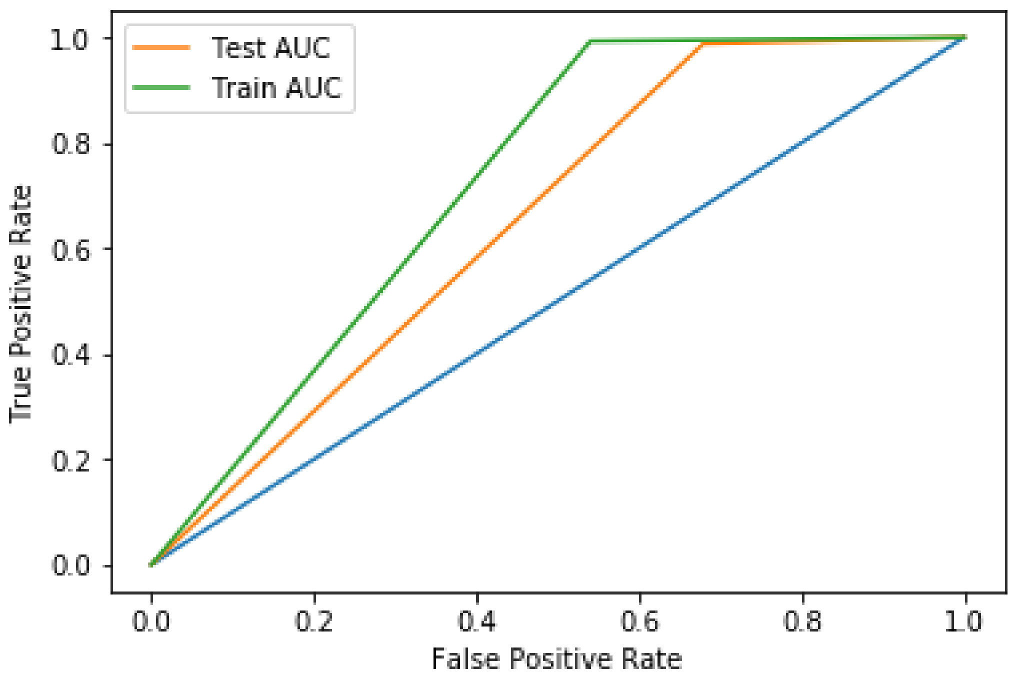



```
In [156]: # Plotting confusion matrix
          print("For train dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```




```
In [157]: #Plotting ROC Curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Extracting features from summary
Bag of Words

```
In [202]: # Splitting summary into train and test
          train_summ,test_summ,Y_train_summ,Y_test_summ = train_test_split(preprocessed_summary
```

```
In [159]: # Using bag of words to vectorize summary
          # For train dataset
          count_vect = CountVectorizer()
          train_vect = count_vect.fit_transform(train_summ)
          print(train_vect.shape)

          # for test dataset
          test_vect = count_vect.transform(test_summ)
          print(test_vect.shape)
```

```
(254919, 26288)
(109252, 26288)
```

```
In [160]: # now we will add vectorized review as a new feature to train  data set
          bow_train_vect = hstack([bow_train_vect,train_vect])
          print(bow_train_vect.shape)
```

```
(254919, 2999932)
```

```
In [161]: # now we will add vectorized review as a new feature to train  data set
          bow_test_vect = hstack([bow_test_vect,test_vect])
          print(bow_test_vect.shape)
```

```
(109252, 2999932)
```

```
In [162]: # Converting tfidf_train_vect and tfidf_test_vect from scipy.sparse.coo.coo_matrix to
          # scipy.sparse.coo.coo_matrix are not subscriptable

          bow_train_vect = sparse.csr_matrix(bow_train_vect)
          bow_test_vect = sparse.csr_matrix(bow_test_vect)
          print(type(bow_train_vect))
          print(type(bow_test_vect))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
```

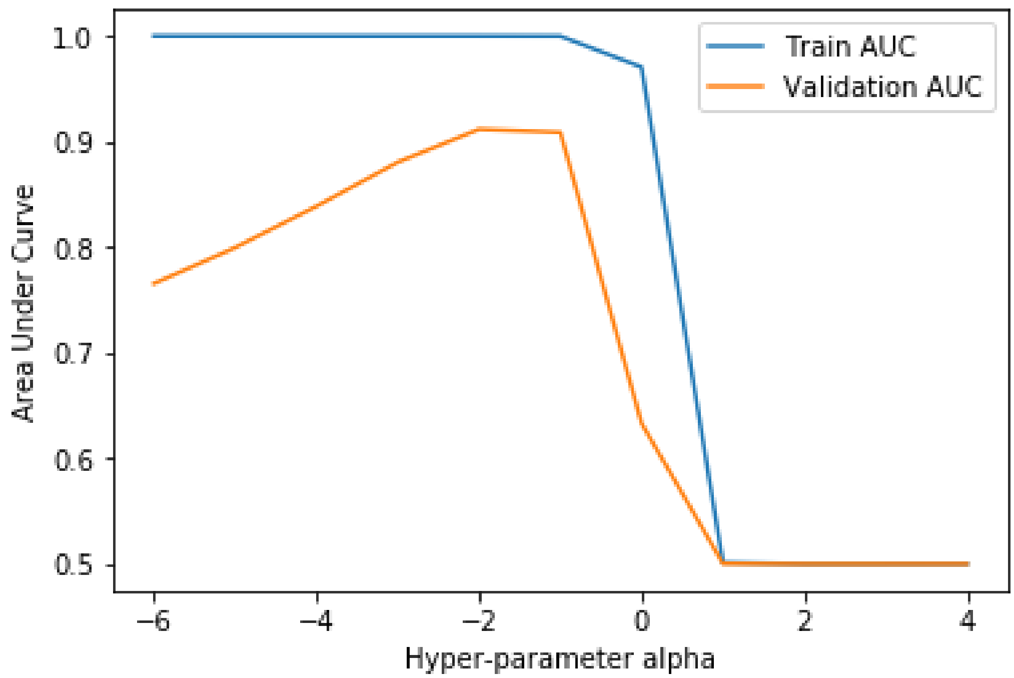
In [163]:
```
# In this section we will train naive bayes model and find training error for variou

train_auc_list = [] # Stores area under curve for each alpha value

for k  in tqdm(alpha):
    clf = MultinomialNB(alpha=k)

    # Trainig our model
    clf.fit(bow_train_vect,Y_train)

    predict_probab = clf.predict_log_proba(bow_train_vect)[:,1] # Returns probabilit

    auc = roc_auc_score(Y_train,predict_probab)
    train_auc_list.append(auc)
```

```
100%|| 11/11 [00:10<00:00,  1.08it/s]
```

In [165]:
```
# We will do time based splitting and do 10 fold cross validation
# This is done as reviews keeps changing with time and hence time based splitting is

# Time series object
tscv = TimeSeriesSplit(n_splits=10)

cv_auc_list = [] # will contain cross validation AUC corresponding to each k

for k in tqdm(alpha):
    # Naive bayes classifier
    clf = MultinomialNB(alpha=k)
    i=0
    auc=0.0
    for train_index,test_index in tscv.split(bow_train_vect):
        x_train = bow_train_vect[0:train_index[-1]][:] # row 0 to train_index(exclud
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = bow_train_vect[train_index[-1]:test_index[-1]][:] # row from train_
        y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t

        clf.fit(x_train,y_train)

        predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for po
        i += 1
        auc += roc_auc_score(y_test,predict_probab)

    cv_auc_list.append(auc/i) # Storing AUC value
```

```
100%|| 11/11 [01:30<00:00,  8.16s/it]
```

In [167]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

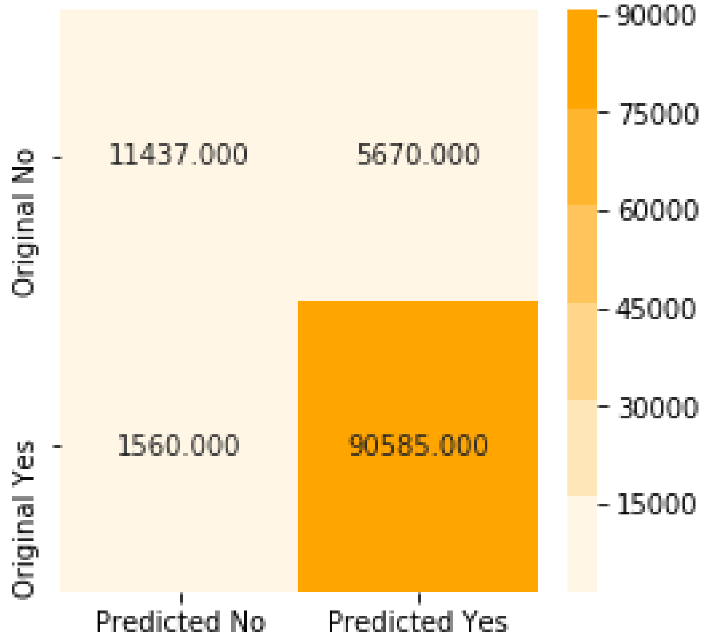


In [168]:
```
# Taking best value of alpha = 0.1 an trainig final model
# 0.01 was not taken as train AUC ia less at 0.1 compared to AUC at 0.01
# Initializing model
final_clf = MultinomialNB(alpha=0.1)

# Training final model
final_clf.fit(bow_train_vect,Y_train)

predict_y = final_clf.predict(bow_test_vect)
predict_probab = final_clf.predict_log_proba(bow_test_vect)[:,1] # Returns probabali
predict_y_train = final_clf.predict(bow_train_vect)

auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for BoW Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for BoW Naive Bayes is 0.940
```

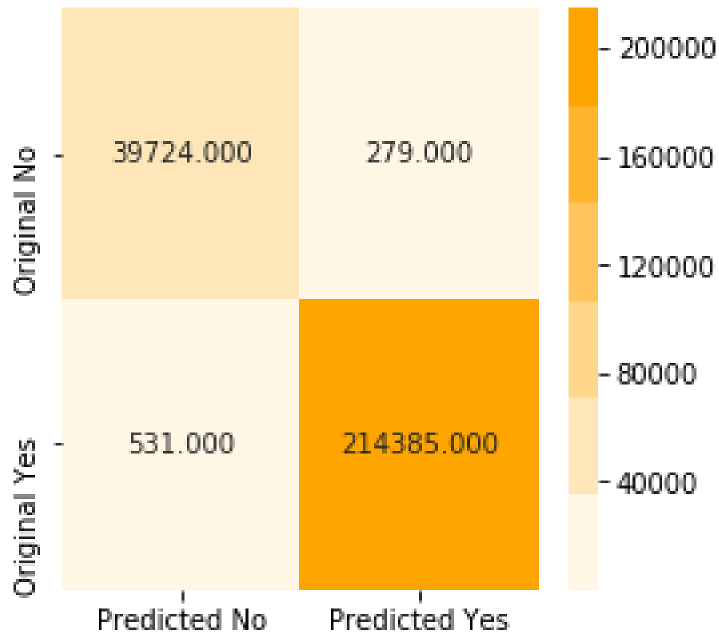
In [169]:
```
# Plotting confusion matrix
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

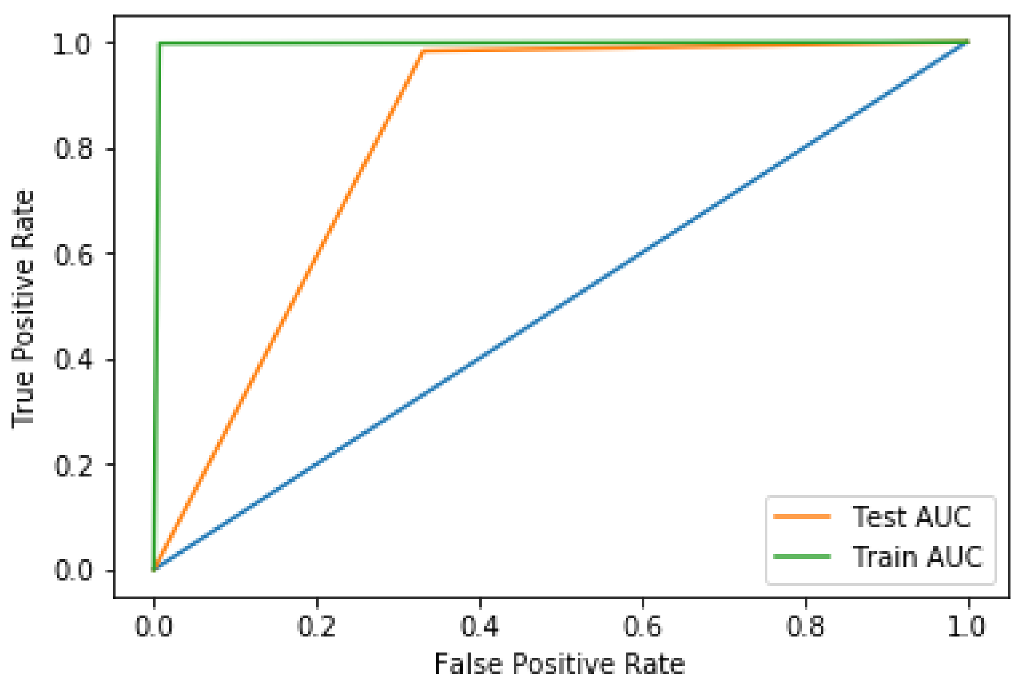



```
In [170]: # Plotting confusion matrix
          print("For train dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



In [171]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Performing hyper parameter tunning using GridSearchCV

In [172]:
```
# Selecting the estimator . Estimator is the model that you will use to train your m
# We will pass this instance to GridSearchCV
clf = MultinomialNB()

# Dictionary of parameters to be searched on
parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

# Value on which model will be evaluated
auc_score = make_scorer(roc_auc_score)

# Calling GridSearchCV .
grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,sco

# Training the gridsearchcv instance
grid_model.fit(bow_train_vect,Y_train)

# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_

predict_probab = optimized_clf.predict_log_proba(bow_test_vect)[:,1] # returns proba
predict_y = optimized_clf.predict(bow_test_vect)
predict_y_train = optimized_clf.predict(bow_train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

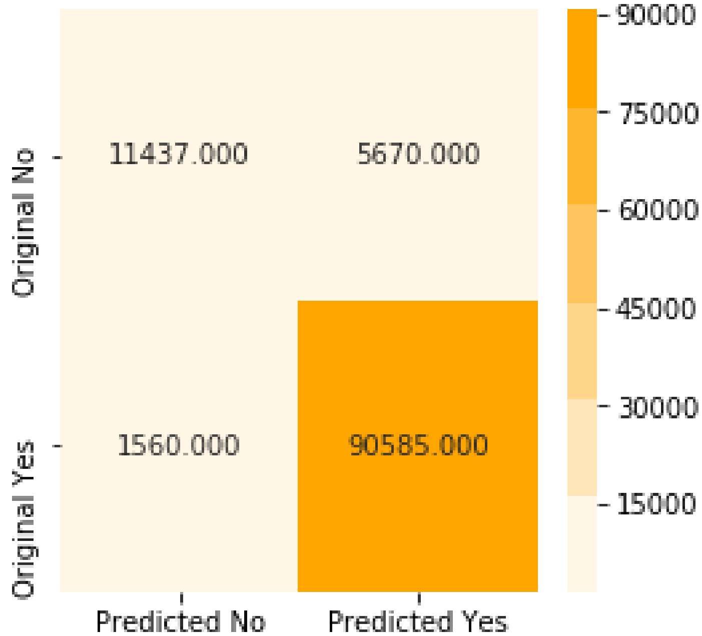
```
AUC is 0.940
```

In [173]:
```
# Printing best parameter selected by GridSearch
print(grid_model.best_params_)
```

```
{'alpha': 0.1}
```

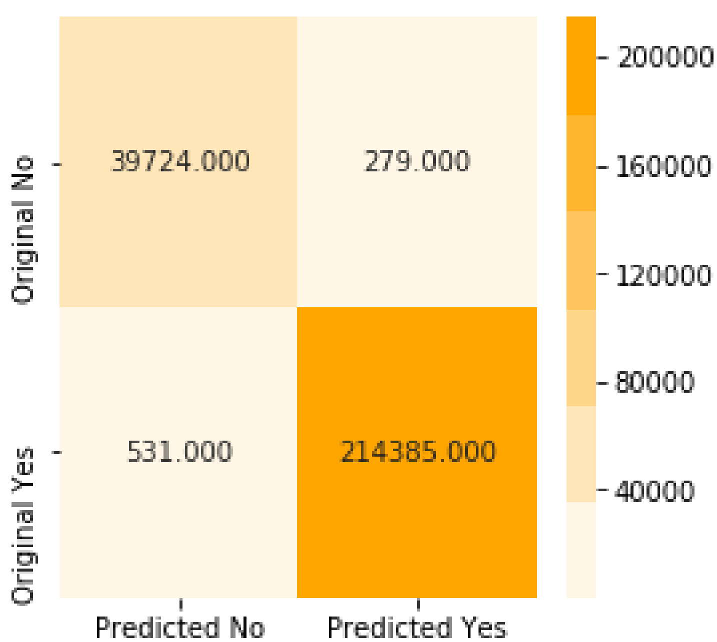
In [174]:
```
# Plotting confusion matrix
print("For test dataset")
confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

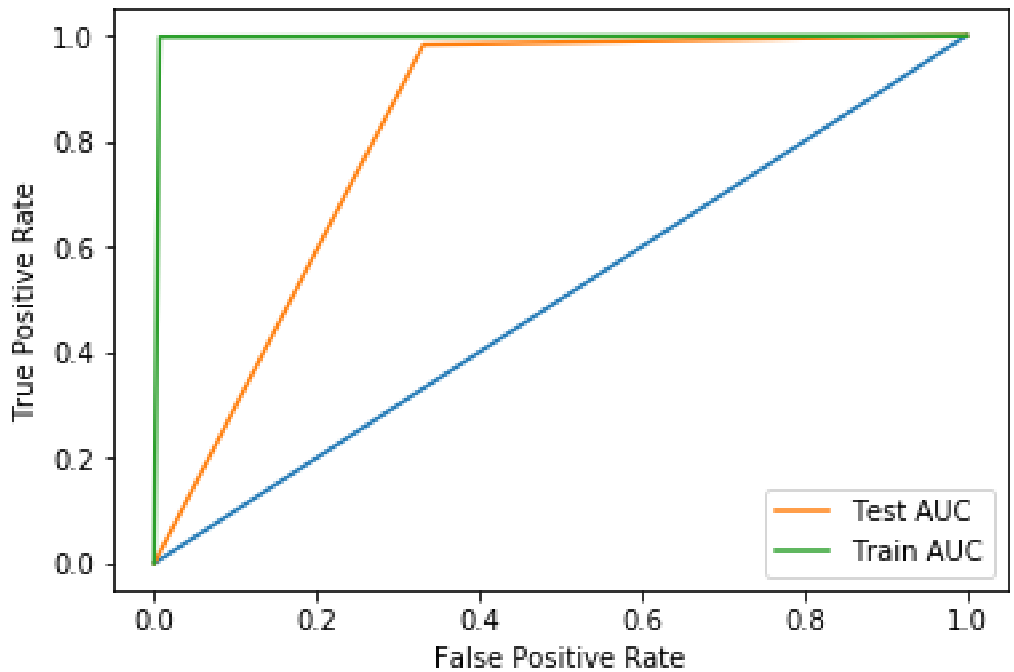



```
In [175]: # Plotting confusion matrix
          print("For train dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



```
In [176]: #Plotting ROC Curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Tfidf vectorization

```
In [215]: # vectorizing train and test dataset using bow
          tfidf_vect = TfidfVectorizer()
          tfidf_train_vect = tfidf_vect.fit_transform(X_train)
          tfidf_test_vect = tfidf_vect.transform(X_test)

In [216]: print(tfidf_train_vect.shape)
          print(tfidf_test_vect.shape)

(254919, 96683)
(109252, 96683)

In [218]: # Splitting summary into train and test
          train_summ,test_summ,Y_train_summ,Y_test_summ = train_test_split(preprocessed_summar

In [220]: # Coverting summary into tfidf vectors.
          tfidf_train_summ = tfidf_vect.fit_transform(train_summ)
          tfidf_test_summ = tfidf_vect.transform(test_summ)
          print(tfidf_train_summ.shape)
          print(tfidf_test_summ.shape)
```

```
(254919, 26288)
(109252, 26288)
```

```
In [221]: # now we will add vectorized review as a new feature to train  data set
          tfidf_train_vect = hstack([tfidf_train_vect,tfidf_train_summ])
          print(tfidf_train_vect.shape)
```

```
(254919, 122971)
```

```
In [222]: # now we will add vectorized review as a new feature to train  data set
          tfidf_test_vect = hstack([tfidf_test_vect,tfidf_test_summ])
          print(tfidf_test_vect.shape)
```

```
(109252, 122971)
```

```
In [223]: # Converting tfidf_train_vect and tfidf_test_vect from scipy.sparse.coo.coo_matrix t
          # scipy.sparse.coo.coo_matrix are not subscriptable

          tfidf_train_vect = sparse.csr_matrix(tfidf_train_vect)
          tfidf_test_vect = sparse.csr_matrix(tfidf_test_vect)
          print(type(tfidf_train_vect))
          print(type(tfidf_test_vect))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
```

```
In [224]: # In this section we will train naive bayes model and find training error for variou

          train_auc_list = [] # Stores area under curve for each alpha value

          for k  in tqdm(alpha):
              clf = MultinomialNB(alpha=k)

              # Trainig our model
              clf.fit(tfidf_train_vect,Y_train)

              predict_probab = clf.predict_log_proba(tfidf_train_vect)[:,1] # Returns probabil

              auc = roc_auc_score(Y_train,predict_probab)
              train_auc_list.append(auc)
```

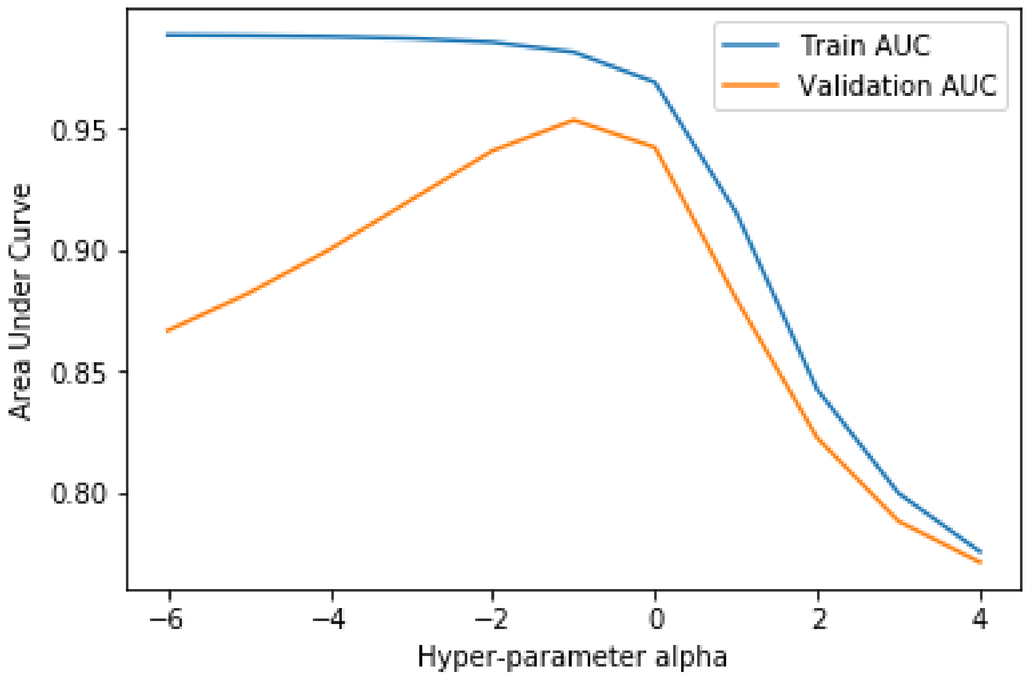
```
100%|| 11/11 [00:04<00:00,  2.57it/s]
```

```
In [225]: # We will do time based splitting and do 10 fold cross validation
          # This is done as reviews keeps changing with time and hence time based splitting is
```

```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

cv_auc_list = [] # will contain cross validation AUC corresponding to each k

for k in tqdm(alpha):
    # Naive bayes classifier
    clf = MultinomialNB(alpha=k)
    i=0
    auc=0.0
    for train_index,test_index in tscv.split(tfidf_train_vect):
        x_train = tfidf_train_vect[0:train_index[-1]][:] # row 0 to train_index(excl
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = tfidf_train_vect[train_index[-1]:test_index[-1]][:] # row from trai
        y_test = Y_train[train_index[-1]:test_index[-1]][:] # row from train_index t

        clf.fit(x_train,y_train)

        predict_probab = clf.predict_proba(x_test)[:,1] # returns probability for po
        i += 1
        auc += roc_auc_score(y_test,predict_probab)

    cv_auc_list.append(auc/i) # Storing AUC value
```

```
100%|| 11/11 [00:43<00:00,  4.05s/it]
```

In [226]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

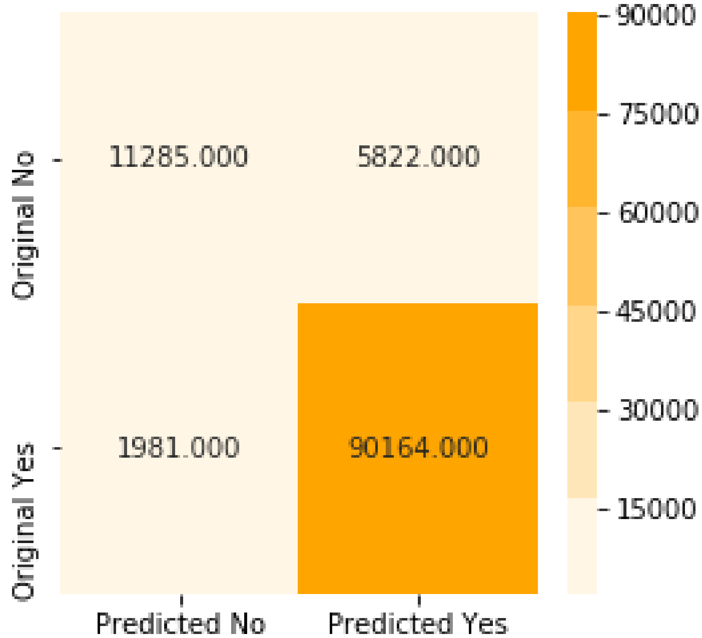



```
In [227]: # Taking best value of alpha = 0.1 an trainig final model
          # Initializing model
          final_clf = MultinomialNB(alpha=0.1)

          # Training final model
          final_clf.fit(tfidf_train_vect,Y_train)

          predict_y = final_clf.predict(tfidf_test_vect)
          predict_probab = final_clf.predict_log_proba(tfidf_test_vect)[:,1] # Returns probaba
          predict_y_train = final_clf.predict(tfidf_train_vect)

          auc = roc_auc_score(Y_test,predict_probab)
          print("Final AUC for tfidf Naive Bayes is {:.3f}".format(auc))
```

```
Final AUC for tfidf Naive Bayes is 0.965
```

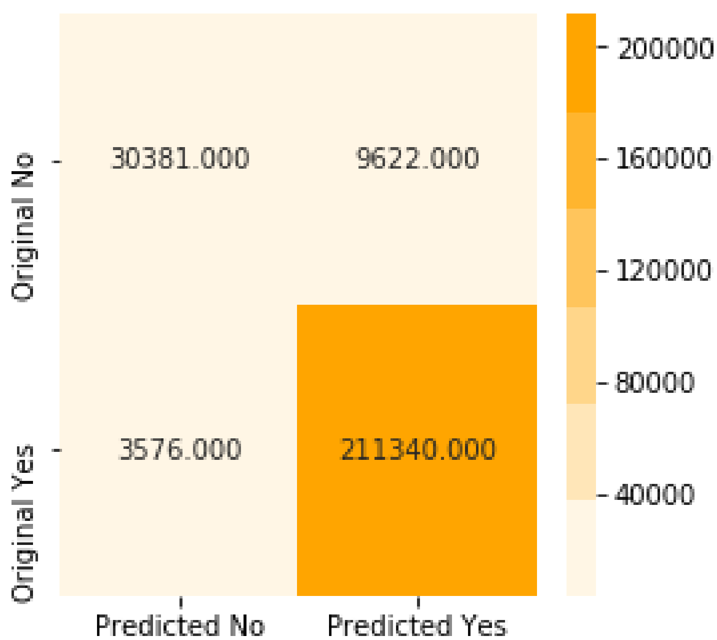
```
In [228]: # Plotting confusion matrix
          print("For Test dataset")
          confusion_matrix_plot(Y_test,predict_y)
```

```
For Test dataset
Confusion matrix
```

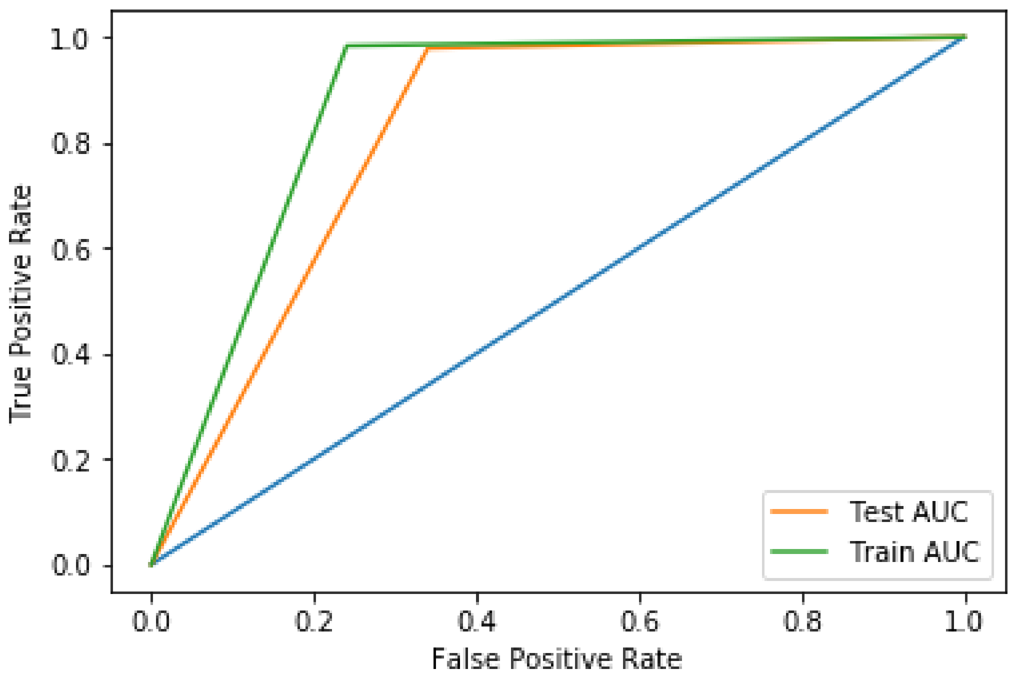



```
In [229]: # Plotting confusion matrix
          print("For Train Dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For Train Dataset
Confusion matrix
```



In [230]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyper parameter tunning using GridSearchCV

In [231]:
```
# Selecting the estimator . Estimator is the model that you will use to train your m
# We will pass this instance to GridSearchCV
clf = MultinomialNB()

# Dictionary of parameters to be searched on
parameters = {'alpha':[0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}

# Value on which model will be evaluated
auc_score = make_scorer(roc_auc_score)

# Calling GridSearchCV .
grid_model = GridSearchCV(estimator = clf,param_grid=parameters,cv=10,refit=True,scor

# Training the gridsearchcv instance
grid_model.fit(tfidf_train_vect,Y_train)

# this gives the best model with best hyper parameter
optimized_clf = grid_model.best_estimator_
```

```
predict_probab = optimized_clf.predict_log_proba(tfidf_test_vect)[:,1] # returns pro
predict_y = optimized_clf.predict(tfidf_test_vect)
predict_y_train = optimized_clf.predict(tfidf_train_vect)

print("AUC is {:.3f}".format(roc_auc_score(Y_test,predict_probab)))
```

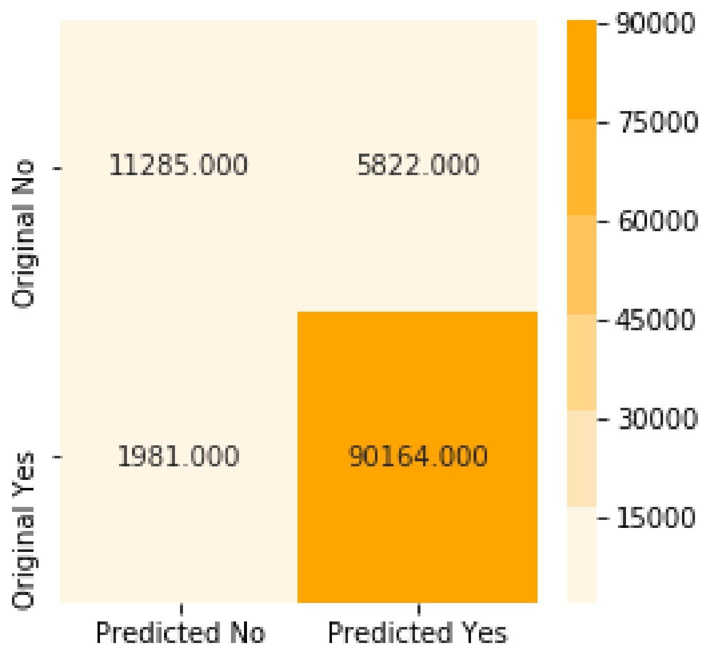
```
AUC is 0.965
```

```
In [232]: # Printing best parameter of grid search
          print(grid_model.best_params_)
```

```
{'alpha': 0.1}
```

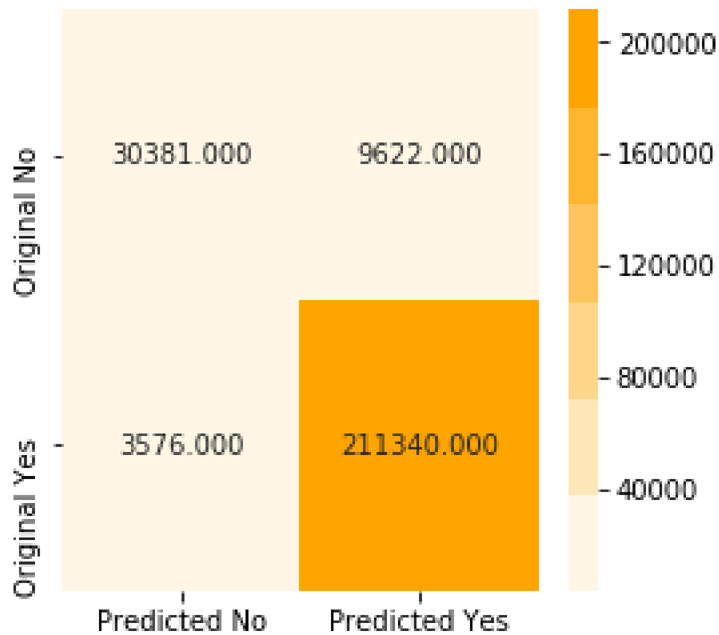
```
In [233]: # Plotting confusion matrix
          print("For test dataset")
          confusion_matrix_plot(Y_test,predict_y)
```

```
For test dataset
Confusion matrix
```

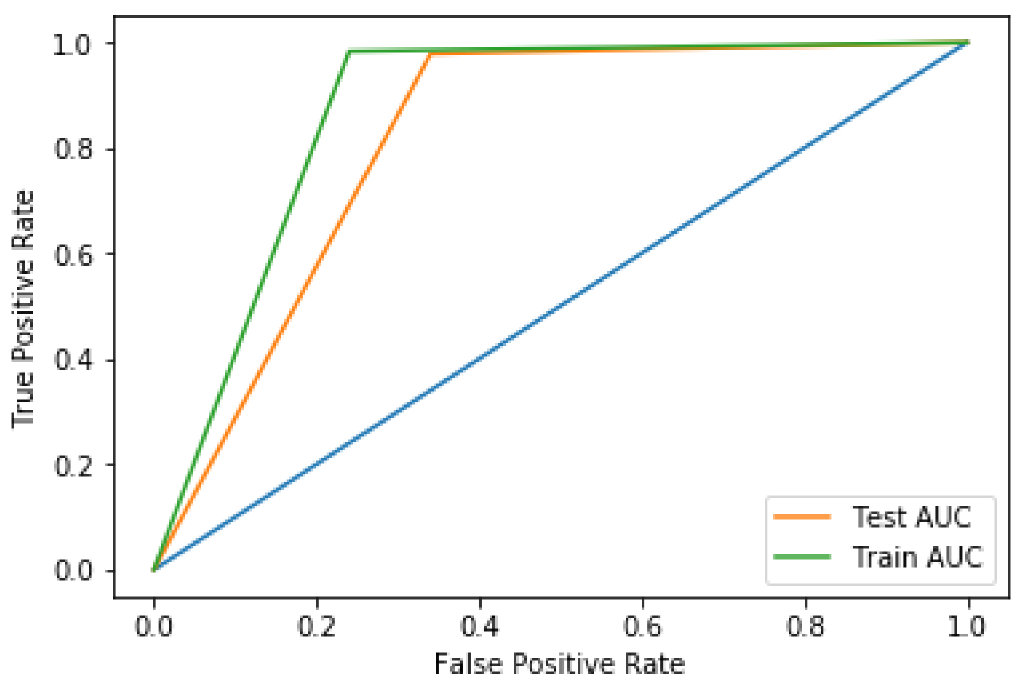



```
In [234]: # Plotting confusion matrix
          print("For train dataset")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
For train dataset
Confusion matrix
```



In [235]:
```
#Plotting ROC Curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



8 [6] Conclusions

In [236]:
```
from prettytable import PrettyTable

# Initializing table object
x = PrettyTable()

x.field_names = ["Vectorizer","Model","Hyper-Parameter alpha","Area Under Curve"]

x.add_row([ "Bow unigram","Naive Bayes","0.1","0.925" ])
x.add_row([ "Bow bigram ","Naive Bayes","0.1","0.928" ])
x.add_row([ "Tfidf unigram","Naive Bayes","0.01","0.919" ])
x.add_row([ "Tfidf bigram ","Naive Bayes","0.01","0.936" ])
x.add_row([ "Bow with review length ","Naive Bayes","0.1","0.915" ])
x.add_row([ "Tfidf with review length ","Naive Bayes","0.1","0.917" ])
x.add_row([ "Bow with summary feature","Naive Bayes","0.1","0.940" ])
x.add_row([ "Tfidf with summary feature","Naive Bayes","0.1","0.965" ])

print(x)
```

```
+----------------------------+-------------+-----------------------+------------------+
|         Vectorizer         |    Model    | Hyper-Parameter alpha | Area Under Curve |
+----------------------------+-------------+-----------------------+------------------+
|        Bow unigram         | Naive Bayes |          0.1          |      0.925       |
|        Bow bigram          | Naive Bayes |          0.1          |      0.928       |
|       Tfidf unigram        | Naive Bayes |          0.01         |      0.919       |
|       Tfidf bigram         | Naive Bayes |          0.01         |      0.936       |
|  Bow with review length    | Naive Bayes |          0.1          |      0.915       |
| Tfidf with review length   | Naive Bayes |          0.1          |      0.917       |
|  Bow with summary feature  | Naive Bayes |          0.1          |      0.940       |
| Tfidf with summary feature | Naive Bayes |          0.1          |      0.965       |
+----------------------------+-------------+-----------------------+------------------+
```

Explaination

Train data and test have been vectorized seperately to prevent data leak problem.

To tune hyper paarameter alpha custom 10-fold cross validation was done on Time Series Split data as reviews keeps changing with time. A graph was plotted to show train and validation AUC and best alpha was selected corresponding to best Validation AUC .

Best model was using the result of custom 10-fold cross validation and Grid Search .

To print top 10 features of positive class and negative class we did as follows:

We sorted the probability of positive and negative features using argsort in ascending order.

Then we selected features corresponding to last 10 indexes from sorted index from above step.

In feature engineering section we have used review length and summary as a feature along with reviews.

We calculated length of each review and vectorized each sumomary and then combined these with reviews using hstack.

Out of all the models BoW with summary feature had best performance although its AUC is less than model trained on Tfidf with summary feature.

```
In [ ]:
```