Amazon_Fine_Food_Reviews_Analysis_Logistic_Regression

April 10, 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
```

```python
# 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]:

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

In [4]:

```python
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[4]:

```
               UserId   ProductId             ProfileName        Time  Score  \
0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
```

```
1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
3  #oc-R11O5J5ZVQE25C  B005HG9ET0           Penguin Chick  1346889600      5
4  #oc-R12KPBODL2B5ZD  B007OSBE1U   Christopher P. Presta  1348617600      1

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

In [5]:
```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 alo
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pre
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of thi
==================================================
```

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 alo
```

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 alo
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pre
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of thi
```

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 th
==================================================
```

```
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 alon
```

```
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 thin
```

```
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', "t
                     'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'h
                     'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'o
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'an
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
                     's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
                     've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
                     "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mig
                     "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 stopw
            preprocessed_reviews.append(sentance.strip())
```

```
100%|| 364171/364171 [02:23<00:00, 2542.58it/s]
```

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

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

[3.2] Preprocessing Review Summary

```
In [24]: ## Similartly you can do preprocessing for review summary also.
         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 stopw
             preprocessed_summary.append(sentance.strip())
```

```
100%|| 364171/364171 [01:32<00:00, 3945.63it/s]
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [0]: #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', 'aahhhs', 'aback', 'abandon', 'abates', 'abbott', 'abby', 'abdominal
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

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

In [0]:
```
#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/modu

# 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_c
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

5.3 [4.3] TF-IDF

In [0]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_names
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.g
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'able find', 'able get',
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

5.4 [4.4] Word2Vec

In [25]:
```
# 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 [26]:
```
# 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, 
```

```
[('terrific', 0.8967643976211548), ('fantastic', 0.8951858878135681), ('awesome', 0.86593192815
==================================================
[('nastiest', 0.8660403490066528), ('greatest', 0.7526767253875732), ('disgusting', 0.75224715
```

In [27]:
```
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', 'di
```

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 [26]: # 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_)))# we are convertin
         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, yticklabel
    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="Validation AUC")
    plt.plot(fpr2,tpr2,label="Train AUC")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
```

```
        plt.legend()
        plt.show()
```

In [27]:
```
# Plotting graph of auc and parameter for training and cross validation error
import math
alpha = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
alpha1 = [math.log10(i) for i in alpha]
def plot_train_vs_auc(train_auc_list,cv_auc_list):
    plt.plot(alpha1,train_auc_list,label="Train AUC")
    plt.xlabel("Log of Hyper-parameter lambda for regularization")
    plt.ylabel("Area Under Curve")
    plt.plot(alpha1,cv_auc_list,label="Validation AUC")
    plt.legend()
    plt.show()
```

6 [5] Assignment 5: Apply Logistic Regression

```
<li><strong>Apply Logistic Regression on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
    </ul>
</li>
<br>
<li><strong>Hyper paramter tuning (find best hyper parameters corresponding the algorithm that
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li><strong>Pertubation Test</strong>
    <ul>
<li>Get the weights W after fit your model with the data X i.e Train data.</li>
<li>Add a noise to the X (X' = X + e) and get the new data set X' (if X is a sparse
```

matrix, X.data+=e)

```
<li>Fit the model again on data X' and get the weights W'</li>
<li>Add a small eps value(to eliminate the divisible by zero error) to W and W i.e
```

W=W+10^-6 and W' = W'+10^-6

```
<li>Now find the % change between W and W' (| (W-W') / (W) |)*100)</li>
<li>Calculate the 0th, 10th, 20th, 30th, ...100th percentiles, and observe any sudden rise in t
```

```
<li> Ex: consider your 99th percentile is 1.3 and your 100th percentiles are 34.6, there is suc
        <li> Print the feature names whose % change is more than a threshold x(in our example i
    </ul>
</li>
<br>
<li><strong>Sparsity</strong>
    <ul>
<li>Calculate sparsity on weight vector obtained after using L1 regularization</li>
    </ul>
</li>
<br><font color='red'>NOTE: Do sparsity and multicollinearity for any one of the vectorizers. B
<br>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Get top 10 important features for both positive and negative classes separately.</li>
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature engine
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table for
    <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 Logistic Regression

7.1 [5.1] Logistic Regression on BOW, SET 1

7.1.1 [5.1.1] Applying Logistic Regression with L1 regularization on BOW, SET 1

In [28]:
```
from sklearn.cross_validation import train_test_split
from sklearn.model_selection import TimeSeriesSplit
# intializing coount vectorizer
bow_vect = CountVectorizer()

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))
```

```
/usr/local/lib/python3.5/site-packages/sklearn/cross_validation.py:41: DeprecationWarning: This
  "This module will be removed in 0.20.", DeprecationWarning)


254919
```

In [29]:
```
# Vectorizing train and test dataset seperately
train_vect = bow_vect.fit_transform(X_train)
test_vect = bow_vect.transform(X_test)
train_vect.shape
```

Out[29]:
```
(254919, 96683)
```

In [30]:
```
# Standarizing data
from sklearn.preprocessing import StandardScaler
train_vect = StandardScaler(with_mean=False).fit_transform(train_vect)
test_vect = StandardScaler(with_mean=False).fit_transform(test_vect)
```

In [31]:
```
# Initializing the logistice regression classifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
from tqdm import tqdm  # this module is used to check the progress of loops
import numpy as np
```

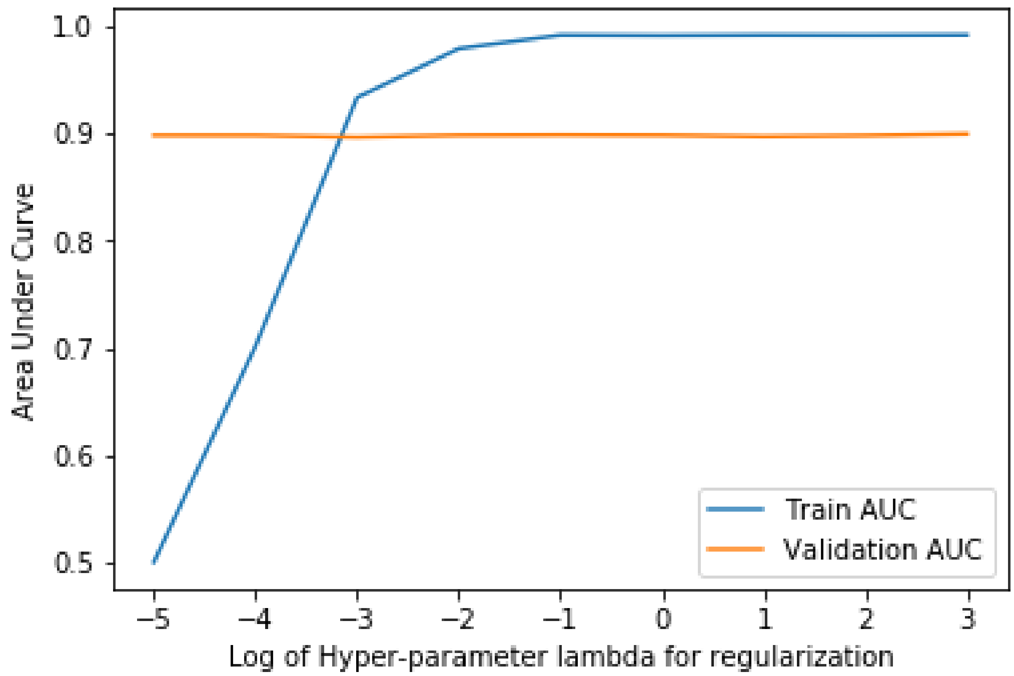
```
param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
train_auc_list = [] # Will contain train auc score for various lambda

# Training and testing on train dataset
for i in tqdm(param_lambda):
    log_clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
    log_clf.fit(train_vect,Y_train)

    predict_probab = log_clf.predict_log_proba(train_vect)[:,1] # Returns log probabi
    predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
    auc = roc_auc_score(Y_train,predict_probab)
    train_auc_list.append(auc)
```

```
100%|| 9/9 [01:25<00:00, 15.93s/it]
```

```
In [32]: # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         # In this section we will perform 5-fold Cross validation on timse series split data

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

         for k in tqdm(param_lambda):
             # Naive bayes classifier
             clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
             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%|| 9/9 [04:35<00:00, 31.47s/it]
```

```
In [33]: # Plotting graph of auc and parameter for training and cross validation error
         plot_train_vs_auc(train_auc_list,cv_auc_list)
```

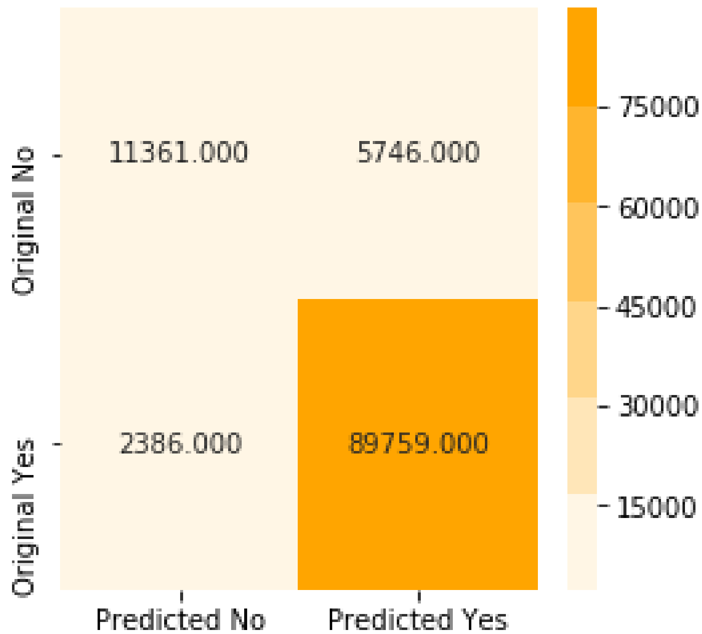



```
In [34]: # Taking best value of lambda = 1 an trainig final model
         # Initializing model
         final_clf = LogisticRegression(penalty='l1',C=0.01,tol=0.1,n_jobs=4,max_iter=1000)

         # 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 Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for BoW Logistic Regression is 0.948
```

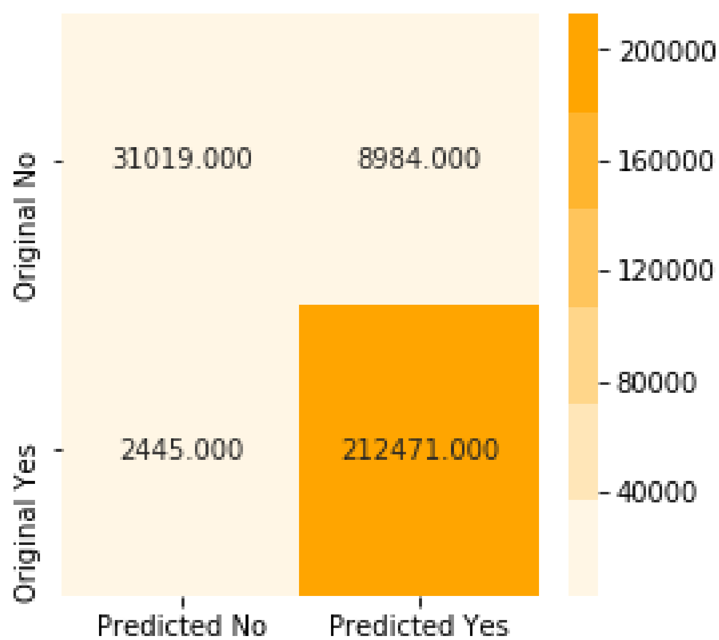
```
In [35]: # Plotting confusion matrix
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

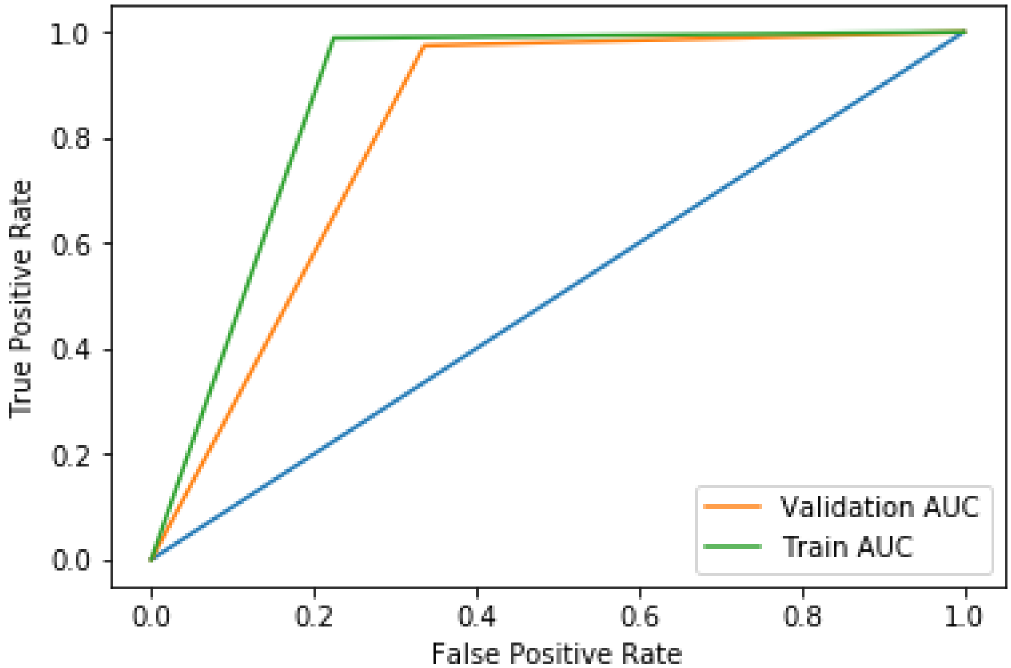



```
In [36]: # Plotting confusion matrix
         print("Confusion Matrix for Train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for Train data
Confusion matrix
```



In [37]:
```
# Plotting ROC AUC curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



In [38]:
```
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 = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=400)
# Dictionary of parameters to be searched on
parameters = {'C':[0.0001,0.001,0.01,0.1,1,10,100,1000]}

# 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 0.934
```

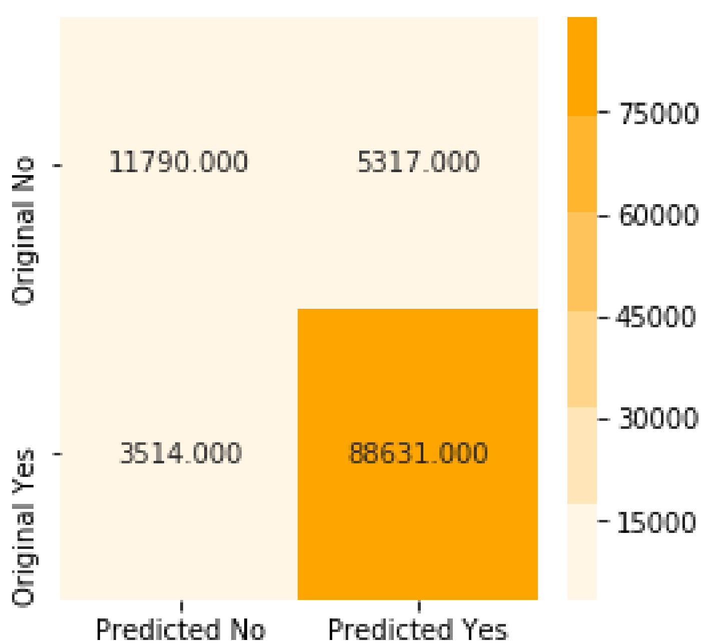
In [39]:
```
# Saving the best model
import pickle
outfile = open("log_reg_clf1","wb")
pickle.dump(optimized_clf,outfile)
outfile.close()
```

In [40]:
```
# Getting the best hyper-parameter of the trained model
best_param = grid_model.best_params_
print(best_param)
```

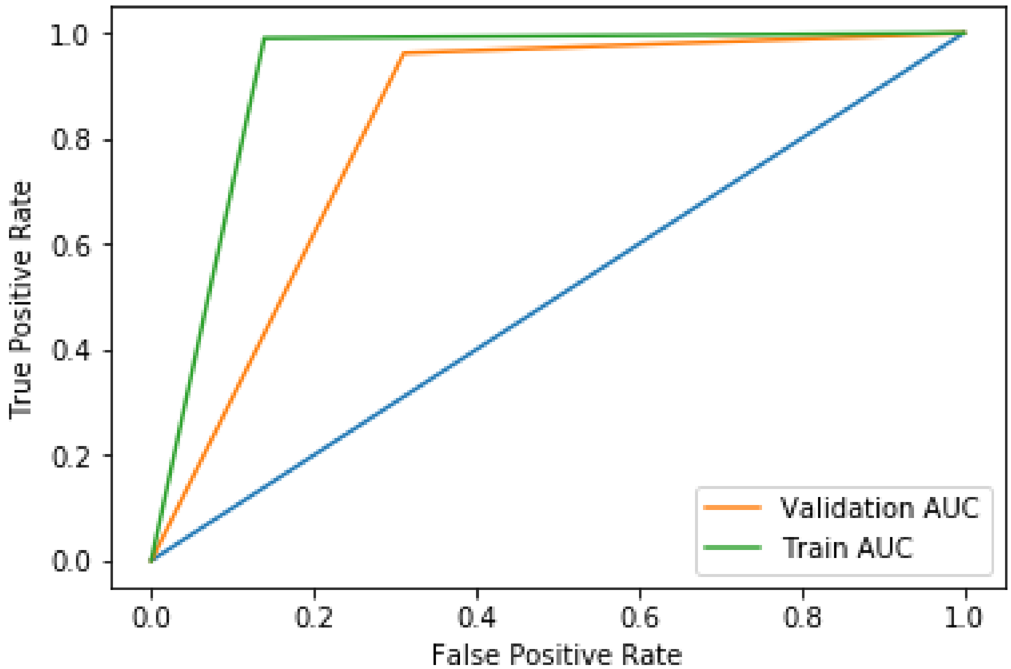
```
{'C': 0.1}
```

In [41]:
```
# Plotting confusion matrix
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion matrix
```



In [42]: #Plotting ROC Curve
```
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



[5.1.1.1] Calculating sparsity on weight vector obtained using L1 regularization on BOW, SET 1

In [43]:
```
# Getting the weight vector from logistic regression classifier
weight_vect = final_clf.coef_
count = 0
for i in tqdm(range(len(weight_vect[0]))):
    if(weight_vect[0][i]==0):
        count += 1

print("count is",count)
print("Sparsity is",count/len(weight_vect[0]))
```

```
100%|| 96683/96683 [00:00<00:00, 902516.68it/s]

count is 78965
Sparsity is 0.8167413092270617
```

7.1.2 [5.1.2] Applying Logistic Regression with L2 regularization on BOW, SET 1

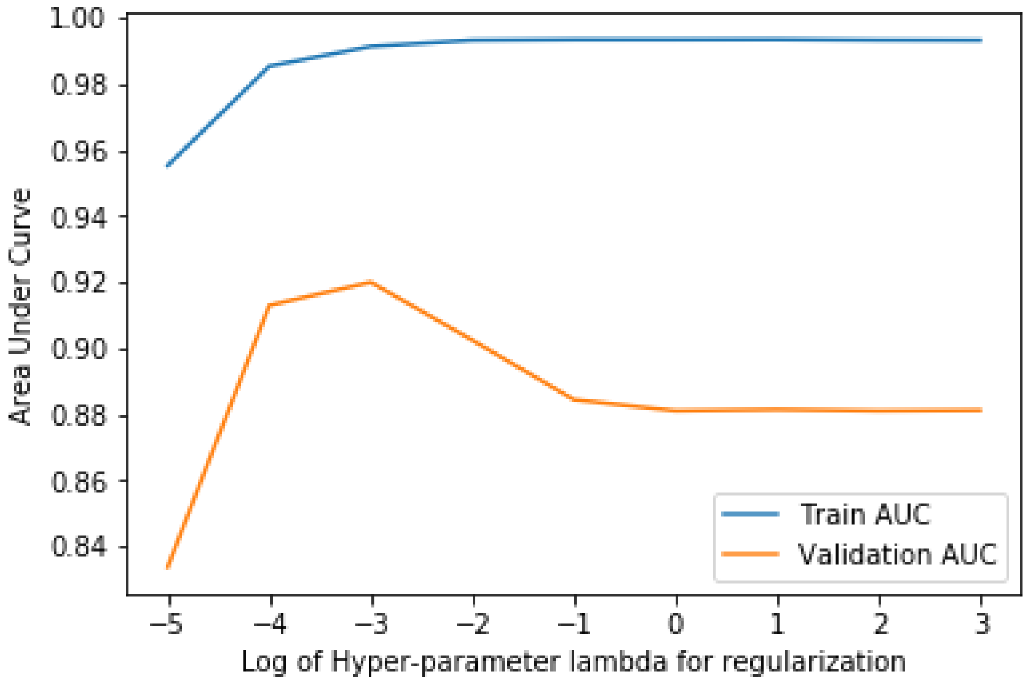
In [44]:
```
# Training logistic regresison model and using L2 regularization.

train_auc_list = [] # Will contain train auc score for various lambda

param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]

# Training and testing on train dataset
for i in tqdm(param_lambda):
    log_clf = LogisticRegression(penalty='l2',C=i,tol=0.1,n_jobs=4,max_iter=200)
    log_clf.fit(train_vect,Y_train)

    predict_probab = log_clf.predict_log_proba(train_vect)[:,1] # Returns log probabi
    predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin

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

```
100%|| 9/9 [02:11<00:00, 17.42s/it]
```

In [45]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

# In this section we will perform 10-fold Cross validation on timse series split data

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

for k in tqdm(param_lambda):
    # Logistic Regression classifier
    clf = LogisticRegression(penalty='l2',C=k,tol=0.1,n_jobs=4,max_iter=200)
    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
        predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and I
        i += 1
        auc += roc_auc_score(y_test,predict_probab)

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

```
100%|| 9/9 [12:45<00:00, 100.23s/it]
```

In [46]:
```python
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

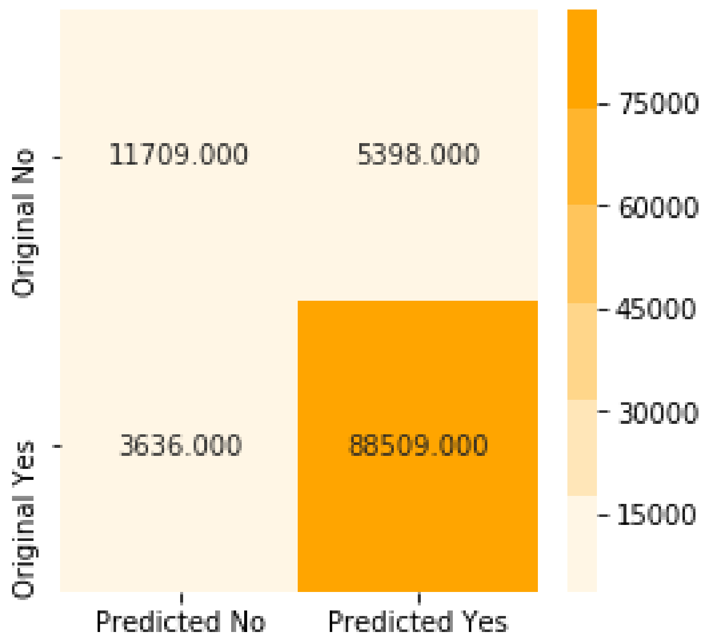


In [47]:
```python
# Taking best value of alpha = 0.001 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l2',C=0.001,tol=0.1,n_jobs=4,max_iter=1000)

# 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_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infinite
predict_y_train = final_clf.predict(train_vect)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for BoW Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for BoW Logistic Regression is 0.931
```

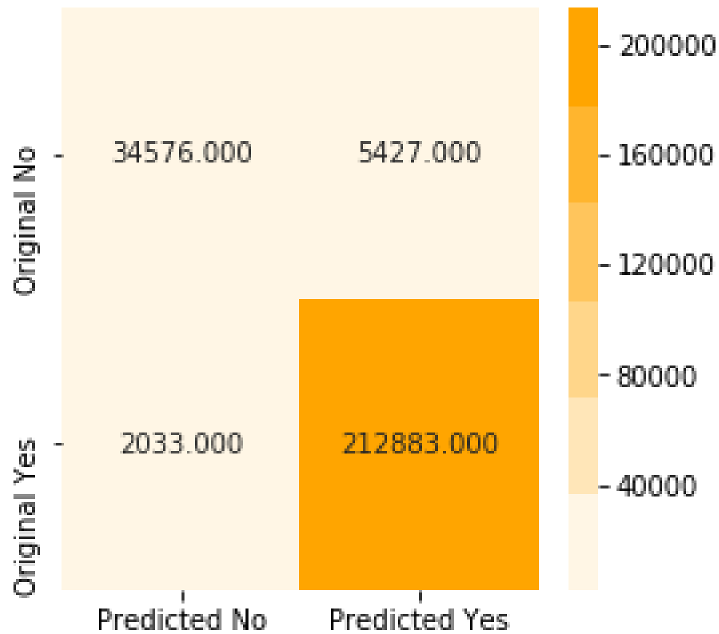
In [48]:
```python
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

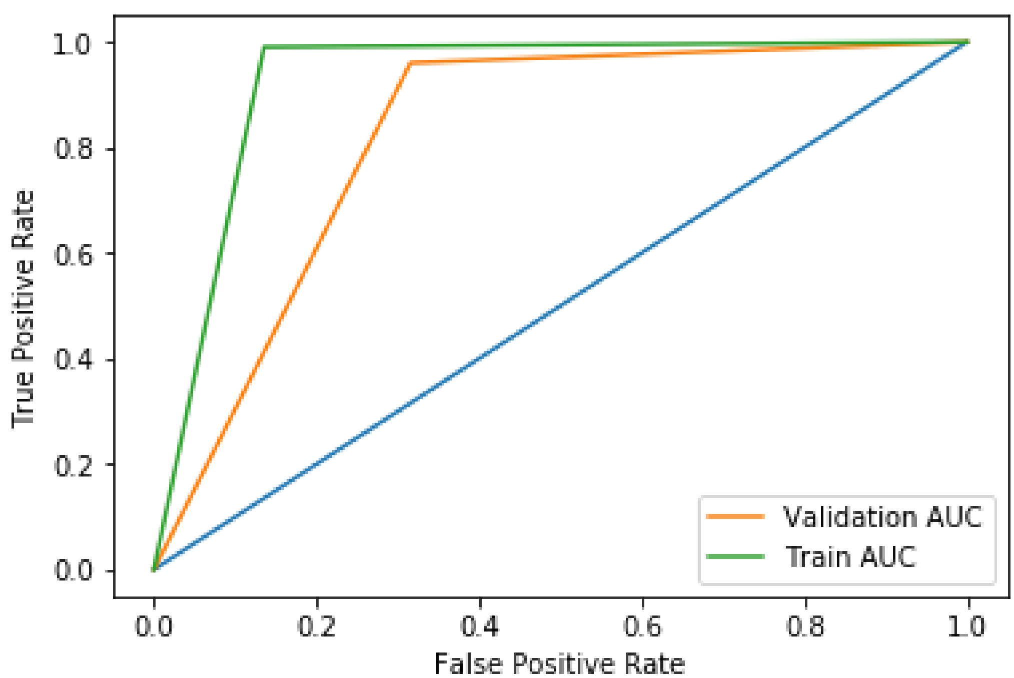



```
In [49]: # Plotting confusion matrix for train data
         print("Confusion Matrix for train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```




```
In [50]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyper-parameter tunning using GridSearchCV

```
In [51]: 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 = LogisticRegression(penalty='l2',tol=0.1,max_iter=400)

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

         # 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_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infinite
         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)))
```

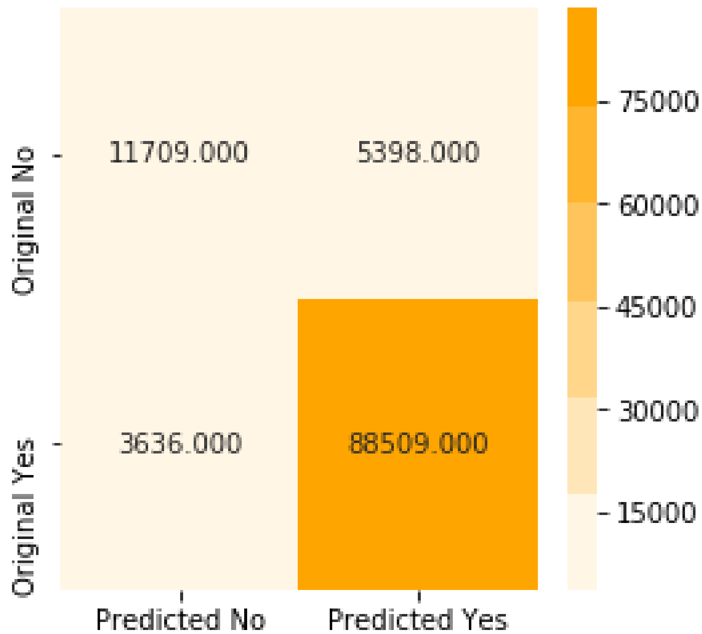
```
AUC is 0.931
```

```
In [52]: # Printing best parameter
         print(grid_model.best_params_)
```

```
{'C': 0.001}
```

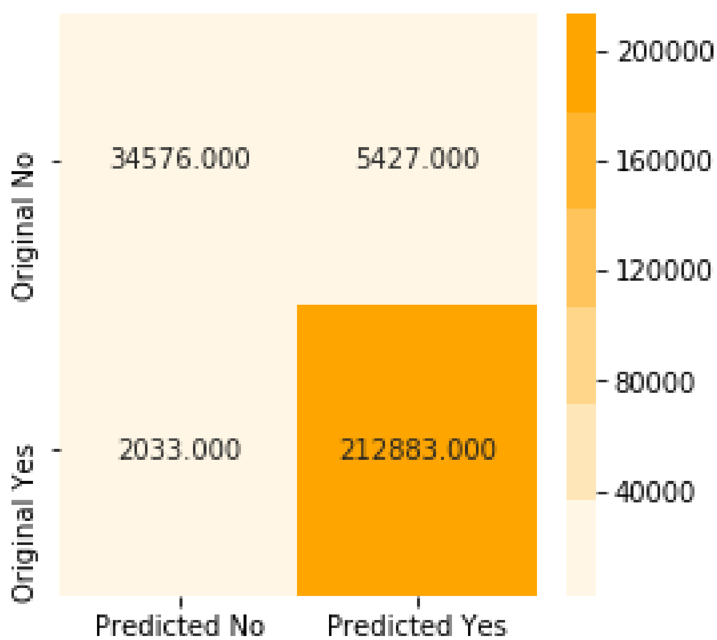
```
In [53]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

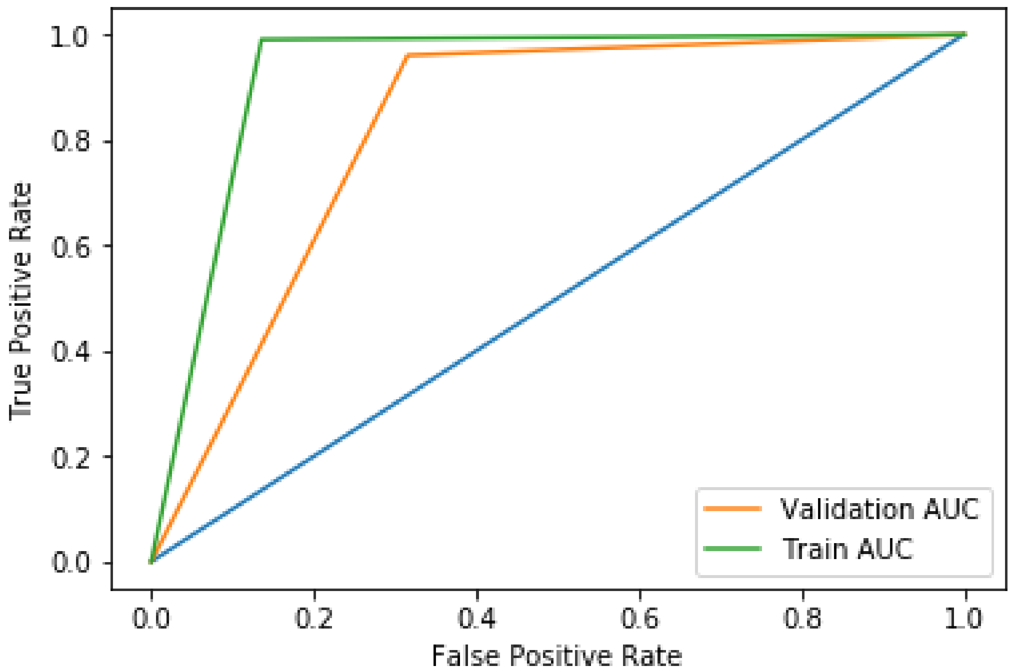



```
In [54]: # Plotting confusion matrix for train data
         print("Confusion Matrix for train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```



In [55]:
```
# Plotting ROC AUC curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



[5.1.2.1] Performing pertubation test (multicollinearity check) on BOW, SET 1

In [56]:
```
# Getting weight vectors of clf
weight_vect = optimized_clf.coef_
# Adding noise to train vect
import copy
train_vect1 = copy.deepcopy(train_vect)

import numpy as np
e = np.random.normal(0,0.000001)

train_vect1.data = train_vect1.data + e  # Adding noise to train vector.
print(train_vect1.shape)
```

```
(254919, 96683)
```

In [57]:
```
# Training our model on new train_vect
# Taking best value of alpha = 1 an trainig final model
```

```
# Initializing model
noisy_clf = LogisticRegression(penalty='l1',C=0.01,tol=0.1,n_jobs=4,max_iter=1000)

# Training final model
noisy_clf.fit(train_vect1,Y_train)

noisy_weight_vect = noisy_clf.coef_

# To remove divide by zero error we are adding very small value to both weight vector
weight_vect = weight_vect + 0.000001
noisy_weight_vect = noisy_weight_vect + 0.000001
```

In [58]:
```
# Calculating percentage change in weight of noisy data w.r.t. original weight.
per_change = abs(((weight_vect - noisy_weight_vect)/weight_vect)) * 100
print("percentage change is",per_change)
```

```
percentage change is [[ 92.64440475  99.98593216  99.98279895 ... 100.2820877  100.07714095
   99.93774918]]
```

In [59]:
```
import math
# Sorting percentage change list for elbow method
sort_index = np.argsort(per_change[0])
print(sort_index)

sort_per_change = [math.log1p(abs(per_change[0][i])) for i in sort_index] # abs() is
```

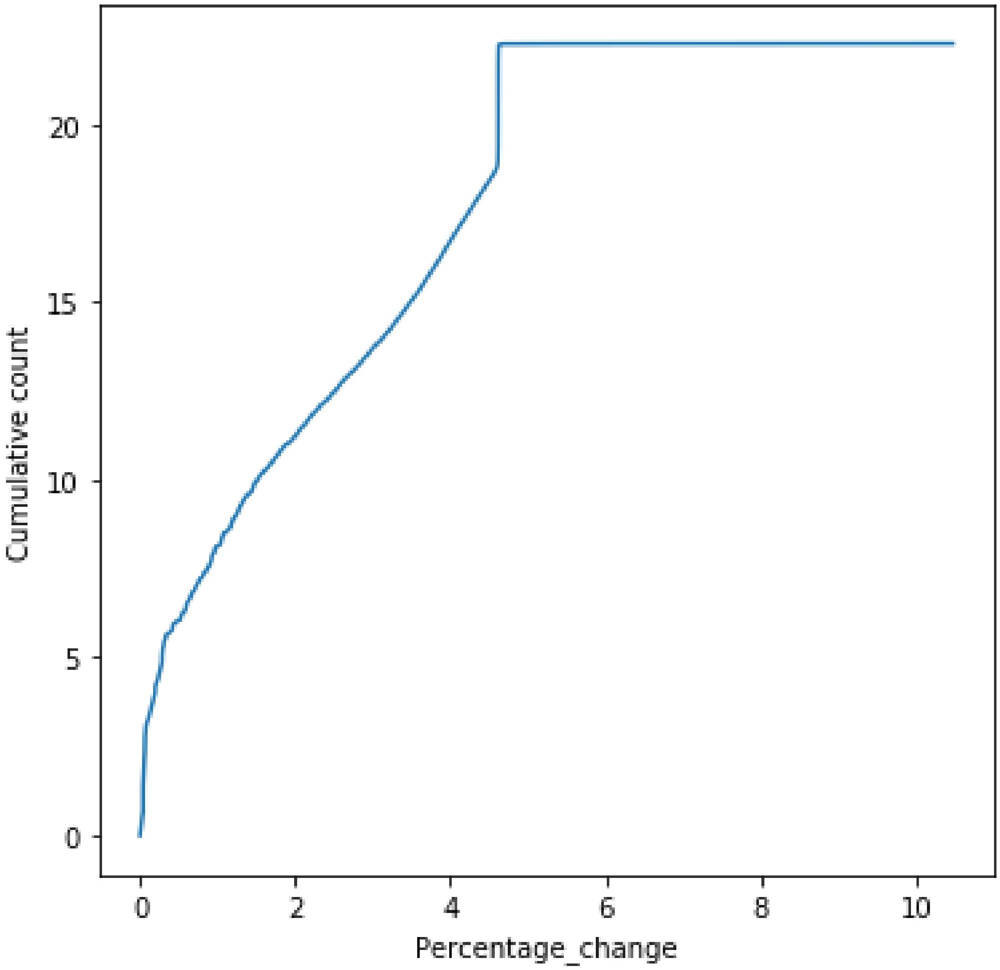
```
[71155 75742 74517 ... 47458 95832 93502]
```

In [60]:
```
# Calculating cumulative count of percentage change list.
# %change  count cumulative_count
# 0.00       3         3
# 2.00       2      (3+2) = 5
# 2.50       5      (5+5) = 10
# and so on we calculate cumulative count of the number of values less than a particu

cumu_lst = np.zeros(len(per_change[0])+1) # This contains n+1 values as for first ent
                                          # cumu_lst[i+1] = cumu_list[i] + count  i s
cumu_lst[0] = 0

for i in range(len(per_change[0])):
    count = 0
    for j in range(0,i):
        if(sort_per_change[i]>sort_per_change[j]):
            count += 1
            cumu_lst[i+1] = cumu_lst[i] + count
```

In [67]:
```
# Getting all the cumulative count in a list and scaling down large values to plot th
cumu_lst1 = [math.log1p(cumu_lst[i]) for i in tqdm(range(1,len(cumu_lst)))]
#print(len(cumu_lst1))
```

```
  0%|          | 0/96683 [00:00<?, ?it/s]
100%|| 96683/96683 [00:00<00:00, 1490343.13it/s]
```

In [68]:
```
# Plotting graph of Percentage change Vs Cumualtive count.
# We will select that percentage change at which graph suddenly changes abruptly.

import matplotlib.pyplot as plt
plt.figure(figsize=(6,6))
plt.plot(sort_per_change,cumu_lst1)
plt.xlabel("Percentage_change")
plt.ylabel("Cumulative count")
plt.show()
```



In [63]:
```
# Getting index of percentage change greater than the threshold change
# Threshold value of percentage change is 0.00% . This means we will remove features a
# Threshold % = antilog(4.3) base e
```

```
# Hence we
per_change_index =[]
for i in tqdm(range(len(per_change[0]))):
    if(per_change[0][i]>0.0):
        per_change_index.append(i)

#print(len(per_change_index))
```

```
100%|| 96683/96683 [00:00<00:00, 997758.26it/s]
```

```
In [64]: # Getitng the name of features
         multicolinear_features = []
         all_features = bow_vect.get_feature_names()
         for i in tqdm(per_change_index):
             multicolinear_features.append(all_features[i])

         print(len(multicolinear_features))
```

```
100%|| 96683/96683 [00:00<00:00, 1477457.99it/s]

96683
```

```
In [65]: # printing only 200 multicollinear features
         # As printing a lot of features gives error while converting ipynb to pdf
         print(multicolinear_features[0:200])
```

```
['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaa', 'aaaaaaaaaaa', 'aaaaaaaaaaaa', 'aaaaaaaaaaaaaa', 'aaaa
```

7.1.3 [5.1.3] Feature Importance on BOW, SET 1

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

```
In [85]: #To get most important features first sort the weight vectors in ascending order and
         # Corresponding to that index.

         top10_pos_feat = weight_vect[0].argsort() #Contains the index of all weights in ascend

         # Top 10 features
         top10_pos_words = [all_features[i] for i in top10_pos_feat[-10:]]
         print(top10_pos_words)
```

```
['wonderful', 'highly', 'loves', 'excellent', 'perfect', 'love', 'good', 'delicious', 'best',
```

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

```
In [86]: #To get most important features first sort the weight vectors in ascending order and
         # Corresponding to that index.

         top10_neg_feat = weight_vect[0].argsort() #Contains the index of all weights in desce

         # Top 10 features
         top10_neg_words = [all_features[i] for i in top10_neg_feat[0:10]]
         print(top10_neg_words)

['not', 'disappointed', 'worst', 'terrible', 'awful', 'money', 'disappointing', 'horrible', 'u
```

7.2 [5.2] Logistic Regression on TFIDF, SET 2

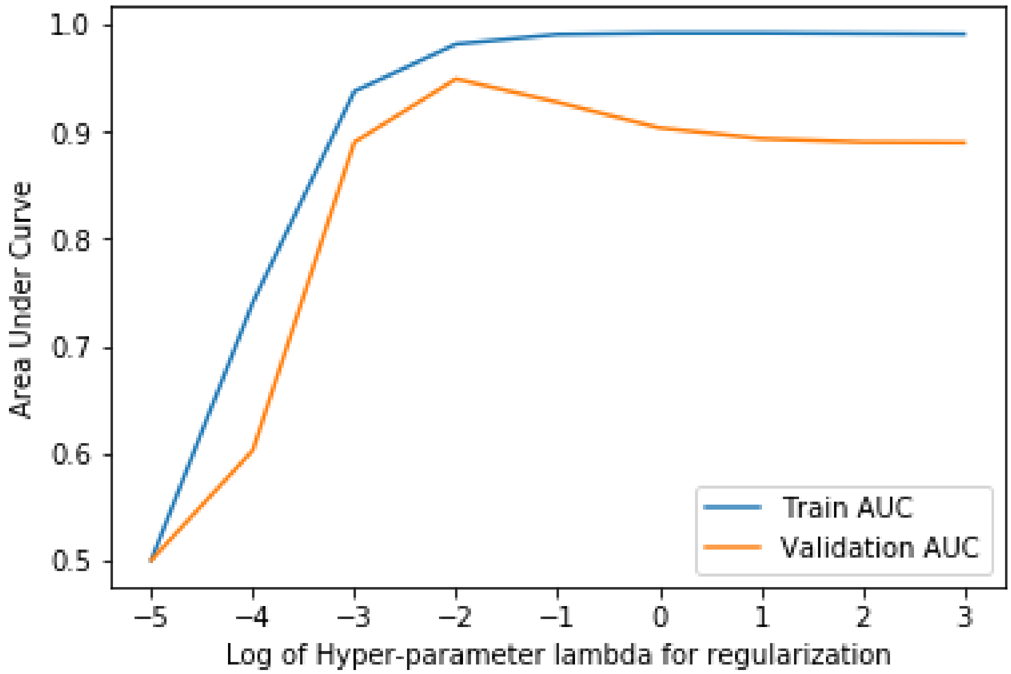
7.2.1 [5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

```
In [110]: # Initializing Tfidf vectorizer
          tfidf_vect = TfidfVectorizer()

In [111]: # Vectorizing train and test dataset seperately
          train_vect = tfidf_vect.fit_transform(X_train)
          test_vect = tfidf_vect.transform(X_test)
          train_vect.shape

Out[111]: (254919, 96683)

In [112]: # Standarizing data
          train_vect = StandardScaler(with_mean=False).fit_transform(train_vect)
          test_vect = StandardScaler(with_mean=False).fit_transform(test_vect)

In [113]: # Initializing the logistice regression classifier

          param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
          train_auc_list = [] # Will contain train auc score for various lambda

          # Training and testing on train dataset
          for i in tqdm(param_lambda):
              log_clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
              log_clf.fit(train_vect,Y_train)

              predict_probab = log_clf.predict_log_proba(train_vect)[:,1] # Returns log probab
              auc = roc_auc_score(Y_train,predict_probab)
              train_auc_list.append(auc)

100%|| 9/9 [01:35<00:00, 21.02s/it]
```

In [114]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

# In this section we will perform 10-fold Cross validation on timse series split dat

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

for k in tqdm(param_lambda):
    # Naive bayes classifier
    clf = LogisticRegression(penalty='l1',C=k,tol=0.1,n_jobs=4,max_iter=400)
    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_inde
        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%|| 9/9 [02:42<00:00, 21.30s/it]
```

In [115]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

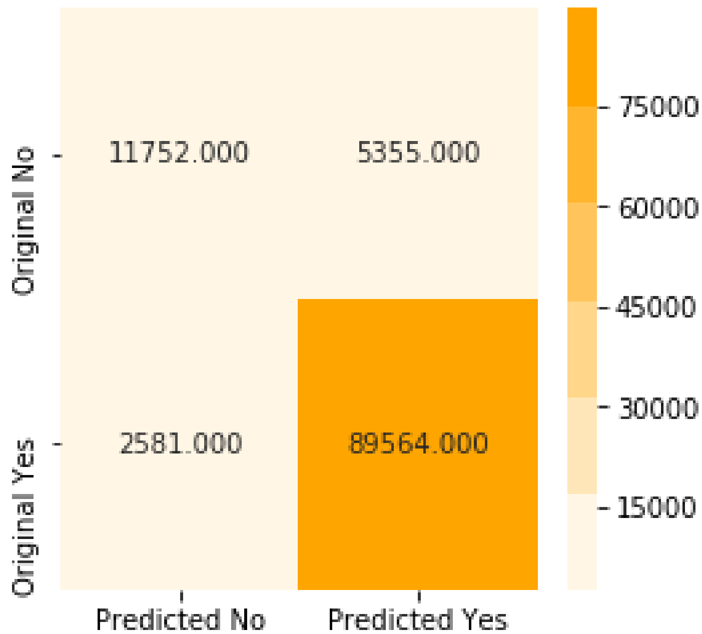


In [116]:
```
# Taking best value of lambda = 0.01 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l1',C=0.01,tol=0.1,n_jobs=4,max_iter=1000)

# 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 f
predict_y_train = final_clf.predict(train_vect)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for Tfidf Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Logistic Regression is 0.957
```

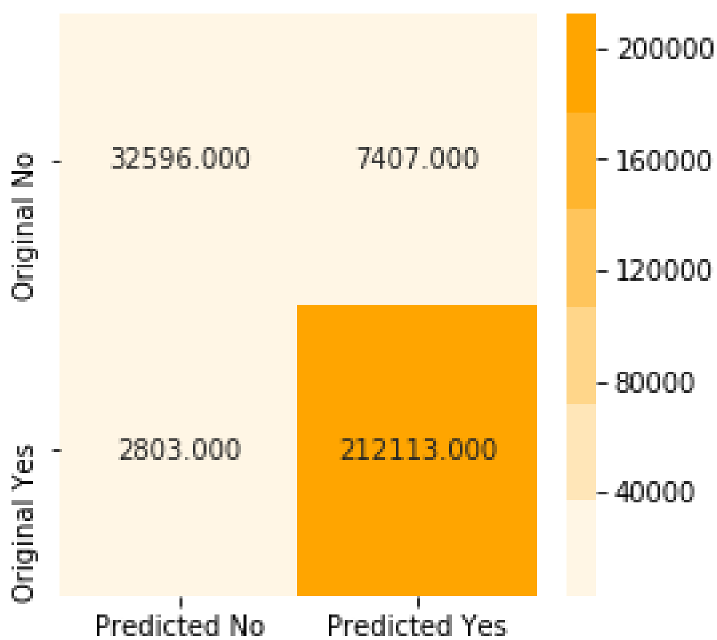
In [117]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

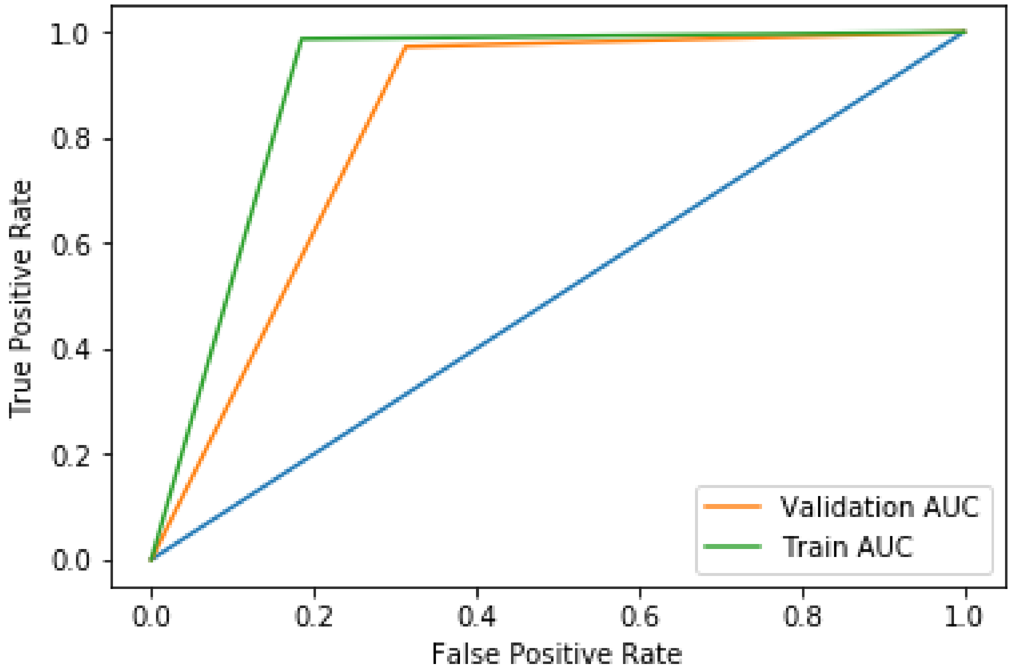



```
In [118]: # Plotting confusion matrix for test data
          print("Confusion Matrix for train data")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```



In [119]:
```
# Plotting ROC AUC curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyper-parameter tunning using GridSearchCv

In [149]:
```
# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = LogisticRegression(penalty='l1',tol=0.1,n_jobs=4,max_iter=400)

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

# 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 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)))
```

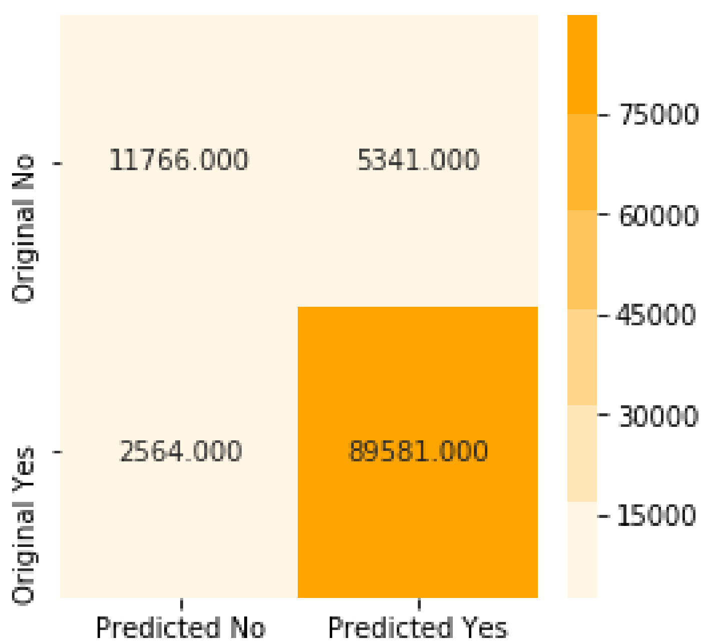
```
AUC is 0.957
```

In [150]:
```
# Getting the best paramater choosen by optimized_clf
print(grid_model.best_params_)
```

```
{'C': 0.01}
```

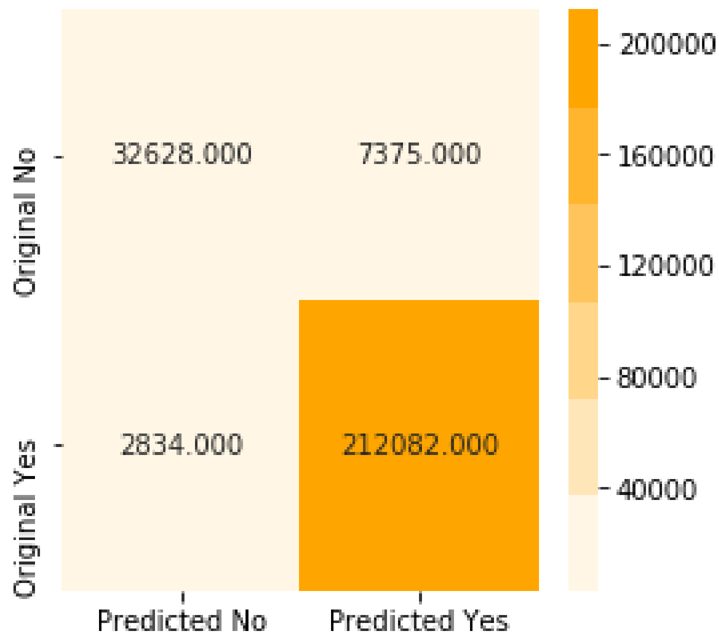
In [151]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

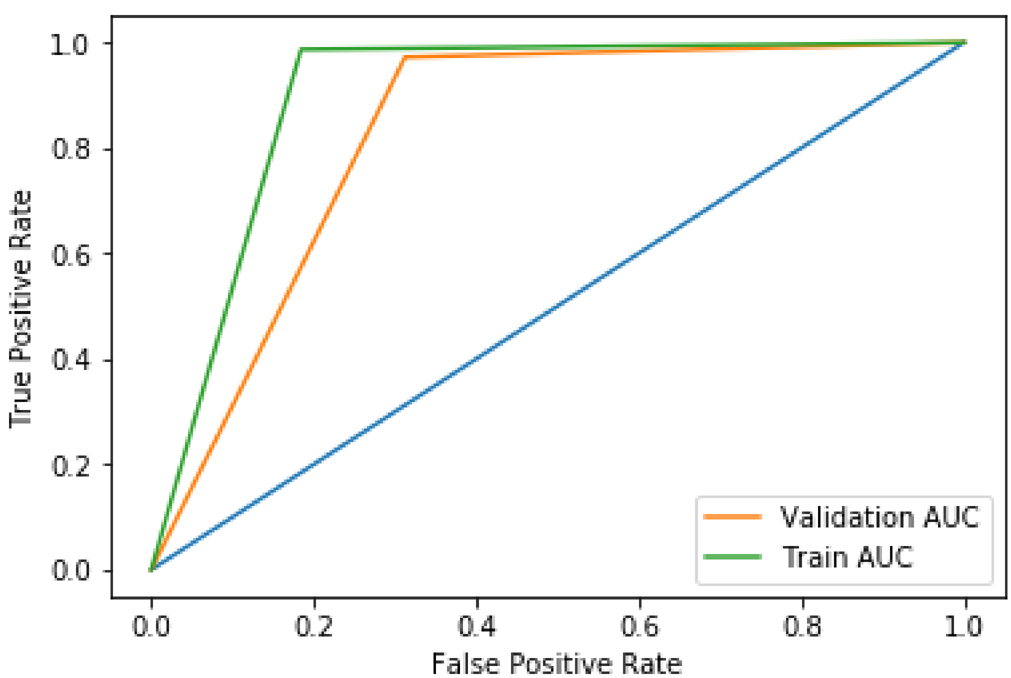


In [152]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for train data")
confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```




```python
In [153]: # Plotting ROC AUC curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



7.2.2 [5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [120]:
```
# Initializing the logistice regression classifier

param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
train_auc_list = [] # Will contain train auc score for various lambda

# Training and testing on train dataset
for i in tqdm(param_lambda):
    log_clf = LogisticRegression(penalty='l2',C=i,tol=0.1,n_jobs=4,max_iter=200)
    log_clf.fit(train_vect,Y_train)

    predict_probab = log_clf.predict_log_proba(train_vect)[:,1] # Returns log probab

    predict_probab = np.nan_to_num(predict_probab) # This replaces Nan and very larg

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

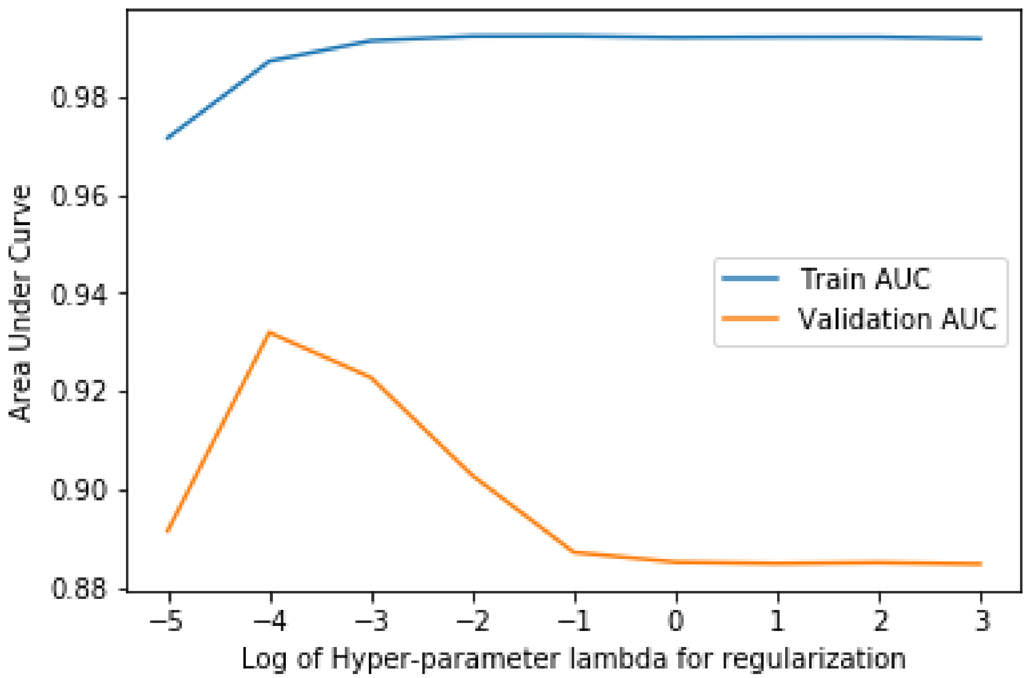
```
100%|| 9/9 [01:06<00:00,  7.90s/it]
```

In [121]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

# In this section we will perform 10-fold Cross validation on timse series split dat

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

for k in tqdm(param_lambda):
    # Naive bayes classifier
    clf = LogisticRegression(penalty='l2',C=k,tol=0.1,n_jobs=4,max_iter=400)
    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_inde
        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
        predict_probab = np.nan_to_num(predict_probab) # This replaces Nan and very
```

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

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

100%|| 9/9 [10:39<00:00, 84.20s/it]

In [122]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

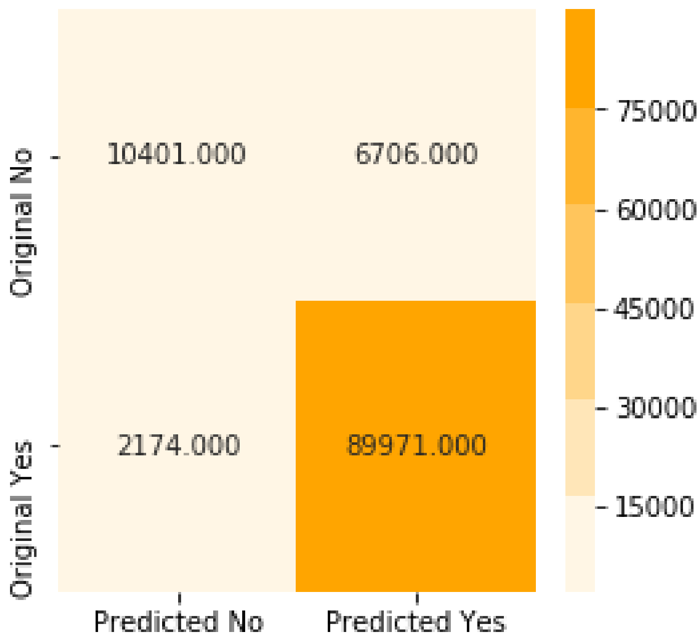


In [123]:
```
# Taking best value of lambda = 1 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l2',C=0.0001,tol=0.1,n_jobs=4,max_iter=1000)

# 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 f
predict_y_train = final_clf.predict(train_vect)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for Tfidf Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Logistic Regression is 0.945
```

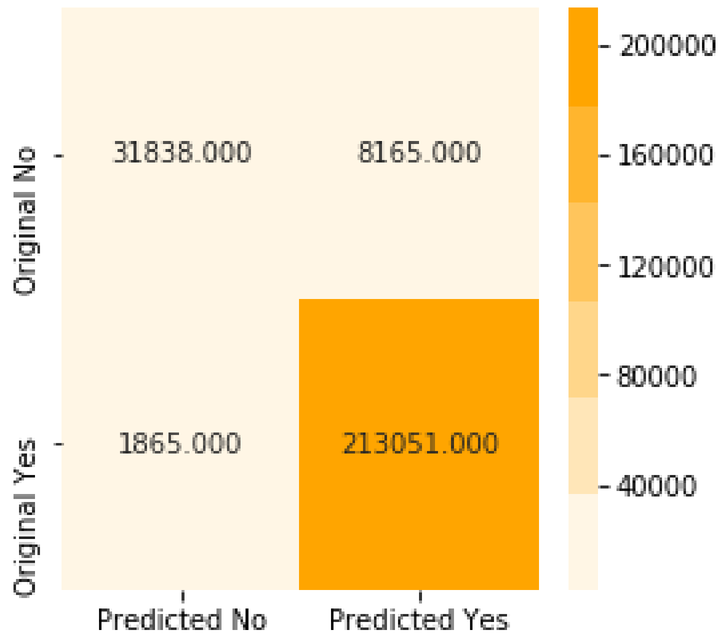
```python
In [124]: # Plotting confusion matrix for test data
          print("Confusion Matrix for test data")
          confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

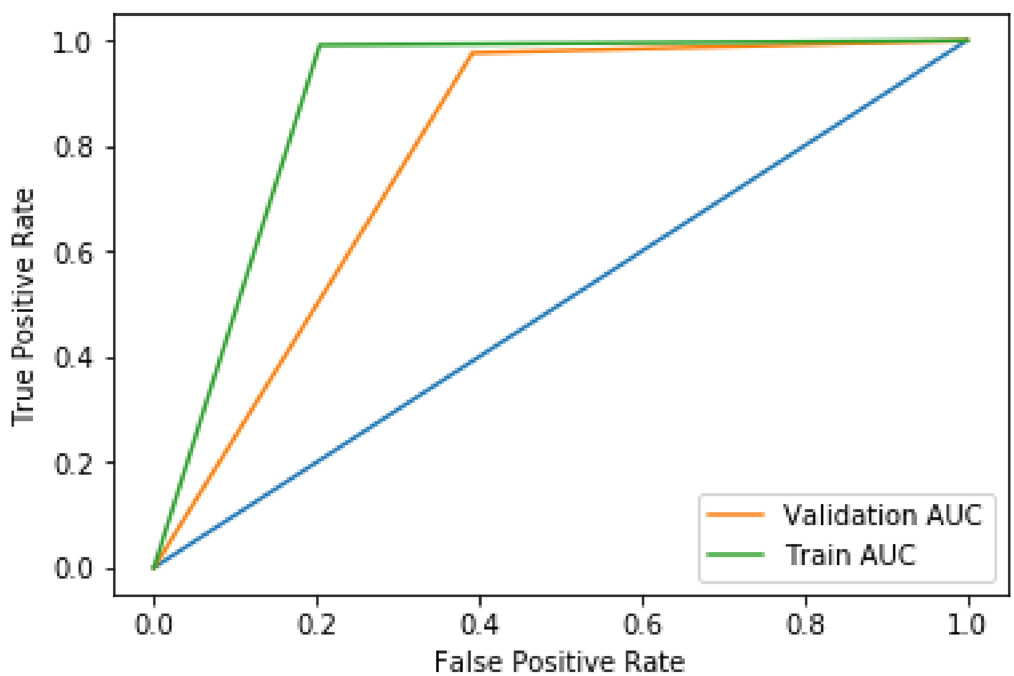



```python
In [125]: # Plotting confusion matrix for test data
          print("Confusion Matrix for train data")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```




```
In [126]: # Plotting ROC AUC curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



```
In [161]: # Selecting the estimator . Estimator is the model that you will use to train your m
          # We will pass this instance to GridSearchCV
          clf = LogisticRegression(penalty='l2',tol=0.1,n_jobs=4,max_iter=400)

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

          # 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)))
```

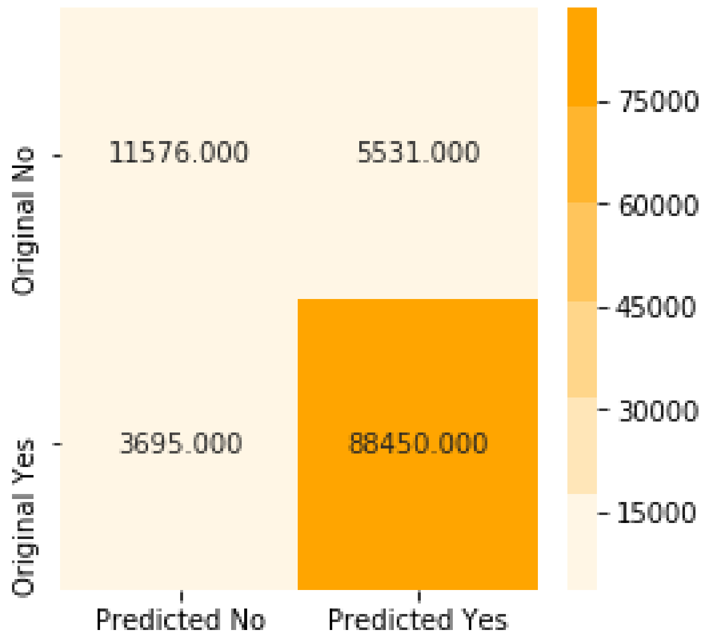
```
AUC is 0.937
```

```
In [162]: # Printing best parameter
          print(grid_model.best_params_)
```

```
{'C': 0.001}
```

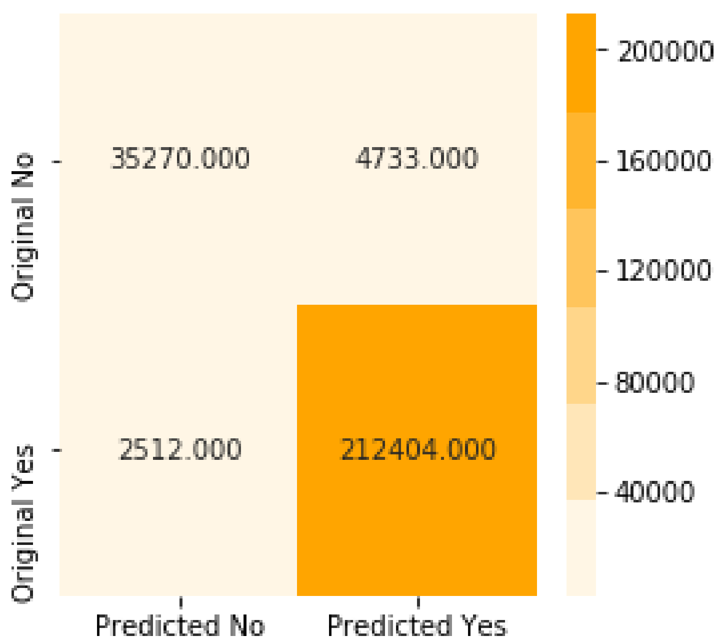
```
In [163]: # Plotting confusion matrix for test data
          print("Confusion Matrix for test data")
          confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

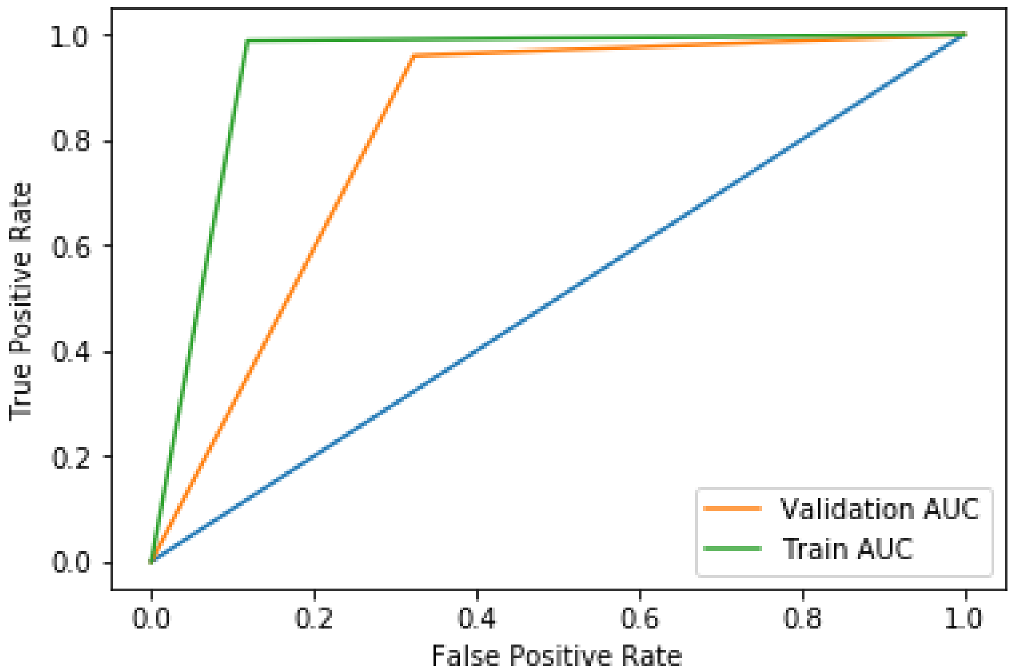



```
In [164]: # Plotting confusion matrix for test data
          print("Confusion Matrix for train data")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```



```
In [165]: # Plotting ROC AUC curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



7.2.3 [5.2.3] Feature Importance on TFIDF, SET 2

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

```
In [166]: #To get most important features first sort the weight vectors in ascending order and
          # Corresponding to that index.

          weight_vect = final_clf.coef_ # Getting weight vectors.

          all_features = tfidf_vect.get_feature_names()  # Getting all the feature names

          top10_pos_feat = weight_vect[0].argsort() #Contains the index of all weights in desc

          # Top 10 features
          top10_pos_words = [all_features[i] for i in top10_pos_feat[-10:]]
          print(top10_pos_words)

['nice', 'favorite', 'excellent', 'loves', 'perfect', 'delicious', 'good', 'love', 'best', 'gr
```

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

```
In [167]: top10_pos_feat = weight_vect[0].argsort() #Contains the index of all weights in desc

          # Top 10 features
          top10_neg_words = [all_features[i] for i in top10_pos_feat[0:10]]
          print(top10_neg_words)
```

```
['not', 'disappointed', 'worst', 'terrible', 'awful', 'disappointing', 'horrible', 'waste', 'u
```

7.3 [5.3] Logistic Regression on AVG W2V, SET 3

7.3.1 [5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

```
In [68]: # Splitting data into train and test dataset

         X = list_of_sentance

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

```
In [69]: # average Word2Vec
         # compute average word2vec for each review of training dataset

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

```
100%|| 254919/254919 [23:51<00:00, 178.12it/s]


254919
50
```

```
In [70]: test_sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(X_test): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             cnt_words =0; # num of words with a valid vector in the sentence/review
```

```
            for word in sent: # for each word in a review/sentence
                if word in w2v_words:
                    vec = w2v_model.wv[word]
                    sent_vec += vec
                    cnt_words += 1
            if cnt_words != 0:
                sent_vec /= cnt_words
            test_sent_vectors.append(sent_vec)
        print(len(test_sent_vectors))
        print(len(test_sent_vectors[0]))
```

```
100%|| 109252/109252 [10:13<00:00, 178.20it/s]


109252
50
```

```
In [71]: # Initializing the logistice regression classifier


         param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
         train_auc_list = [] # Will contain train auc score for various lambda

         # Training and testing on train dataset
         for i in tqdm(param_lambda):
             log_clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
             log_clf.fit(train_sent_vectors,Y_train)

             predict_probab = log_clf.predict_log_proba(train_sent_vectors)[:,1] # Returns log
             predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
             auc = roc_auc_score(Y_train,predict_probab)
             train_auc_list.append(auc)
```

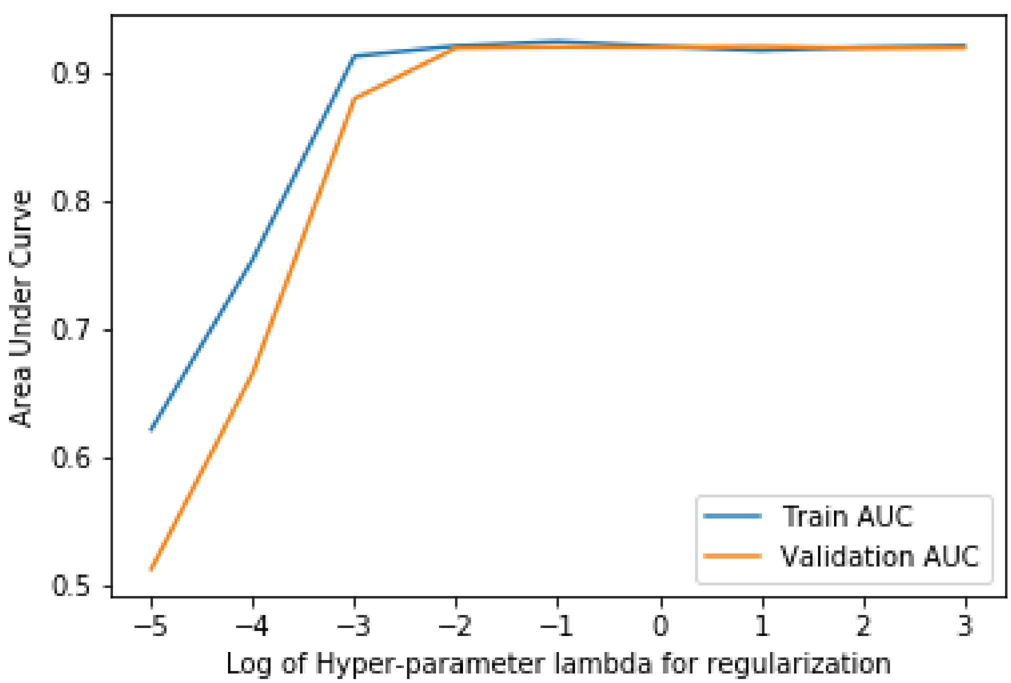
```
100%|| 9/9 [00:18<00:00,  2.10s/it]
```

```
In [72]: # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         # In this section we will perform 5-fold Cross validation on timse series split data

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

         for k in tqdm(param_lambda):
             # Naive bayes classifier
             clf = LogisticRegression(penalty='l1',C=k,tol=0.1,n_jobs=4,max_iter=200)
             i=0
             auc=0.0
```

```
    for train_index,test_index in tscv.split(train_sent_vectors):
        x_train = train_sent_vectors[0:train_index[-1]][:] # row 0 to train_index(exc
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = train_sent_vectors[train_index[-1]:test_index[-1]][:] # row from tra
        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%|| 9/9 [01:08<00:00,  8.03s/it]
```

In [73]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```



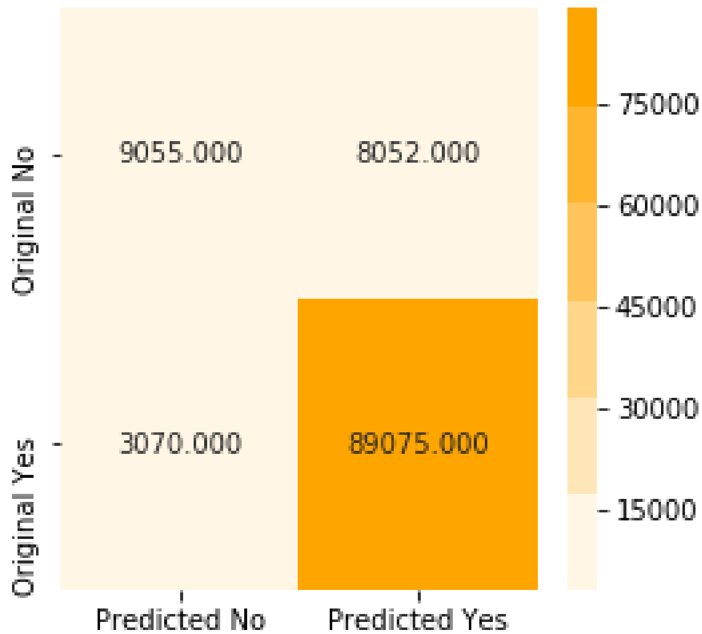
In [77]:
```
# Taking best value of lambda = 1 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l1',C=1,tol=0.1,n_jobs=4,max_iter=1000)
```

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

predict_y = final_clf.predict(test_sent_vectors)
predict_probab = final_clf.predict_log_proba(test_sent_vectors)[:,1] # Returns probab
predict_y_train = final_clf.predict(train_sent_vectors)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for BoW Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for BoW Logistic Regression is 0.920
```

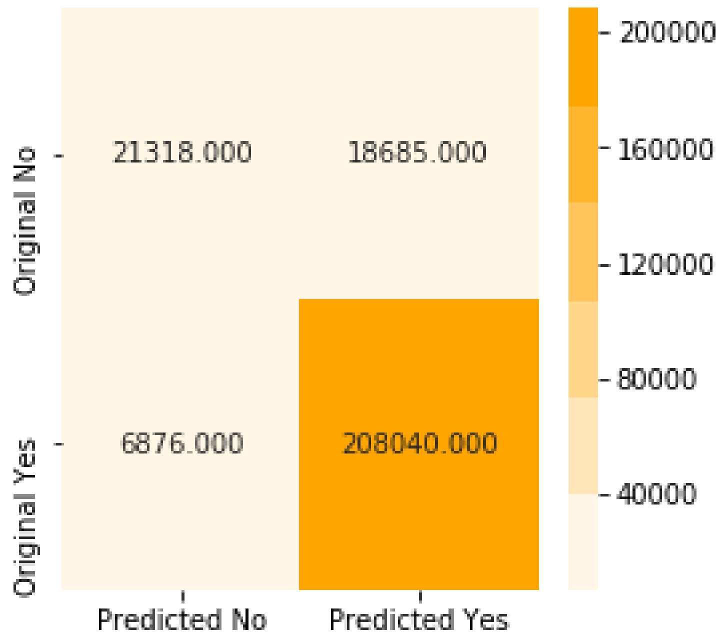
In [78]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

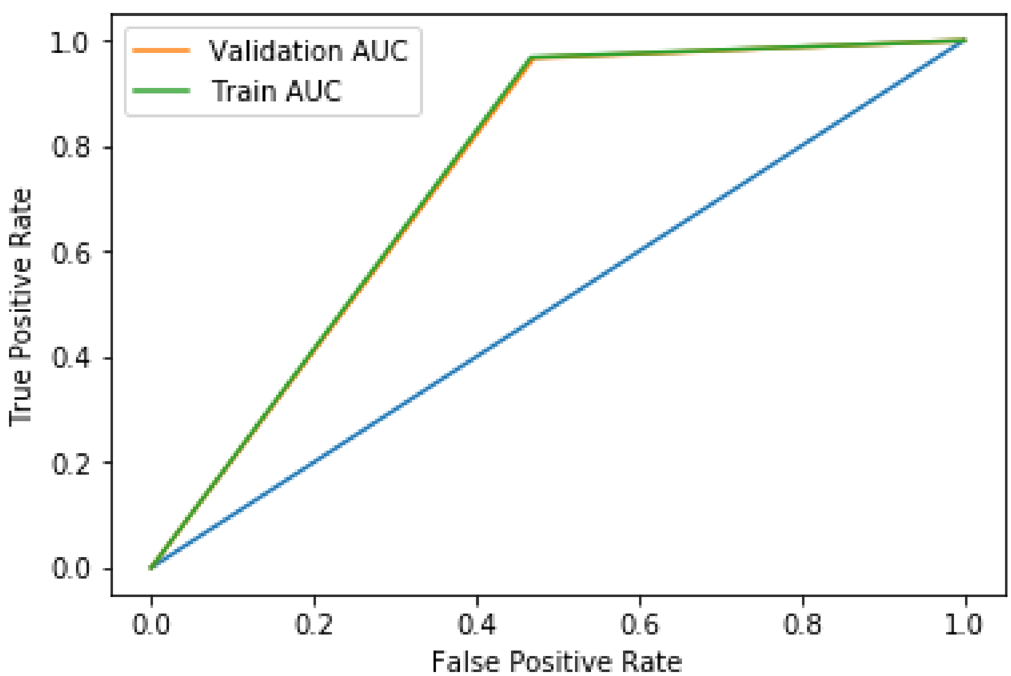


In [79]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```



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



```
In [191]: # Selecting the estimator . Estimator is the model that you will use to train your m
          # We will pass this instance to GridSearchCV
          clf = LogisticRegression(penalty='l1',tol=0.1,n_jobs=4,max_iter=400)

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

          # 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_sent_vectors,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_sent_vectors)[:,1] # returns p
          predict_y = optimized_clf.predict(test_sent_vectors)
          predict_y_train = optimized_clf.predict(train_sent_vectors)

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

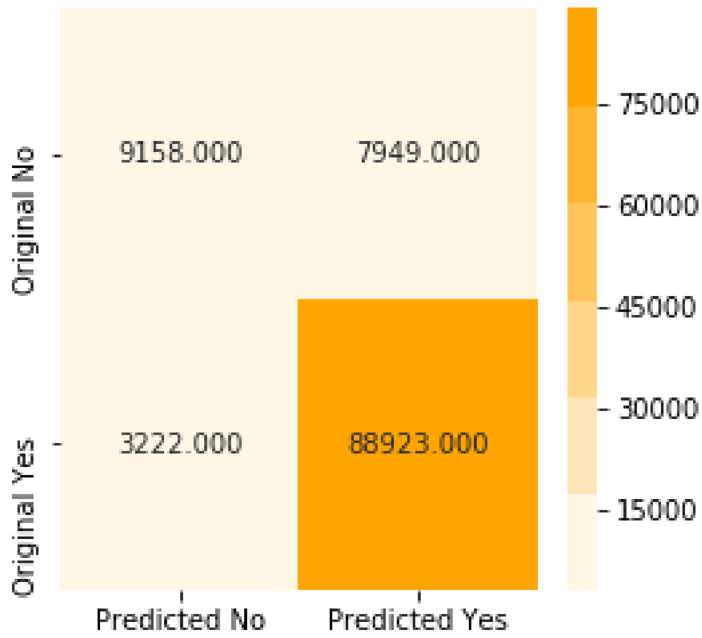
```
AUC is 0.917
```

```
In [192]: # Printing best hyper-parameter
          print(grid_model.best_params_)
```

```
{'C': 100}
```

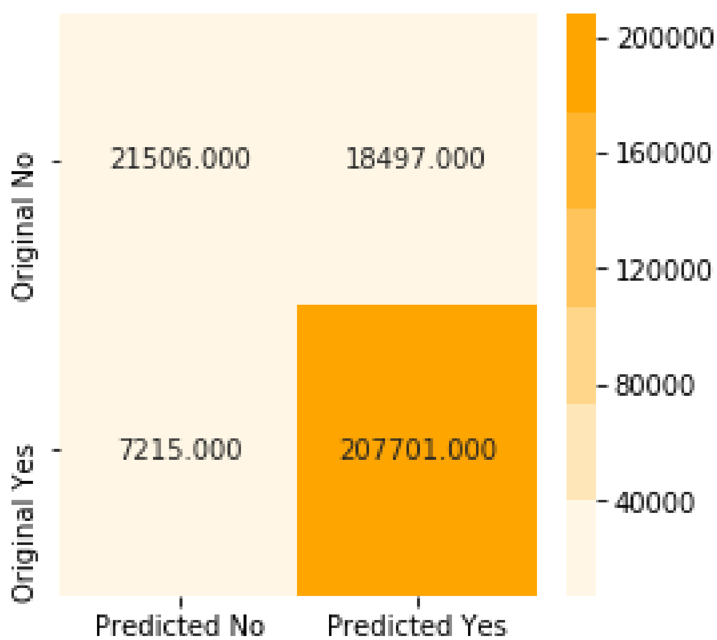
```
In [193]: # Plotting confusion matrix for test data
          print("Confusion Matrix for test data")
          confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

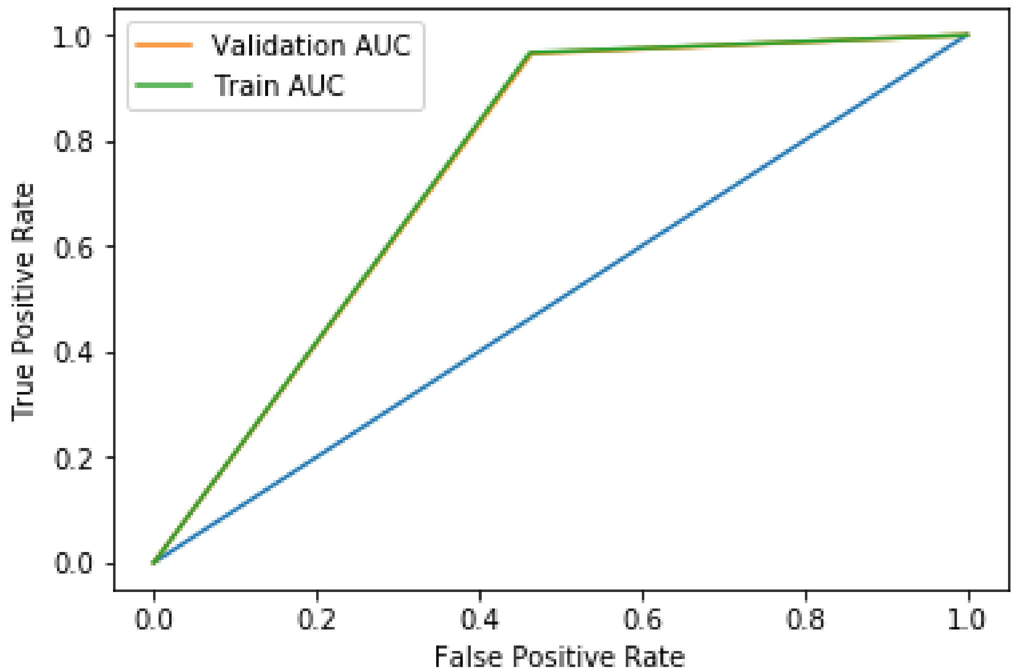



```
In [195]: # Plotting confusion matrix for test data
          print("Confusion Matrix for train data")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```



In [196]: # Plotting ROC AUC curve
```
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



7.3.2 [5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

In [74]: # Initializing the logistice regression classifier

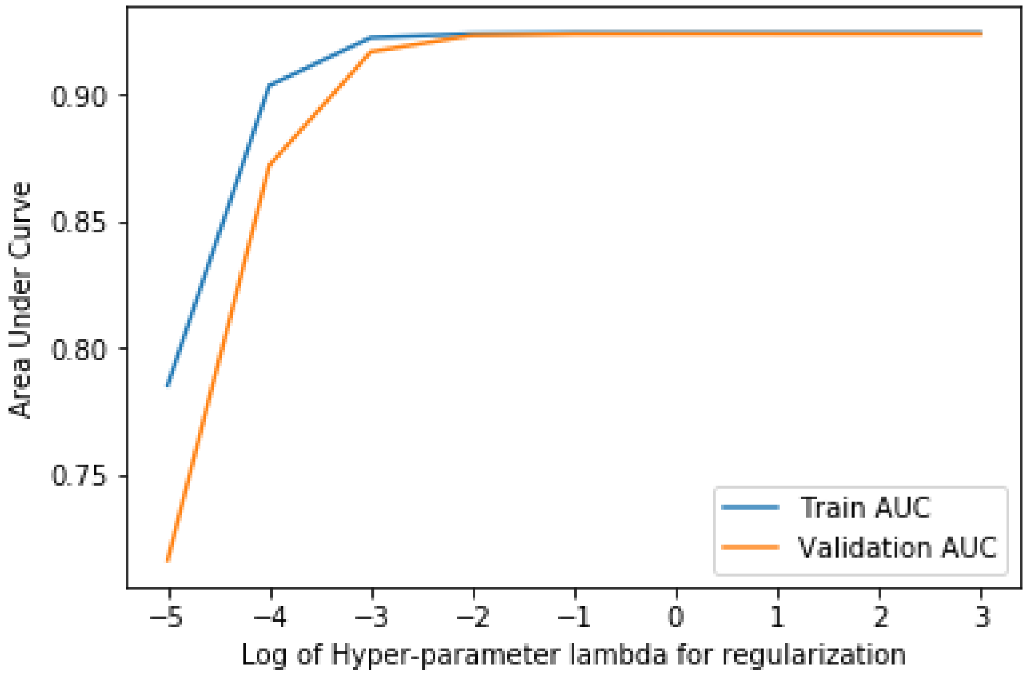
```
param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
train_auc_list = [] # Will contain train auc score for various lambda

# Training and testing on train dataset
for i in tqdm(param_lambda):
    log_clf = LogisticRegression(penalty='l2',C=i,tol=0.1,n_jobs=4,max_iter=200)
    log_clf.fit(train_sent_vectors,Y_train)

    predict_probab = log_clf.predict_log_proba(train_sent_vectors)[:,1] # Returns log
    predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
    auc = roc_auc_score(Y_train,predict_probab)
    train_auc_list.append(auc)
```

```
100%|| 9/9 [00:25<00:00,  3.01s/it]
```

In [75]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

# In this section we will perform 5-fold Cross validation on timse series split data

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

for k in tqdm(param_lambda):
    # Naive bayes classifier
    clf = LogisticRegression(penalty='l2',C=k,tol=0.1,n_jobs=4,max_iter=200)
    i=0
    auc=0.0
    for train_index,test_index in tscv.split(train_sent_vectors):
        x_train = train_sent_vectors[0:train_index[-1]][:] # row 0 to train_index(exc
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = train_sent_vectors[train_index[-1]:test_index[-1]][:] # row from tra
        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%|| 9/9 [01:48<00:00, 13.09s/it]
```

In [76]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

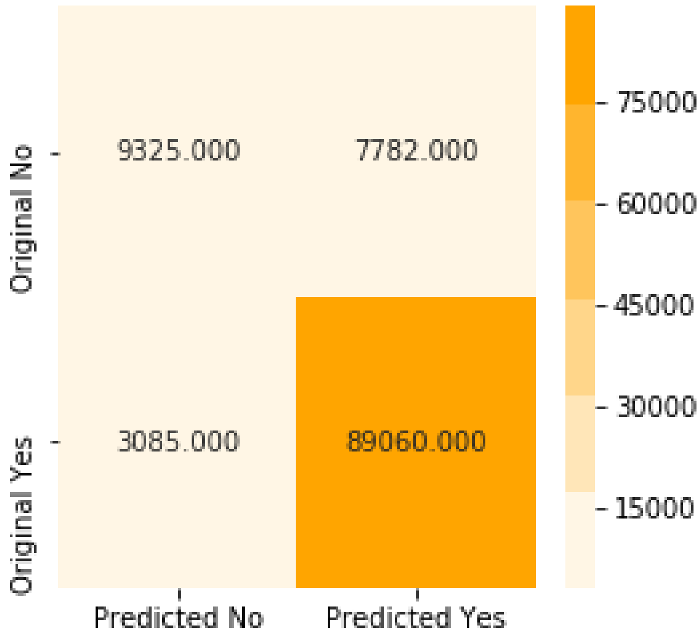



```
In [81]: # Taking best value of lambda = 0.001 an trainig final model
         # Initializing model
         final_clf = LogisticRegression(penalty='l2',C=10,tol=0.1,n_jobs=4,max_iter=1000)

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

         predict_y = final_clf.predict(test_sent_vectors)
         predict_probab = final_clf.predict_log_proba(test_sent_vectors)[:,1] # Returns probab
         predict_y_train = final_clf.predict(train_sent_vectors)
         auc = roc_auc_score(Y_test,predict_probab)
         print("Final AUC for Tfidf Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Logistic Regression is 0.923
```

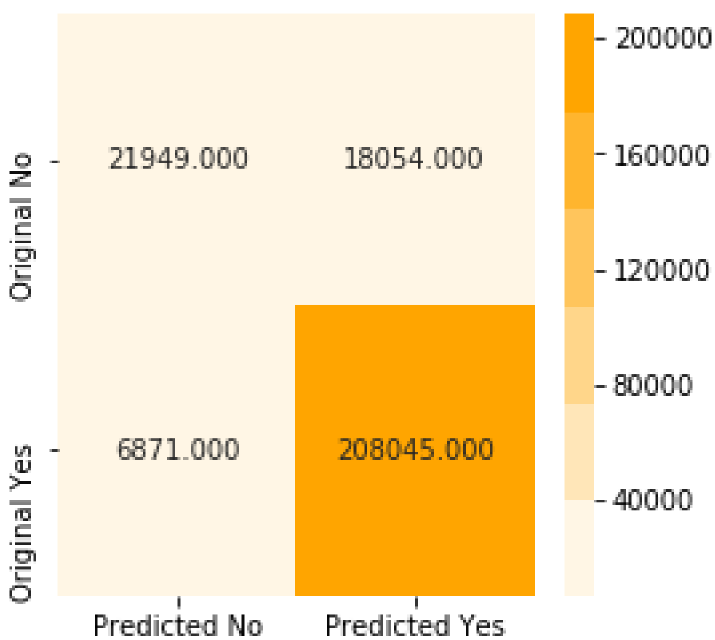
```
In [82]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

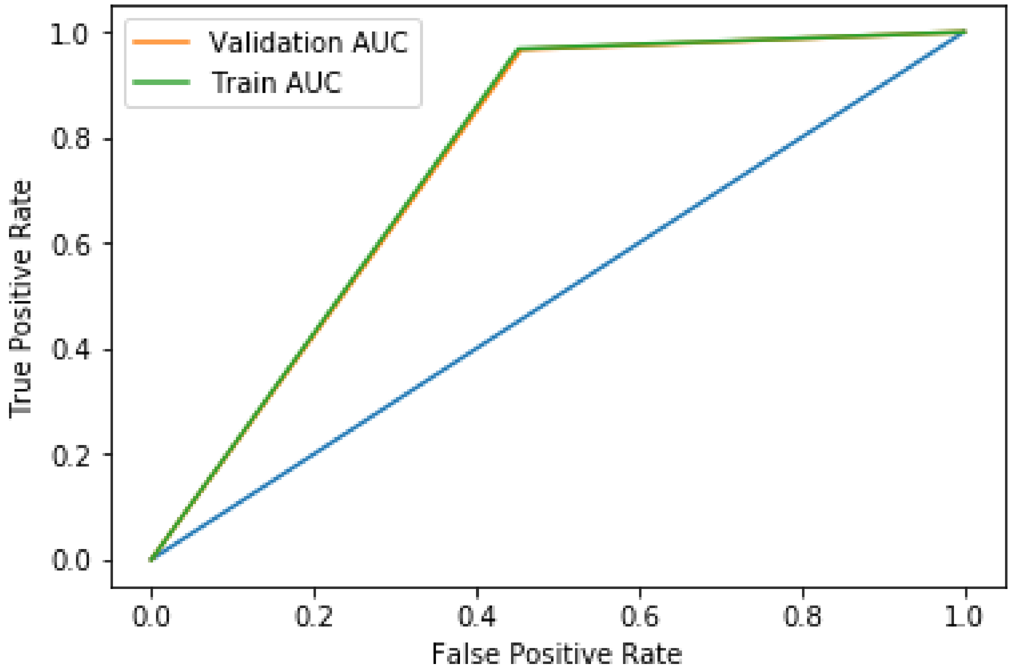



```
In [83]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```



In [84]:
```
# Plotting ROC AUC curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



In [204]:
```
# Selecting the estimator . Estimator is the model that you will use to train your m
# We will pass this instance to GridSearchCV
clf = LogisticRegression(penalty='l2',tol=0.1,n_jobs=4,max_iter=400)

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

# 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_sent_vectors,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_sent_vectors)[:,1] # returns p
predict_y = optimized_clf.predict(test_sent_vectors)
predict_y_train = optimized_clf.predict(train_sent_vectors)

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

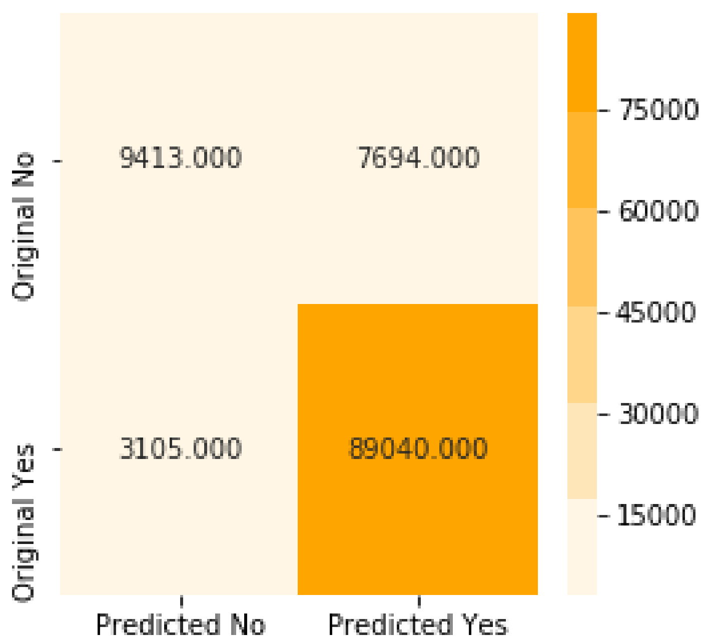
```
AUC is 0.924
```

```
In [205]: # Printing best hyper-parameter
          print(grid_model.best_params_)
```

```
{'C': 10}
```

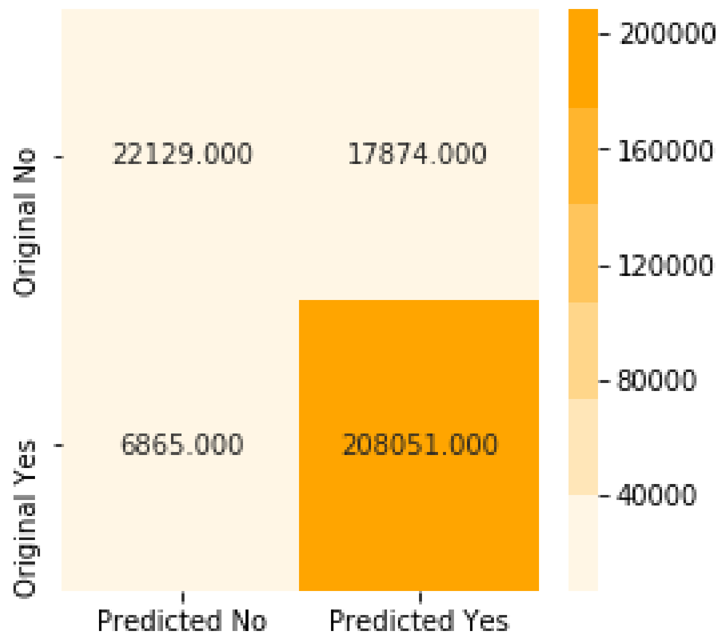
```
In [206]: # Plotting confusion matrix for test data
          print("Confusion Matrix for test data")
          confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

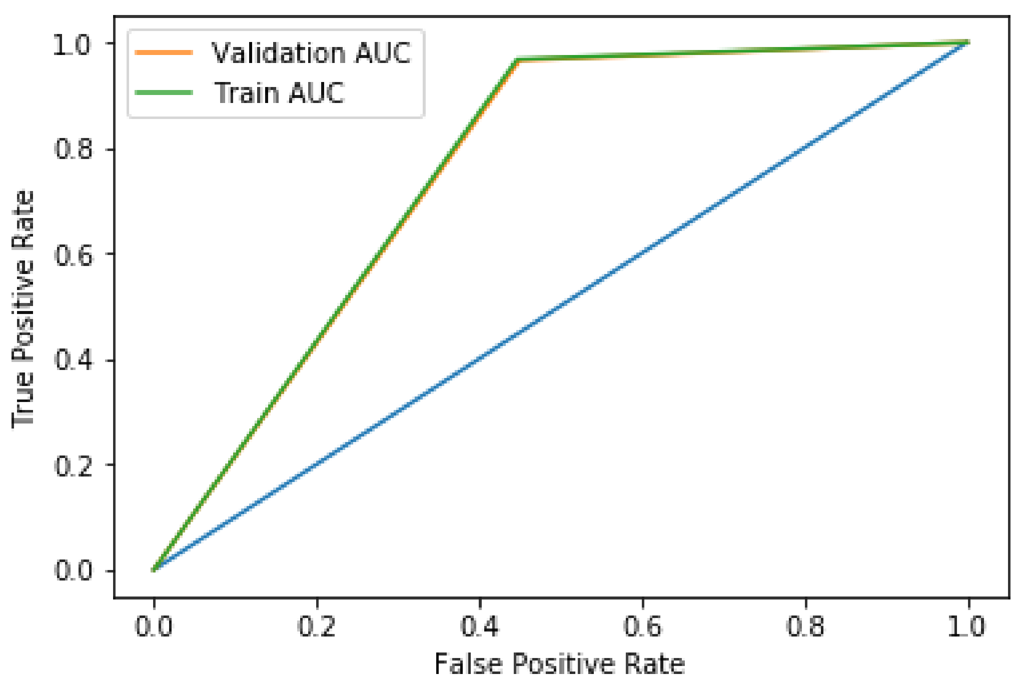



```
In [207]: # Plotting confusion matrix for test data
          print("Confusion Matrix for test data")
          confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```




```
In [208]: # Plotting ROC AUC curve
          plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



7.4 [5.4] Logistic Regression on TFIDF W2V, SET 4

7.4.1 [5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

In [31]:
```
from sklearn.cross_validation import train_test_split
from sklearn.model_selection import TimeSeriesSplit
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
from tqdm import tqdm  # this module is used to check the progress of loops
import numpy as np
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer
```

```
c:\users\rites\appdata\local\programs\python\python36\lib\site-packages\sklearn\cross_validatio
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [32]:
```
# X_train contains sentences for training and X_test contains sentances for testing t
# Calculating TfidfW2V for X_train
Y = final['Score']

X_train,X_test,Y_train,Y_test = train_test_split(preprocessed_reviews,Y,test_size=0.3

# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
train_model = TfidfVectorizer()
train_tfidf_matrix = train_model.fit_transform(X_train)
# we are converting a dictionary with word as a key, and the idf as a value
train_dictionary = dict(zip(train_model.get_feature_names(), list(train_model.idf_)))
```

In [33]:
```
# Calculating TfidfW2V for X_test

# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
test_model = TfidfVectorizer()
test_tfidf_matrix = test_model.fit_transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a value
test_dictionary = dict(zip(test_model.get_feature_names(), list(test_model.idf_)))
```

In [34]:
```
X_train,X_test,Y_train,Y_test = train_test_split(list_of_sentance,Y,test_size=0.3,ranc
```

In [35]:
```
# TF-IDF weighted Word2Vec for X_train
train_tfidf_feat = train_model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

train_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review of X_train is
row=0;
for sent in tqdm(X_train): # 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 train_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 values of word in this review
                tf_idf = train_dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += 1
        if weight_sum != 0:
            sent_vec /= weight_sum
        train_tfidf_sent_vectors.append(sent_vec)
        row += 1
```

```
100%|| 254919/254919 [8:13:32<00:00,  9.69it/s]
```

In [61]:
```
import pickle
outfile = open("train_tfidf_avg_w2v","wb")
pickle.dump(train_tfidf_sent_vectors,outfile)
outfile.close()
```

In [36]:
```
# TF-IDF weighted Word2Vec for X_test
test_tfidf_feat = test_model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

test_tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review of X_train is 
row=0;
for sent in tqdm(X_test): # 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 test_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 = test_dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += 1
    if weight_sum != 0:
        sent_vec /= weight_sum
    test_tfidf_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|| 109252/109252 [2:22:05<00:00, 11.15it/s]
```

```
In [62]: import pickle
         outfile = open("test_tfidf_avg_w2v","wb")
         pickle.dump(test_tfidf_sent_vectors,outfile)
         outfile.close()
```

```
In [37]: param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
         train_auc_list = [] # Will contain train auc score for various lambda

         # Training and testing on train dataset
         for i in tqdm(param_lambda):
             log_clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
             log_clf.fit(train_tfidf_sent_vectors,Y_train)

             predict_probab = log_clf.predict_log_proba(train_tfidf_sent_vectors)[:,1] # Retur
             predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
             auc = roc_auc_score(Y_train,predict_probab)
             train_auc_list.append(auc)
```

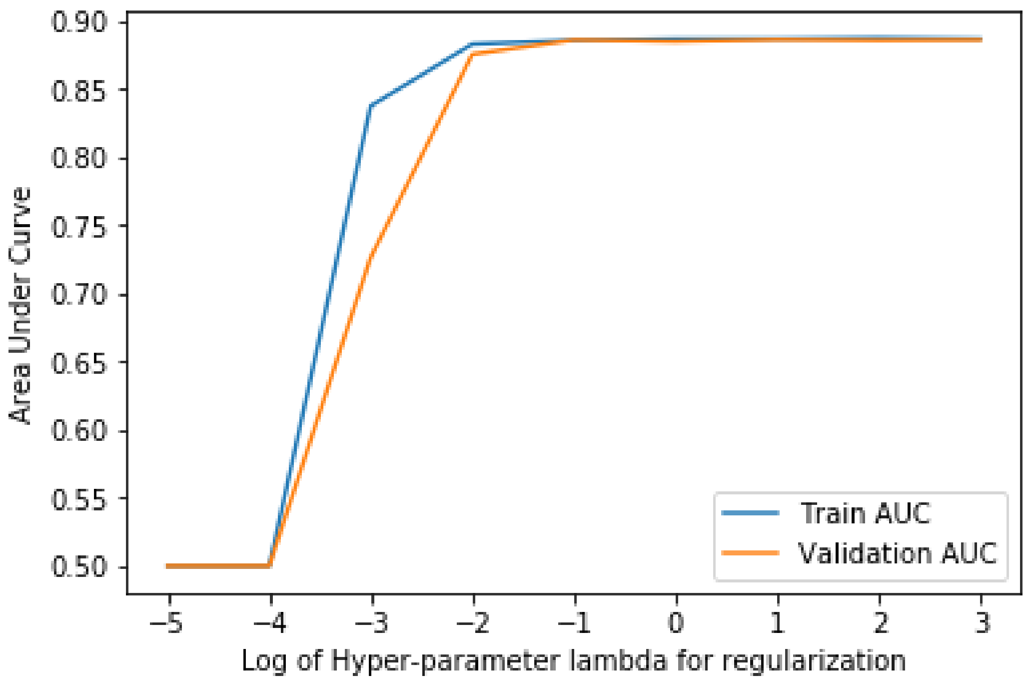
```
100%|| 9/9 [00:18<00:00,  2.15s/it]
```

```
In [41]: # Time series object
         tscv = TimeSeriesSplit(n_splits=10)

         # In this section we will perform 5-fold Cross validation on timse series split data

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

         for k in tqdm(param_lambda):
             # Naive bayes classifier
             clf = LogisticRegression(penalty='l1',C=k,tol=0.1,n_jobs=4,max_iter=200)
             i=0
             auc=0.0
             for train_index,test_index in tscv.split(train_tfidf_sent_vectors):
                 x_train = train_tfidf_sent_vectors[0:train_index[-1]][:] # row 0 to train_ind
                 y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
                 x_test = train_tfidf_sent_vectors[train_index[-1]:test_index[-1]][:] # row fr
                 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%|| 9/9 [01:02<00:00,  7.45s/it]
```

In [42]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

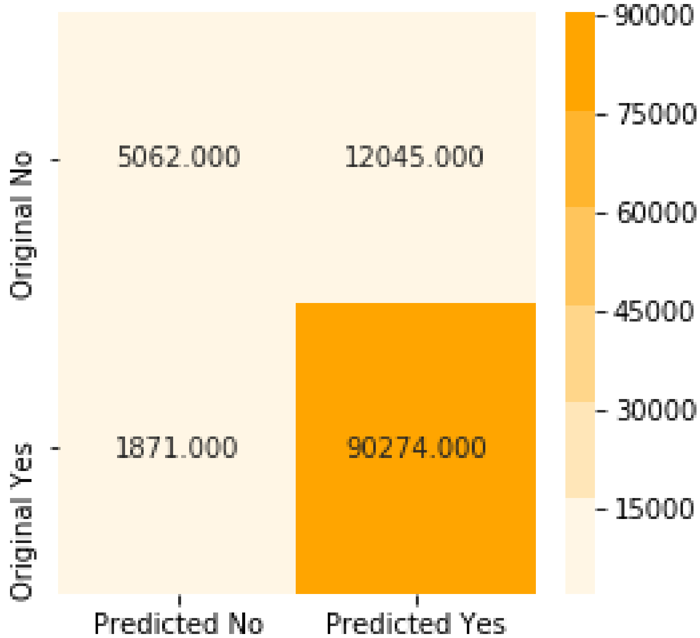


In [44]:
```
# Taking best value of lambda = 1 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l1',C=1,tol=0.1,n_jobs=4,max_iter=1000)

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

predict_y = final_clf.predict(test_tfidf_sent_vectors)
predict_probab = final_clf.predict_log_proba(test_tfidf_sent_vectors)[:,1] # Returns p
predict_y_train = final_clf.predict(train_tfidf_sent_vectors)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for Tfidf Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Logistic Regression is 0.887
```

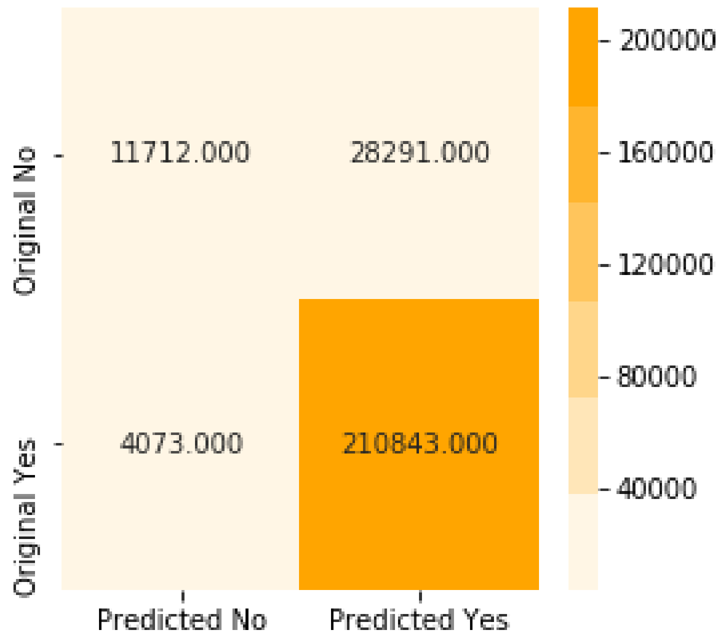
```
In [45]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

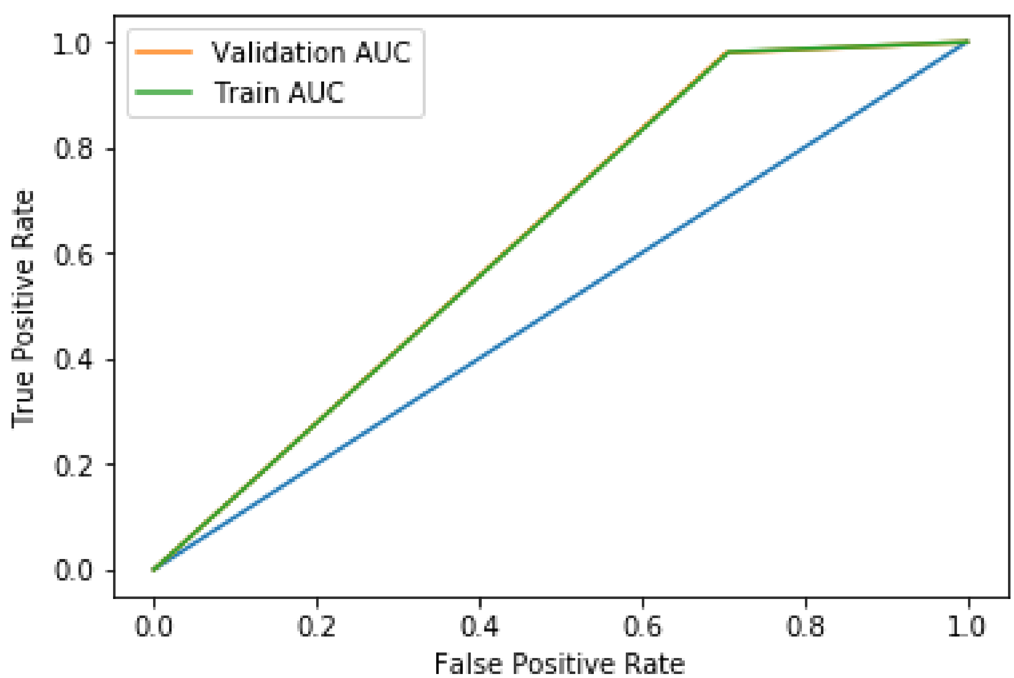



```
In [46]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```




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



Hyper Paramater tuninng using GridSearchcv

In [56]:
```
# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = LogisticRegression(penalty='l1',tol=0.1,n_jobs=4,max_iter=400)

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

# 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_tfidf_sent_vectors,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_tfidf_sent_vectors)[:,1] # retu
predict_y = optimized_clf.predict(test_tfidf_sent_vectors)
predict_y_train = optimized_clf.predict(train_tfidf_sent_vectors)

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

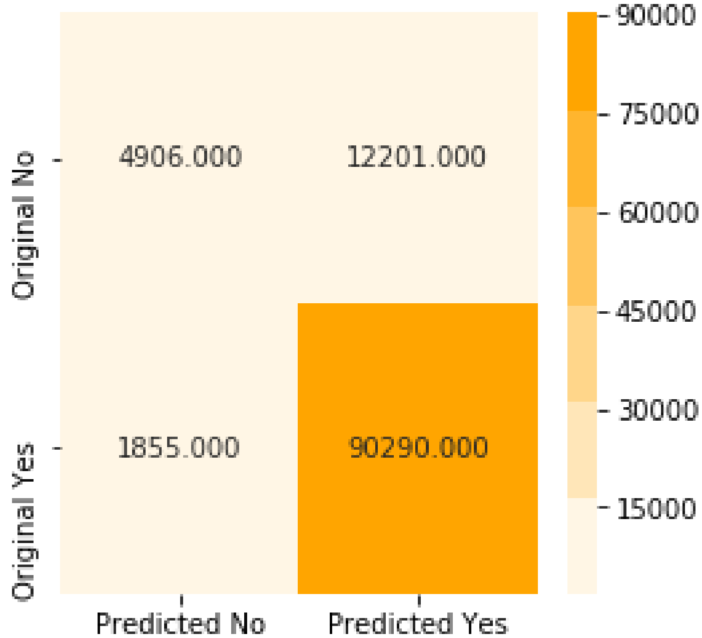
```
AUC is 0.886
```

In [59]:
```
# Printing best parameter
print(grid_model.best_params_)
```

```
{'C': 100}
```

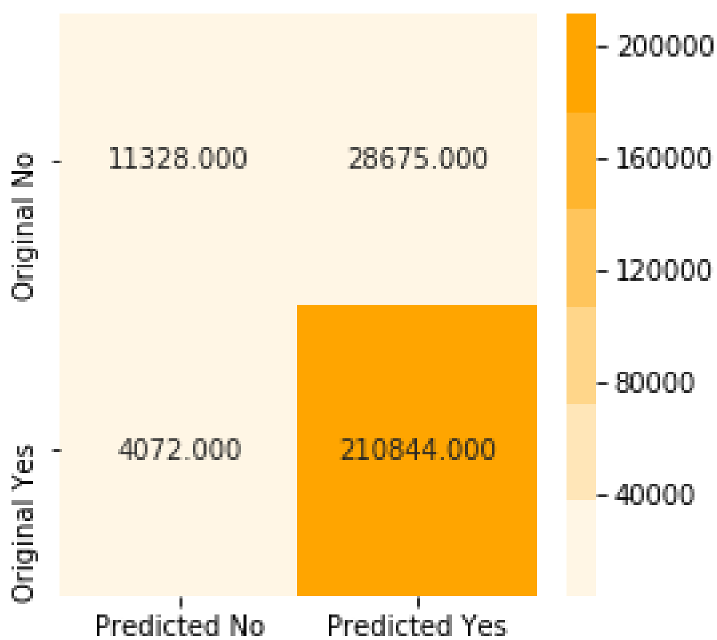
In [57]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

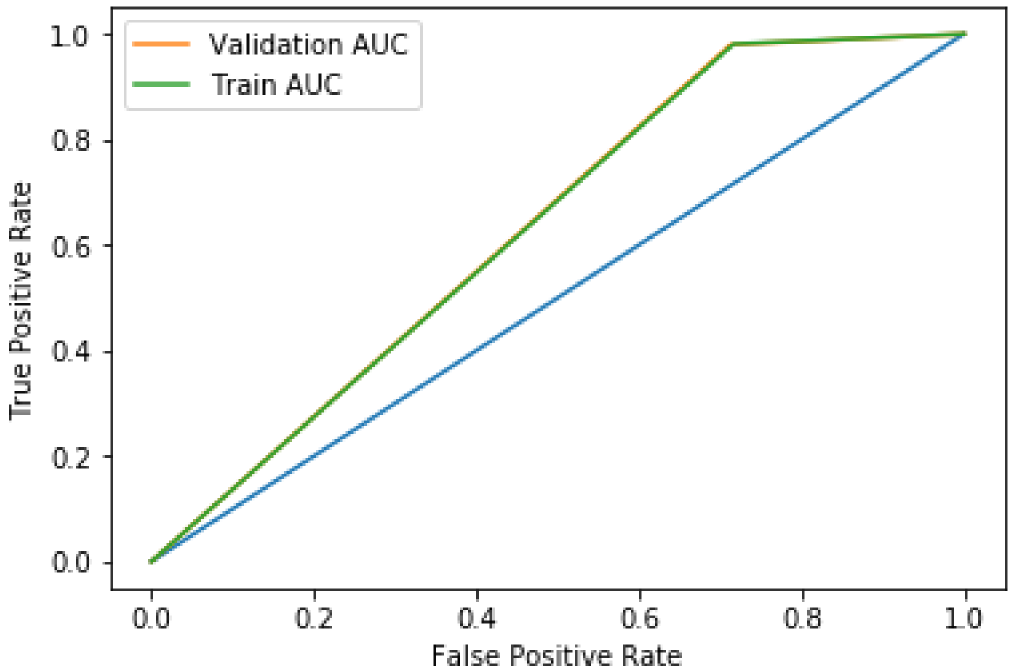



```
In [58]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```



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



7.4.2 [5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

In [48]:
```
param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
train_auc_list = [] # Will contain train auc score for various lambda

# Training and testing on train dataset
for i in tqdm(param_lambda):
    log_clf = LogisticRegression(penalty='l2',C=i,tol=0.1,n_jobs=4,max_iter=200)
    log_clf.fit(train_tfidf_sent_vectors,Y_train)

    predict_probab = log_clf.predict_log_proba(train_tfidf_sent_vectors)[:,1] # Retur
    predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
    auc = roc_auc_score(Y_train,predict_probab)
    train_auc_list.append(auc)
```

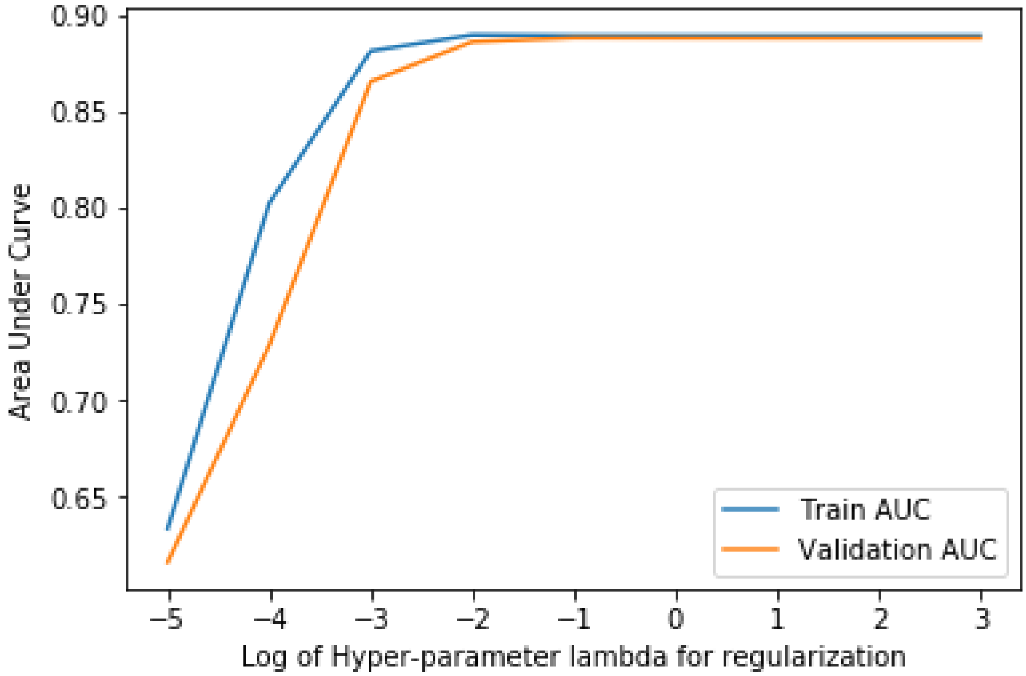
```
100%|| 9/9 [00:20<00:00,  2.36s/it]
```

In [49]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)
```

```
# In this section we will perform 5-fold Cross validation on timse series split data

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

for k in tqdm(param_lambda):
    # Naive bayes classifier
    clf = LogisticRegression(penalty='l2',C=k,tol=0.1,n_jobs=4,max_iter=200)
    i=0
    auc=0.0
    for train_index,test_index in tscv.split(train_tfidf_sent_vectors):
        x_train = train_tfidf_sent_vectors[0:train_index[-1]][:] # row 0 to train_ind
        y_train = Y_train[0:train_index[-1]][:] # row 0 to train_index(excluding)
        x_test = train_tfidf_sent_vectors[train_index[-1]:test_index[-1]][:] # row fr
        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%|| 9/9 [01:28<00:00, 10.45s/it]
```

In [50]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

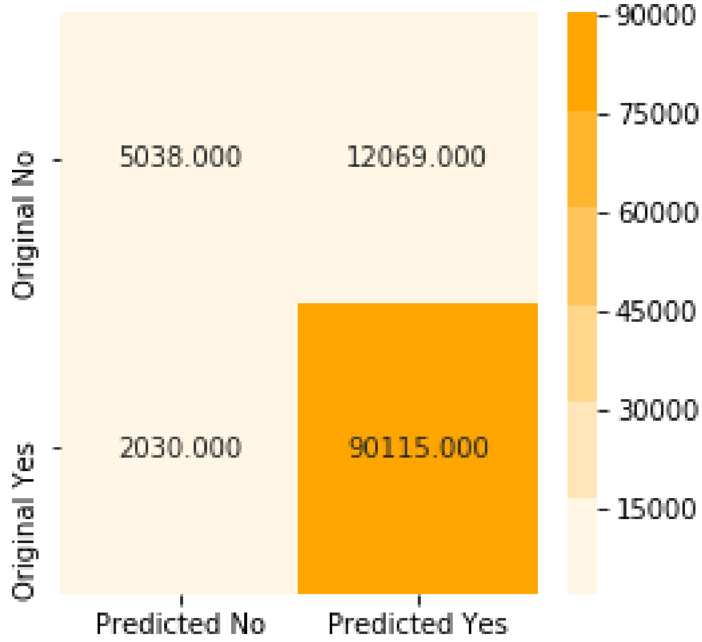


In [51]:
```
# Taking best value of lambda = 1 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l2',C=1,tol=0.1,n_jobs=4,max_iter=1000)

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

predict_y = final_clf.predict(test_tfidf_sent_vectors)
predict_probab = final_clf.predict_log_proba(test_tfidf_sent_vectors)[:,1] # Returns 
predict_y_train = final_clf.predict(train_tfidf_sent_vectors)
auc = roc_auc_score(Y_test,predict_probab)
print("Final AUC for Tfidf Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for Tfidf Logistic Regression is 0.888
```

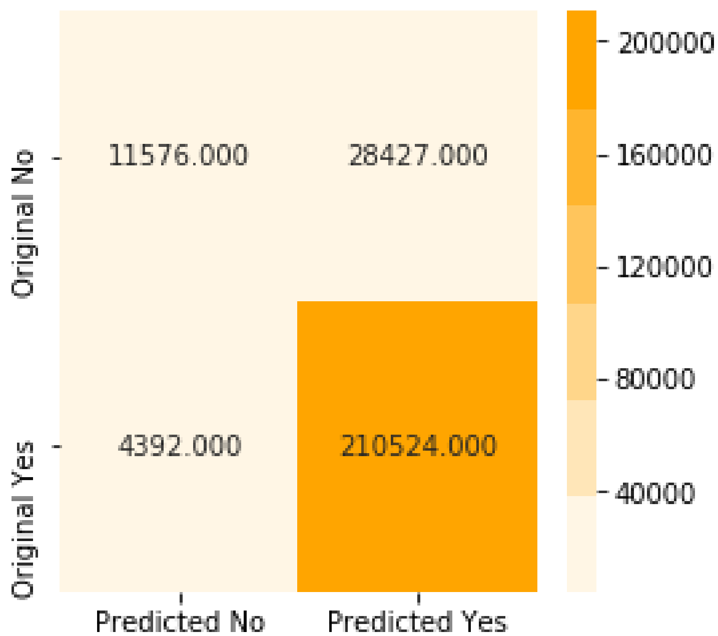
In [52]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

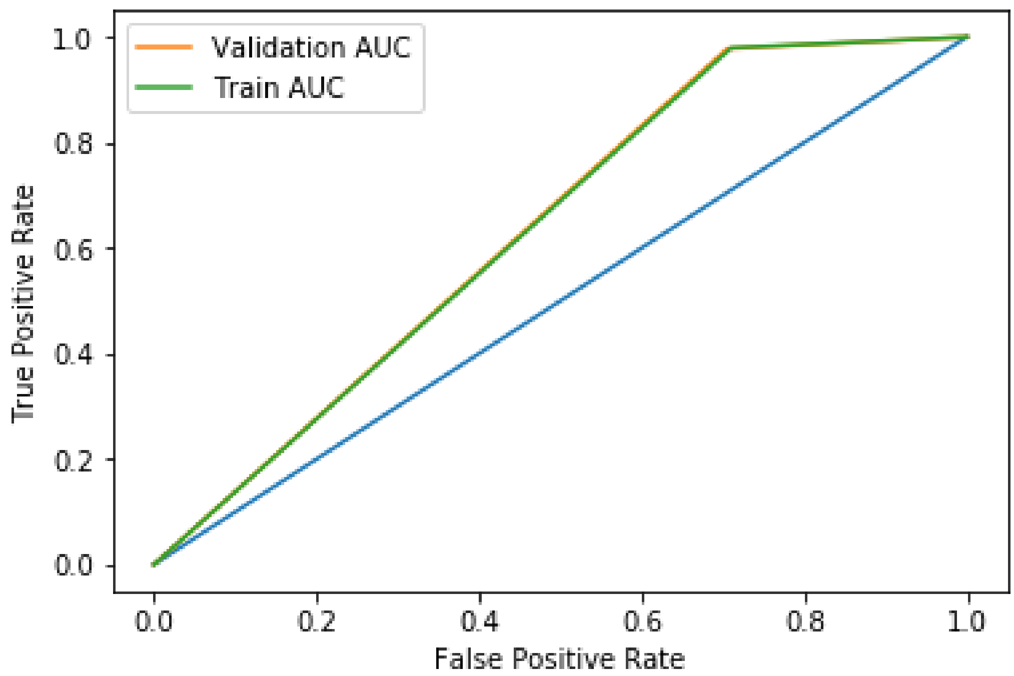



```
In [53]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```



In [54]:
```
# Plotting ROC AUC curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Hyper Parameter tuning using grid search

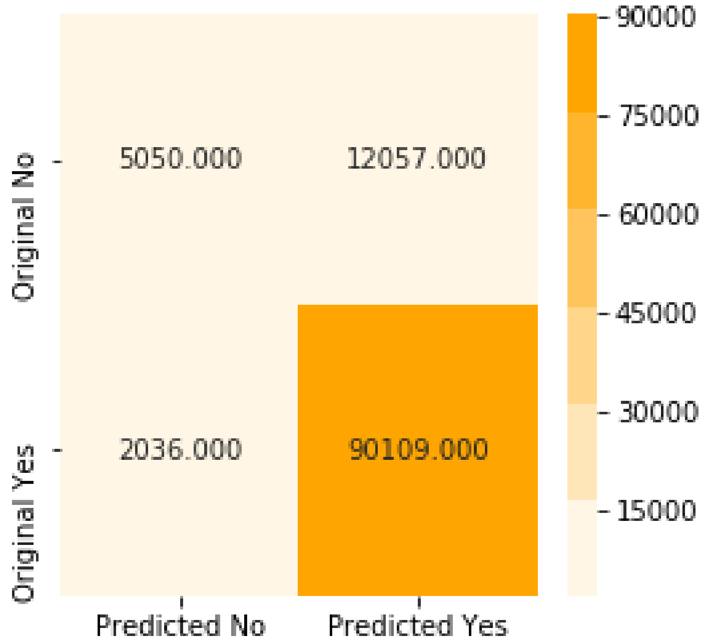
In [63]:
```
# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = LogisticRegression(penalty='l2',tol=0.1,n_jobs=4,max_iter=400)

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

# 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_tfidf_sent_vectors,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_tfidf_sent_vectors)[:,1] # retu
        predict_y = optimized_clf.predict(test_tfidf_sent_vectors)
        predict_y_train = optimized_clf.predict(train_tfidf_sent_vectors)

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

```
AUC is 0.888
```

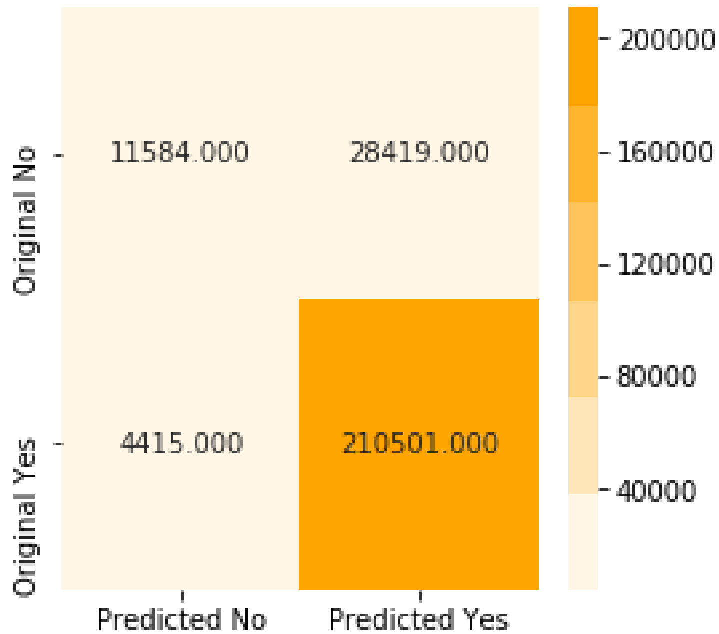
```
In [64]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

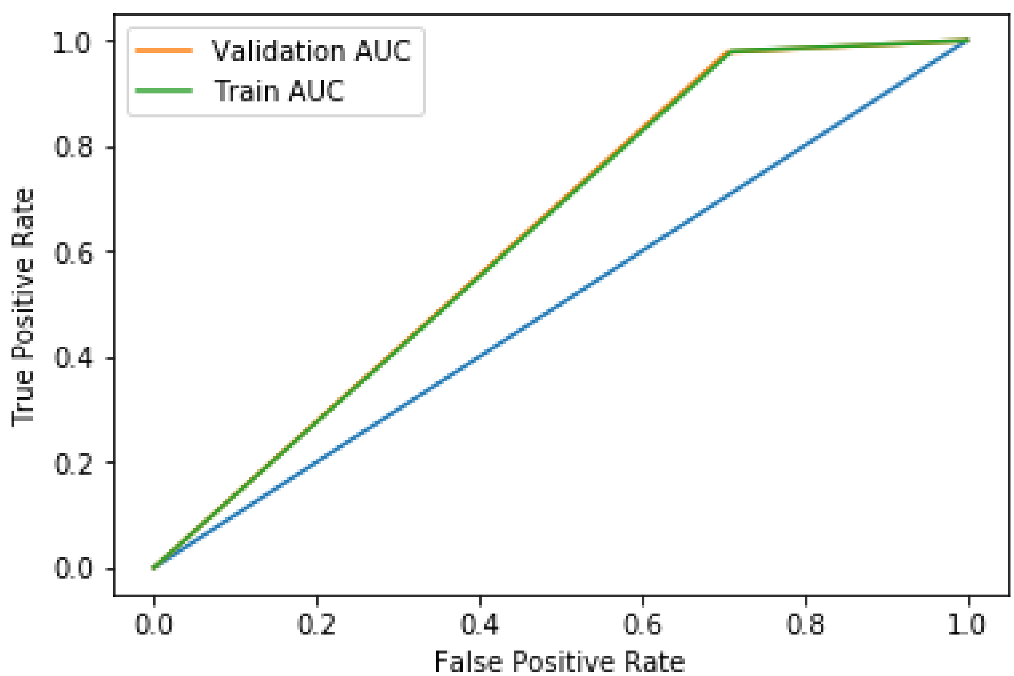



```
In [65]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for test data
Confusion matrix
```



In [66]:
```
# Plotting ROC AUC curve
plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Feature engineering
Using review length as a feature

In [35]:
```
# 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 [36]:
```
# 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,)
```

In [37]:
```
# 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 [38]:
```
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, 96684)
```

In [39]:
```
# 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, 96684)
```

```
In [40]: 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 [41]: # 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 [43]: # Standarizing data
         bow_train_vect = StandardScaler(with_mean=False).fit_transform(bow_train_vect)
         bow_test_vect = StandardScaler(with_mean=False).fit_transform(bow_test_vect)
```

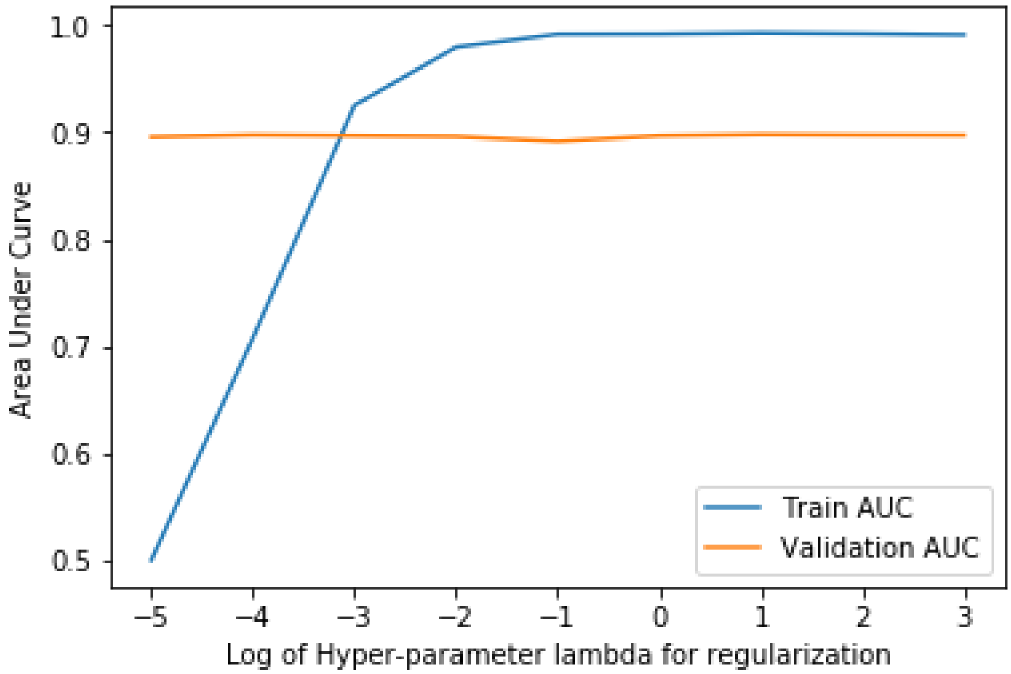
```
In [52]: # In this section we will train naive bayes model and find training error for various
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import roc_auc_score
         from tqdm import tqdm  # this module is used to check the progress of loops
         import numpy as np

         param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
         train_auc_list = [] # Will contain train auc score for various lambda

         # Training and testing on train dataset
         for i in tqdm(param_lambda):
             log_clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
             log_clf.fit(bow_train_vect,Y_train)

             predict_probab = log_clf.predict_log_proba(bow_train_vect)[:,1] # Returns log pro
             predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
             auc = roc_auc_score(Y_train,predict_probab)
             train_auc_list.append(auc)
```

```
100%|| 9/9 [02:47<00:00, 34.23s/it]
```

In [53]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

# In this section we will perform 5-fold Cross validation on timse series split data

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

for k in tqdm(param_lambda):
    # Naive bayes classifier
    clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
    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(excludi
        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_i
        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%|| 9/9 [06:59<00:00, 55.41s/it]
```

In [56]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```

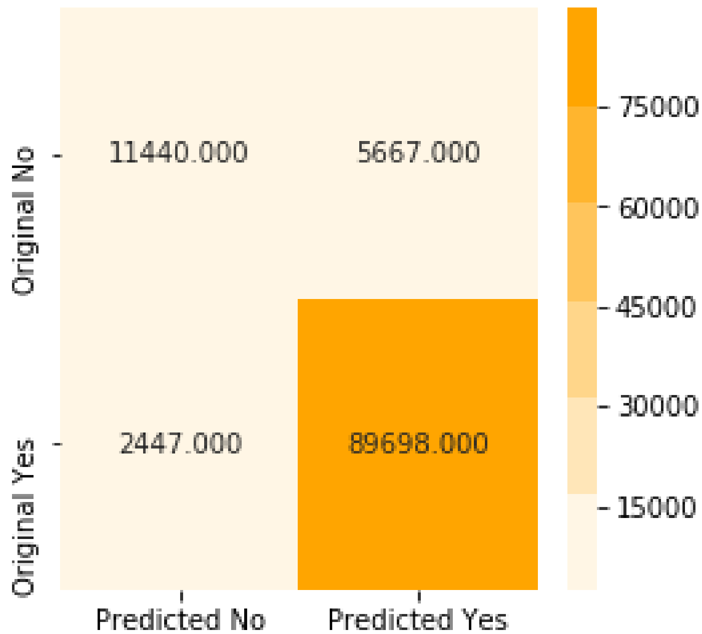



```
In [59]: # Taking best value of lambda = 1 an trainig final model
         # Initializing model
         final_clf = LogisticRegression(penalty='l1',C=0.01,tol=0.1,n_jobs=4,max_iter=1000)

         # 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 Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for BoW Logistic Regression is 0.949
```

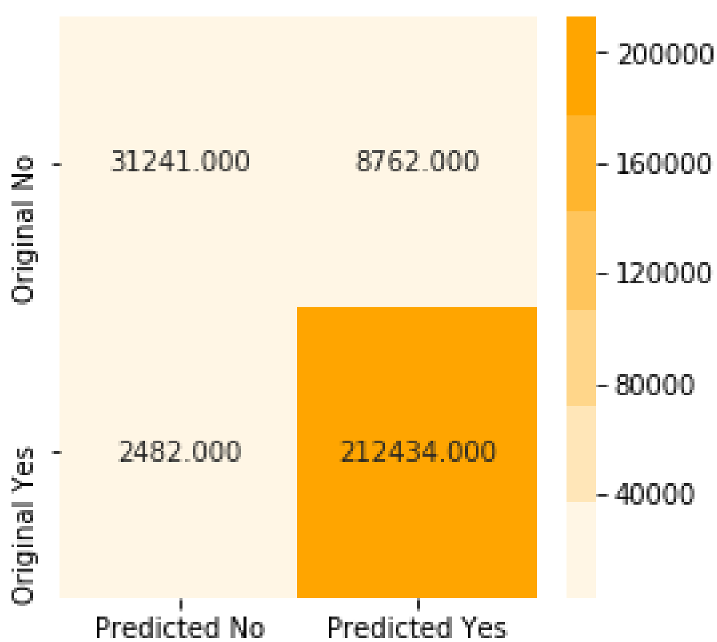
```
In [60]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

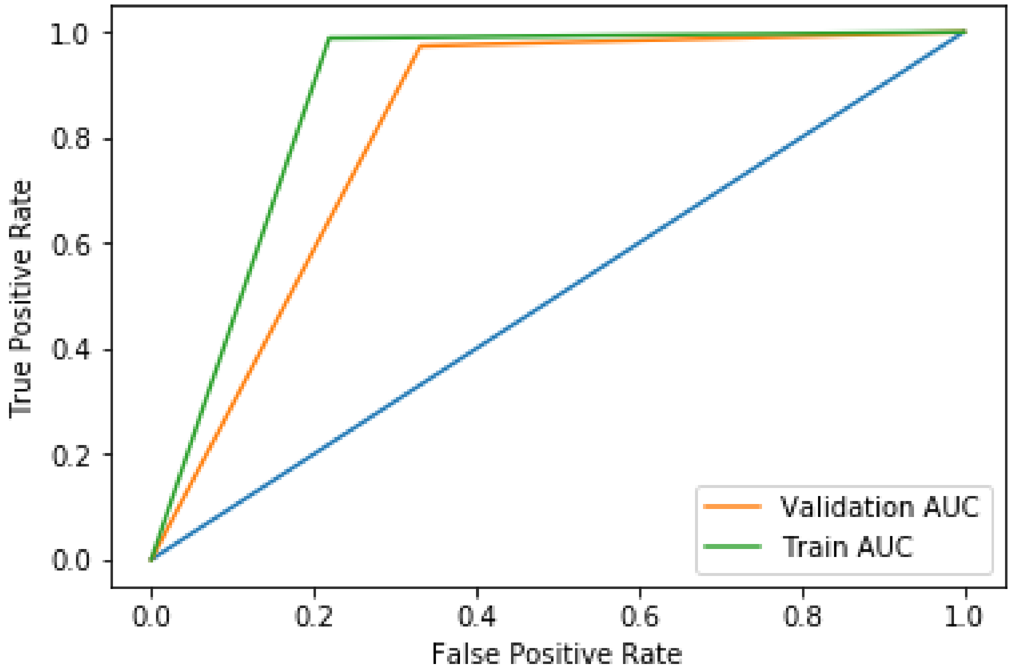



```
In [61]: # Plotting confusion matrix for train data
         print("Confusion Matrix for train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```



```
In [62]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Using grid search CV

```
In [64]: 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 = LogisticRegression(penalty='l1',tol=0.1,n_jobs=4,max_iter=400)

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

         # 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 probab
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)))
```

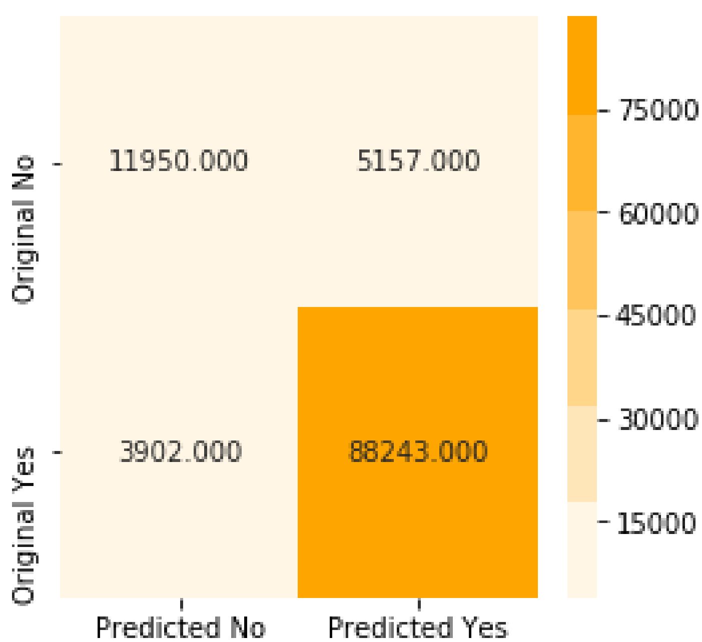
```
AUC is 0.931
```

```
In [65]: # Printing best parameter selected by grid dearch
         print(grid_model.best_params_)
```

```
{'C': 0.1}
```

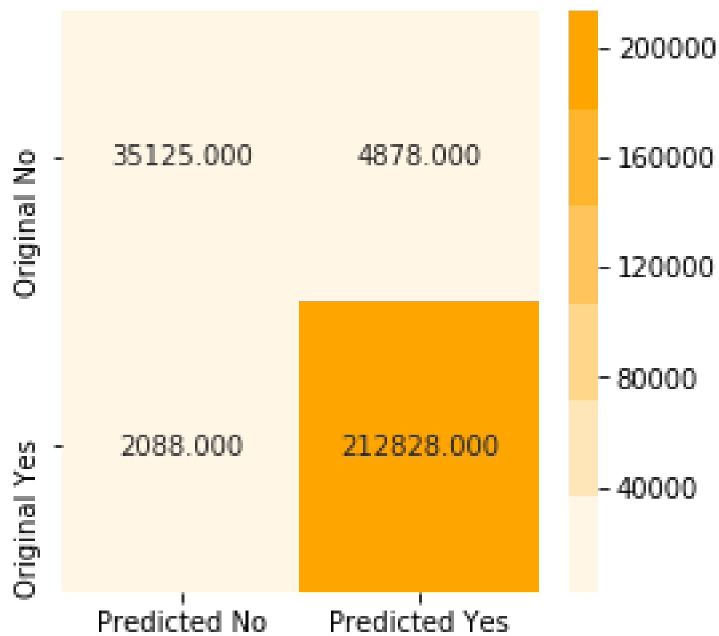
```
In [66]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

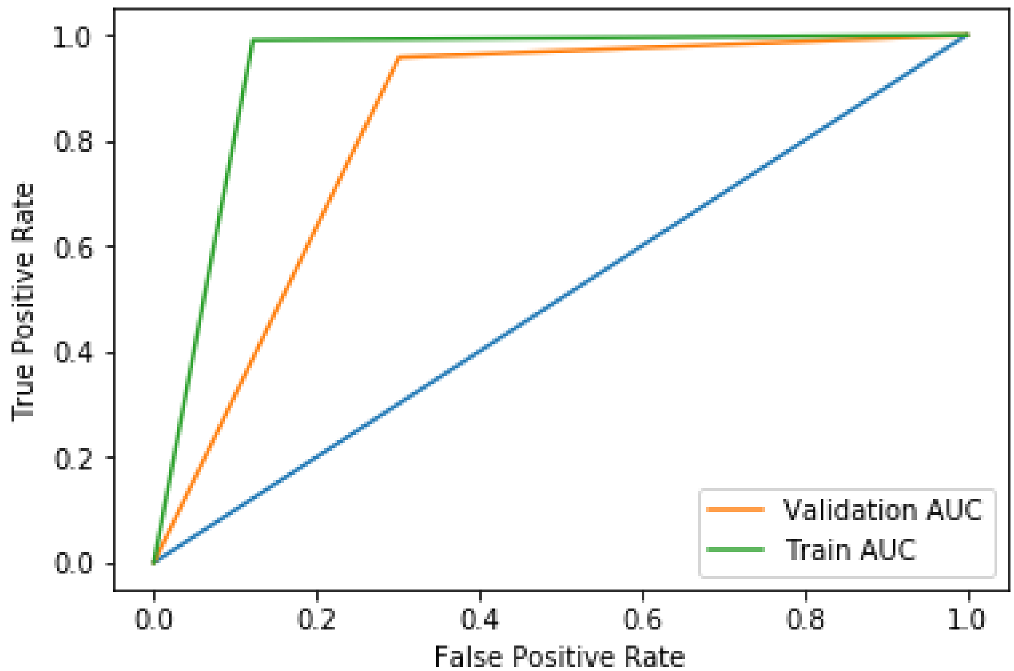


```
In [67]: # Plotting confusion matrix for train data
         print("Confusion Matrix for train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```




```
In [68]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Using Summary as a feature

```
In [69]: # Splitting summary into train and test
         train_summ,test_summ,Y_train_summ,Y_test_summ = train_test_split(preprocessed_summary
```

```
In [70]: # 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 [71]: # 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, 122972)
```

In [72]:
```
# 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, 122972)
```

In [73]:
```
# 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 [74]:
```
# In this section we will train naive bayes model and find training error for various

param_lambda = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000]
train_auc_list = [] # Will contain train auc score for various lambda

# Training and testing on train dataset
for i in tqdm(param_lambda):
    log_clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
    log_clf.fit(bow_train_vect,Y_train)

    predict_probab = log_clf.predict_log_proba(bow_train_vect)[:,1] # Returns log pro
    predict_probab = np.nan_to_num(predict_probab,copy=True)  # Tackles NaN and Infin
    auc = roc_auc_score(Y_train,predict_probab)
    train_auc_list.append(auc)
```

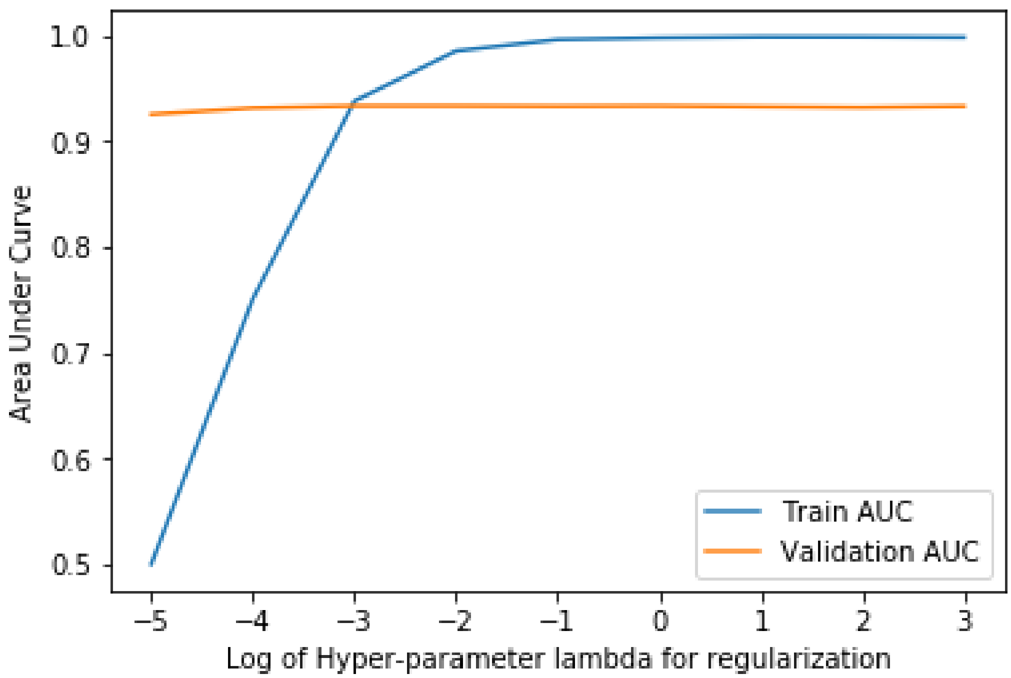
```
100%|| 9/9 [06:13<00:00, 67.61s/it]
```

In [75]:
```
# Time series object
tscv = TimeSeriesSplit(n_splits=10)

# In this section we will perform 5-fold Cross validation on timse series split data

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

for k in tqdm(param_lambda):
    # Naive bayes classifier
    clf = LogisticRegression(penalty='l1',C=i,tol=0.1,n_jobs=4,max_iter=200)
    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(excludi
            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_i
            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%|| 9/9 [17:37<00:00, 111.77s/it]
```

In [76]:
```
# Plotting graph of auc and parameter for training and cross validation error
plot_train_vs_auc(train_auc_list,cv_auc_list)
```



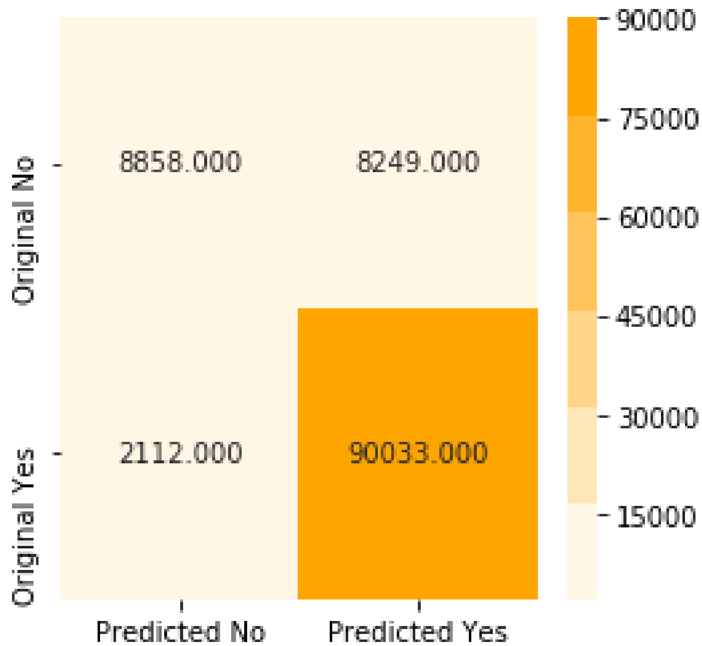
In [79]:
```
# Taking best value of lambda = 0.01 an trainig final model
# Initializing model
final_clf = LogisticRegression(penalty='l1',C=0.1,tol=0.1,n_jobs=4,max_iter=1000)
```

```
# 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 Logistic Regression is {:.3f}".format(auc))
```

```
Final AUC for BoW Logistic Regression is 0.928
```

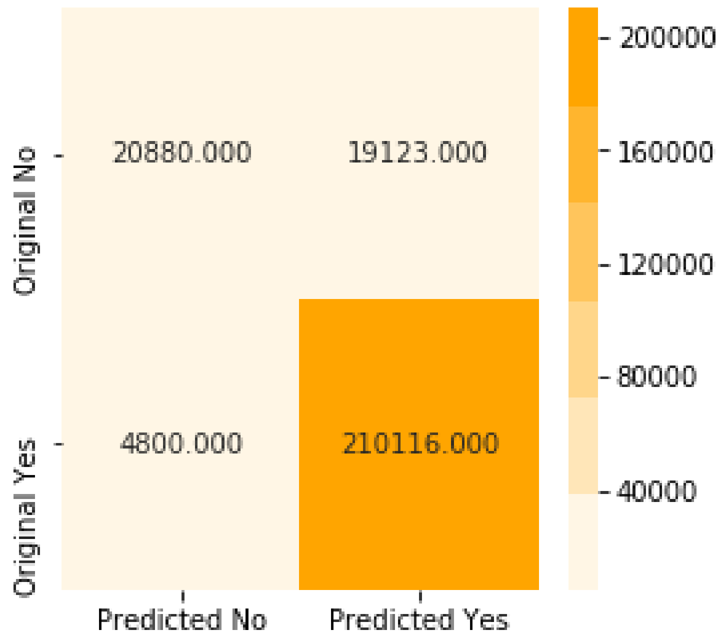
```
In [80]: # Plotting confusion matrix for test data
         print("Confusion Matrix for test data")
         confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

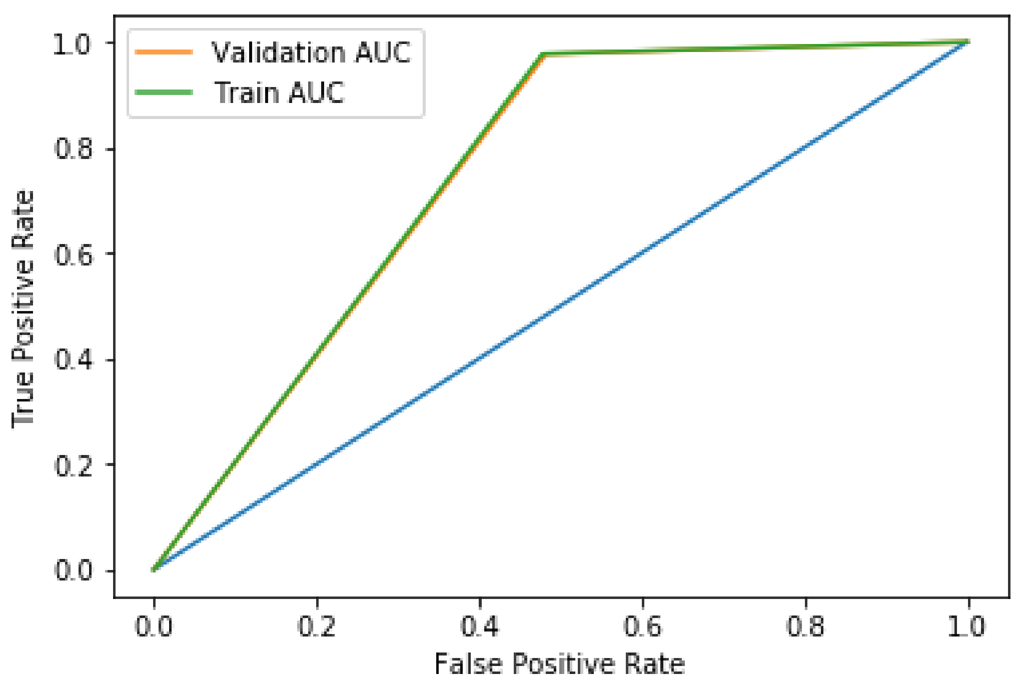



```
In [81]: # Plotting confusion matrix for train data
         print("Confusion Matrix for train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```




```
In [82]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



Using Grid Search

In [87]:
```
# Selecting the estimator . Estimator is the model that you will use to train your mo
# We will pass this instance to GridSearchCV
clf = LogisticRegression(penalty='l1',tol=0.1,n_jobs=4,max_iter=400)

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

# 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 probab
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)))
```

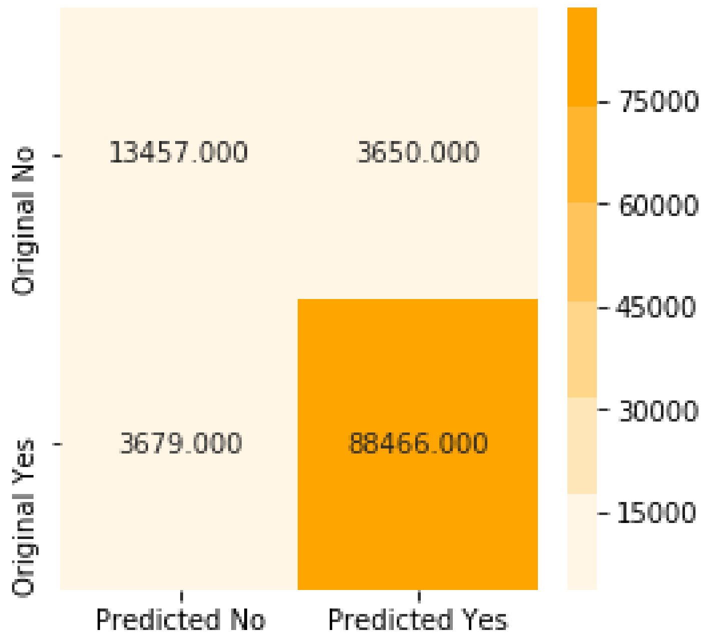
```
AUC is 0.953
```

In [88]:
```
# Printing best parameter selected by grid dearch
print(grid_model.best_params_)
```

```
{'C': 10}
```

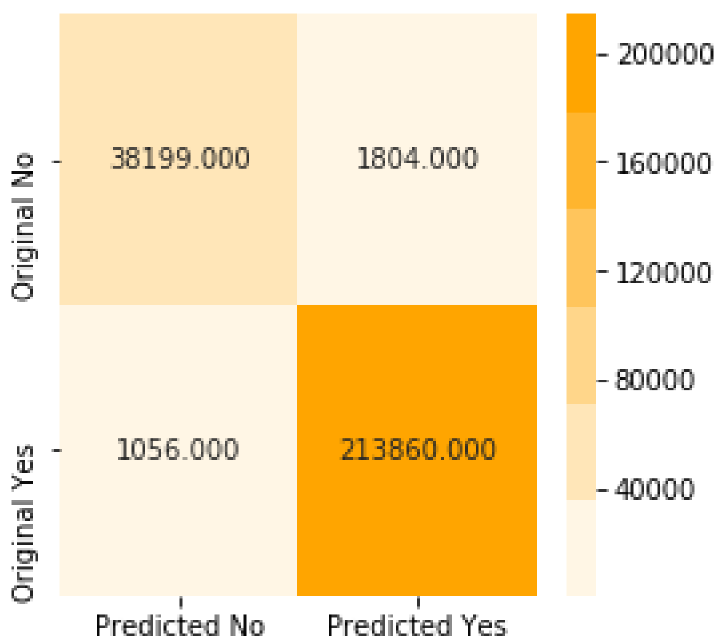
In [89]:
```
# Plotting confusion matrix for test data
print("Confusion Matrix for test data")
confusion_matrix_plot(Y_test,predict_y)
```

```
Confusion Matrix for test data
Confusion matrix
```

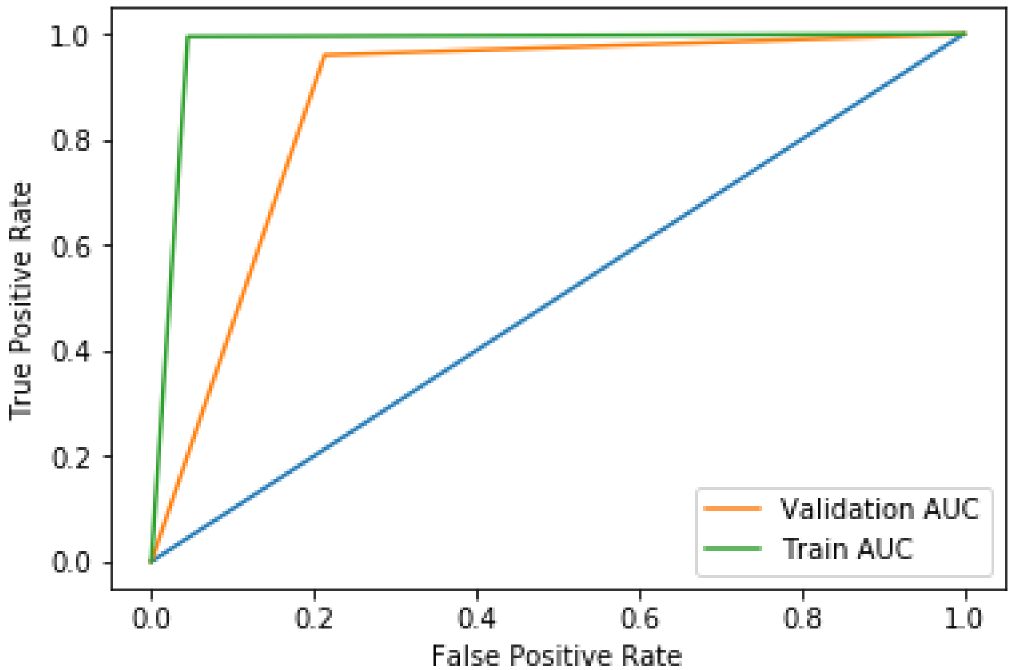



```
In [90]: # Plotting confusion matrix for train data
         print("Confusion Matrix for train data")
         confusion_matrix_plot(Y_train,predict_y_train)
```

```
Confusion Matrix for train data
Confusion matrix
```



```
In [91]: # Plotting ROC AUC curve
         plot_roc_curve(Y_test,predict_y,Y_train,predict_y_train)
```



8 [6] Conclusions

```
In [93]: from prettytable import PrettyTable

         # Initializing table object
         x = PrettyTable()

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

         x.add_row([ "Bow","Logistic Regression L1 regularized","0.1","0.934" ])
         x.add_row([ "Bow","Logistic Regression L2 regularized","0.001","0.931" ])
         x.add_row([ "Tfidf","Logistic Regression L1 regularized","0.01","0.957" ])
         x.add_row([ "Tfidf","Logistic Regression L2 regularized","0.001","0.937" ])
         x.add_row([ "AvgW2V","Logistic Regression L1 regularized","100","0.917" ])
         x.add_row([ "AvgW2V","Logistic Regression L2 regularized","10","0.924" ])
         x.add_row([ "Tfidf weighted W2V","Logistic Regression L1 regularized","1.0","0.887" ]
         x.add_row([ "Tfidf weighted W2V","Logistic Regression L2 regularized","1.0","0.888" ]
         x.add_row([ "Bow with review length ","Logistic Regression L1 regularized","0.1","0.9
```

```
x.add_row([ "Bow with summary feature","Logistic Regression L1 regularized","10","0.95

print(x)
```

```
+--------------------------+-------------------------------------+-----------------------+-----
|        Vectorizer        |                Model                | Hyper-Parameter alpha | Area
+--------------------------+-------------------------------------+-----------------------+-----
|           Bow            | Logistic Regression L1 regularized |          0.1          |
|           Bow            | Logistic Regression L2 regularized |         0.001         |
|          Tfidf           | Logistic Regression L1 regularized |          0.01         |
|          Tfidf           | Logistic Regression L2 regularized |         0.001         |
|          AvgW2V          | Logistic Regression L1 regularized |          100          |
|          AvgW2V          | Logistic Regression L2 regularized |           10          |
|    Tfidf weighted W2V    | Logistic Regression L1 regularized |          1.0          |
|    Tfidf weighted W2V    | Logistic Regression L2 regularized |          1.0          |
| Bow with review length   | Logistic Regression L1 regularized |          0.1          |
| Bow with summary feature | Logistic Regression L1 regularized |           10          |
+--------------------------+-------------------------------------+-----------------------+-----
```

Explaination of results

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 weight vectors using argsort in ascending order.

To print top 10 positive features we selected features corresponding to last 10 indexes from sorted index from above step.

To print top 10 negative features 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 review features.

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 along with having highest AUC of 0.953