05 Amazon Fine Food Reviews Analysis_Logistic Regression

February 26, 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 [88]:
```
%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
import sys

from sklearn.model_selection import train_test_split
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
```

In [89]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')
```

```python
# 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 poin
# 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 
# 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 negati
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[89]:

```
   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 [90]:

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

```
In [91]: print(display.shape)
         display.head()
```

```
(80668, 7)
```

```
Out[91]:                UserId   ProductId             ProfileName        Time  Score  \
         0  #oc-R115TNMSPFT9I7  B005ZBZLT4                 Breyton  1331510400      2
         1  #oc-R11D9D7SHXIJB9  B005HG9ESG  Louis E. Emory "hoppy"  1342396800      5
         2  #oc-R11DNU2NBKQ23Z  B005ZBZLT4        Kim Cieszykowski  1348531200      1
         3  #oc-R1105J5ZVQE25C  B005HG9ESG            Penguin Chick  1346889600      5
         4  #oc-R12KPBODL2B5ZD  B007OSBEV0   Christopher P. Presta  1348617600      1

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

```
In [92]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[92]:               UserId   ProductId                    ProfileName        Time  \
         80638  AZY10LLTJ71NX  B001ATMQK2  undertheshrine "undertheshrine"  1296691200

                Score                                               Text  COUNT(*)
         80638      5  I bought this 6 pack because for the price tha...         5
```

```
In [93]: display['COUNT(*)'].sum()
```

```
Out[93]: 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 [94]: display= pd.read_sql_query("""
         SELECT *
         FROM Reviews
         WHERE Score != 3 AND UserId="AR5J8UI46CURR"
         ORDER BY ProductID
         """, con)
         display.head()
```

```
Out[94]:        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 [95]: #Sorting data according to ProductId in ascending order
         sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal
```

```
In [96]: #Deduplication of entries
         final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
         final.shape
```

```
Out[96]: (364173, 10)
```

```
In [97]: #Checking to see how much % of data still remains
         (final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

```
Out[97]: 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 [98]: display= pd.read_sql_query("""
         SELECT *
         FROM Reviews
         WHERE Score != 3 AND Id=44737 OR Id=64422
         ORDER BY ProductID
         """, con)

         display.head()
```

```
Out[98]:       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 [99]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [100]: #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[100]: 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 [101]:
```
# 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 [102]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
```

```
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

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

```
In [103]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-al
          from bs4 import BeautifulSoup

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

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

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

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

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

```
In [104]: # 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 [105]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

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

In [106]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

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

In [107]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

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

In [108]:
```
# 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', 'oursel
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', '
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has',
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throu
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off',
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 't
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've",
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn'
```

```
                    "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                    "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                    'won', "won't", 'wouldn', "wouldn't"])
```

In [109]:
```
# Sampling the data
final = final.sample(n=100000)
```

In [110]:
```
# 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%|| 100000/100000 [00:57<00:00, 1736.54it/s]
```

In [111]:
```
preprocessed_reviews[1500]
```

Out[111]:
```
'using kashi golean oatmeal years used able buy locally no longer ordered online kas
```

[3.2] Preprocessing Review Summary

In [112]:
```
## Similartly you can do preprocessing for review summary also.
```

In [113]:
```
## Similarly you can do preprocessing for review summary also.

# Combining all the above stundents
from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
for summary in tqdm(final['Summary'].values):
    summary = re.sub(r"http\S+", "", summary)
    summary = BeautifulSoup(summary, 'lxml').get_text()
    summary = decontracted(summary)
    summary = re.sub("\S*\d\S*", "", summary).strip()
    summary = re.sub('[^A-Za-z]+', ' ', summary)
    # https://gist.github.com/sebleier/554280
    summary = ' '.join(e.lower() for e in summary.split() if e.lower() not in stopwo

    preprocessed_summary.append(summary.strip())
```

```
100%|| 100000/100000 [00:36<00:00, 2757.20it/s]
```

```
In [114]: final['CleanedText'] = preprocessed_reviews #adding a column of CleanedText which di
          final['CleanedText'] = final['CleanedText'].astype('str')

          final['CleanedSummary'] = preprocessed_summary #adding a column of CleanedSummary wh
          final['CleanedSummary'] = final['CleanedSummary'].astype('str')

          final['Text_Summary'] = final['CleanedSummary'] + final['CleanedText']

          # # store final table into an SQlLite table for future.
          # conn = sqlite3.connect('final.sqlite')
          # c=conn.cursor()
          # conn.text_factory = str
          # final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
          #               index=True, index_label=None, chunksize=None, dtype=None)
          # conn.close()
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [115]: # #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])
```

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

```
In [116]: # #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/

          # # 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_big
```

5.3 [4.3] TF-IDF

In [117]:
```
# tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
# tf_idf_vect.fit(preprocessed_reviews)
# print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_na
# 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_
```

5.4 [4.4] Word2Vec

In [118]:
```
# # 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 [119]:
```
# # 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-negative30
#         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 = Tru
```

In [120]:
```
# 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])
```

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

[4.4.1.1] Avg W2v

In [121]:
```
# # 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 nee
#     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]))
```

[4.4.1.2] TFIDF weighted W2v

In [122]:
```
# # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
# model = TfidfVectorizer()
# tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# # we are converting a dictionary with word as a key, and the idf as a value
# dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [123]:
```
# # 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 = tf

# tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in thi
# 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
```

6 [5] Assignment 5: Apply Logistic Regression

Apply Logistic Regression on these feature sets
SET 1:Review text, preprocessed one converted into vectors using (BOW)
SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)
Hyper paramter tuning (find best hyper parameters corresponding the algorithm that you choose)
Find the best hyper parameter which will give the maximum AUC value
Find the best hyper paramter using k-fold cross validation or simple cross validation data
Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

```
</ul>
</li>
<br>
<li><strong>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)
Fit the model again on data X' and get the weights W'
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
Now find the % change between W and W' (| (W-W') / (W) |)*100)
Calculate the 0th, 10th, 20th, 30th, …100th percentiles, and observe any sudden rise in the values of percentage_change_vector
Ex: consider your 99th percentile is 1.3 and your 100th percentiles are 34.6, there is sudden rise from 1.3 to 34.6, now calculate the 99.1, 99.2, 99.3,…, 100th percentile values and get the proper value after which there is sudden rise the values, assume it is 2.5

```
    <li> Print the feature names whose % change is more than a threshold x(in our example it's
    </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 fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into

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

7 Applying Logistic Regression

In [124]:
```
# Please write all the code with proper documentation
```

In [125]:
```
# Source: https://docs.python.org/3/library/pickle.html

# Saving data to pickle file
def topicklefile(obj, file_name):
    pickle.dump(obj,open(file_name+'.pkl', 'wb'))
```

In [126]:
```
# Data from pickle file
def frompicklefile(file_name):
    data = pickle.load(open(file_name+'.pkl', 'rb'))
    return data
```

In [127]:
```
# Sort 'Time' column
final = final.sort_values(by='Time', ascending=True)
```

In [128]:
```
# Source: https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.

# Train Test split for train and test data
def data_split(X,y):
    # split the data set into train and test
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_s
    topicklefile(X_train, 'X_train')
    topicklefile(X_test, 'X_test')
    topicklefile(y_train, 'y_train')
    topicklefile(y_test, 'y_test')
```

In [129]:
```
def apply_avgw2v_train_test(X_train, X_test):

    # Training own Word2Vec model using your own text corpus
    list_of_sent_train = []
    for sent in X_train:#final['Text_Summary'].values:
        list_of_sent_train.append(sent.split())
    list_of_sent_test = []
    for sent in X_test:#final['Text_Summary'].values:
        list_of_sent_test.append(sent.split())

    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sent_train,min_count=5,size=50, workers=8)
```

```
    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])

    # compute average word2vec for each review for train data
    avgw2v_train = []; # the avg-w2v for each sentence/review is stored in this list
    for sent in tqdm(list_of_sent_train): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        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
        avgw2v_train.append(sent_vec)
#     print(len(avgw2v_train))
#     print(len(avgw2v_train[0]))

    # compute average word2vec for each review for test data
    avgw2v_test = []; # the avg-w2v for each sentence/review is stored in this list
    for sent in tqdm(list_of_sent_test): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        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
        avgw2v_test.append(sent_vec)
#     print(len(avgw2v_test))
#     print(len(avgw2v_test[0]))

    return avgw2v_train, avgw2v_test
```

In [130]:
```
def apply_tfidfw2v_train_test(X_train, X_test):

    # Training own Word2Vec model using your own text corpus
    list_of_sent_train = []
    for sent in X_train:#final['Text_Summary'].values:
        list_of_sent_train.append(sent.split())
    list_of_sent_test = []
    for sent in X_test:#final['Text_Summary'].values:
        list_of_sent_test.append(sent.split())
```

```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sent_train,min_count=5,size=50, workers=16)

w2v_words = list(w2v_model.wv.vocab)

model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(X_train)
# 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_)))

# 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 =

tfidfw2v_train = []; # the tfidf-w2v for each sentence/review is stored in this
row=0;
for sent in tqdm(list_of_sent_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 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
    tfidfw2v_train.append(sent_vec)
    row += 1


tf_idf_matrix = model.transform(X_test)
# 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_)))

# 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 =

tfidfw2v_test = []; # the tfidf-w2v for each sentence/review is stored in this l
row=0;
for sent in tqdm(list_of_sent_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 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
            tfidfw2v_test.append(sent_vec)
            row += 1


        return tfidfw2v_train, tfidfw2v_test
```

In [131]:
```
# Applying BOW on train and test data and creating the
from sklearn.preprocessing import StandardScaler
from scipy.sparse import hstack

#Standardize 'bow_train' data features by removing the mean and scaling to unit vari
std_scalar1 = StandardScaler(copy=True, with_mean=False, with_std=True)
std_scalar2 = StandardScaler(copy=True, with_mean=True, with_std=True)

def apply_vectorizers_train_test(model_name, train_data, test_data):

    if model_name == 'BOW':
        #Applying BoW on Train data
        count_vect = CountVectorizer()

        #Applying BoW on Test data
        train_vect = count_vect.fit_transform(train_data)

        #Applying BoW on Test data similar to the bow_train data
        test_vect = count_vect.transform(test_data)

        # Standardise train data
        train_vect = std_scalar1.fit_transform(train_vect)
        # Standardize the unseen bow_test data
        test_vect = std_scalar1.transform(test_vect)

        topicklefile(train_vect, 'train_vect')
        topicklefile(test_vect, 'test_vect')

        print("'train_vect' and 'test_vect' are the pickle files.")
```

```
        return count_vect

    elif model_name == 'TF-IDF':
        #Applying TF-IDF on Train data
        count_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)

        #Applying BoW on Test data
        train_vect = count_vect.fit_transform(train_data)

        #Applying BoW on Test data similar to the bow_train data
        test_vect = count_vect.transform(test_data)

        # Standardise train data
        train_vect = std_scalar1.fit_transform(train_vect)
        # Standardize the unseen bow_test data
        test_vect = std_scalar1.transform(test_vect)

        topicklefile(train_vect, 'train_vect')
        topicklefile(test_vect, 'test_vect')

        print("'train_vect' and 'test_vect' are the pickle files.")
        return count_vect

    elif model_name == 'AvgW2V':
        train_vect, test_vect = apply_avgw2v_train_test(train_data, test_data)

        # Standardise train data
        train_vect = std_scalar2.fit_transform(train_vect)
        # Standardize the unseen bow_test data
        test_vect = std_scalar2.transform(test_vect)

        topicklefile(train_vect, 'train_vect')
        topicklefile(test_vect, 'test_vect')
        print("'train_vect' and 'test_vect' are the pickle files.")

    elif model_name == 'TF-IDF W2V':
        train_vect, test_vect = apply_tfidfw2v_train_test(train_data, test_data)

        # Standardise train data
        train_vect = std_scalar2.fit_transform(train_vect)
        # Standardize the unseen bow_test data
        test_vect = std_scalar2.transform(test_vect)

        topicklefile(train_vect, 'train_vect')
        topicklefile(test_vect, 'test_vect')
        print("'train_vect' and 'test_vect' are the pickle files.")

    else:
```

```
            #Error Message
            print('Model specified is not valid! Please check.')
```

In [132]:
```
def applying_logistic_regression(penalty, dual_given, c_values, train_data, y_train)

    parameters = {'C':c_values}
    lr_clf = LogisticRegression(penalty, dual=dual_given)
    clf = GridSearchCV(lr_clf, parameters, cv=10, scoring= 'roc_auc', n_jobs=4, retu
    clf.fit(train_data, y_train)

    c_optimal = clf.best_params_.get('C')

    train_auc= clf.cv_results_['mean_train_score']
    train_auc_std= clf.cv_results_['std_train_score']
    cv_auc = clf.cv_results_['mean_test_score']
    cv_auc_std= clf.cv_results_['std_test_score']

    return clf, c_optimal, train_auc, train_auc_std, cv_auc, cv_auc_std
```

In [133]:
```
def train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std):
    plt.plot(c_values, train_auc, label='Train AUC')

    # Source: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(c_values,train_auc - train_auc_std,train_auc + train_auc_

    plt.plot(c_values, cv_auc, label='CV AUC')
    # Source: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(c_values,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.
    plt.legend()
    plt.xlabel("C: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()
```

In [134]:
```
# instantiate learning model C = optimal_C
# def naive_bayes_optimal(optimal_alpha):
#     nb_optimal = MultinomialNB(alpha=optimal_alpha)
#     return nb_optimal

def log_reg_optimal(optimal_c, penalty_given, dual_given):
    log_reg_optimal = LogisticRegression(penalty=penalty_given, dual=dual_given, C=op
    return log_reg_optimal
```

In [135]:
```
def retrain_log_reg(log_reg_optimal, train_vec, y_train, test_vec, y_test):

    # fitting the model with optimal K for training data
    log_reg_optimal.fit(train_vec, y_train)
```

```
        # predict the response for the unseen bow_test data
        y_pred = log_reg_optimal.predict(test_vec)
```

```
In [136]: # Confusion Matrix
          def cm_fig(log_reg_optimal, y_test, test_vec):
              cm = pd.DataFrame(confusion_matrix(y_test, log_reg_optimal.predict(test_vec)))
              # print(confusion_matrix(y_test, y_pred))

              plt.figure(1, figsize=(18,5))
              plt.subplot(121)
              plt.title("Confusion Matrix")
              sns.set(font_scale=1.4)
              sns.heatmap(cm, cmap= 'gist_earth', annot=True, annot_kws={'size':15}, fmt='g')
```

```
In [137]: #Reference: https://stackoverflow.com/questions/52910061/implementing-roc-curves-for
          def error_plot(log_reg_optimal, train_vec, y_train, test_vec, y_test):
              train_fpr, train_tpr, thresholds = roc_curve(y_train, log_reg_optimal.predict_pro
              test_fpr, test_tpr, thresholds = roc_curve(y_test, log_reg_optimal.predict_proba

              plt.plot(train_fpr, train_tpr, label="train AUC = %0.3f" %auc(train_fpr, train_tp
              plt.plot(test_fpr, test_tpr, label="train AUC = %0.3f" %auc(test_fpr, test_tpr))
              plt.plot([0.0, 1.0], [0.0, 1.0],'k--')
              plt.legend()
              plt.xlabel("C: hyperparameter")
              plt.ylabel("AUC")
              plt.title("ERROR PLOTS")
              plt.show()

              return auc(test_fpr, test_tpr)
```

```
In [138]: def get_features_top(count_vect, log_reg_optimal):
              features=count_vect.get_feature_names()
              feature_prob=log_reg_optimal.coef_.ravel()
          #     print(features)
          #     print('='*100)
          #     print(feature_prob)
              df_feature_proba = pd.DataFrame({'features':features, 'probabilities':feature_pro
              df_feature_proba = df_feature_proba.sort_values(by=['probabilities'],ascending=Fa
          #     print(df_feature_proba)
              return df_feature_proba[:11], df_feature_proba[-11:]
```

```
In [139]: def pertubation_test(log_reg_optimal, train_vect, y_train, elbow_point, count_vect):
              epsilon = sys.float_info.epsilon
              weight_vec = log_reg_optimal.coef_
          #     print(weight_vec)
          #     print(weight_vec.shape)
          #     print('='*100)
              train_vect.data += epsilon
              print(weight_vec.shape)
```

```
#     train_vect_with_noise = train_vect_with_noise.reshape(weight_vec.shape)

    log_reg_optimal.fit(train_vect, y_train)
    weight_vec_with_noise = log_reg_optimal.coef_
#     print(weight_vec_with_noise)
#     print('='*100)
    percentage_change_vector = abs((weight_vec-weight_vec_with_noise) / (weight_vec)
    percentage_change_array = np.asarray(percentage_change_vector)
    percentage_change_array = percentage_change_array.tolist()
    percentage_change_array = percentage_change_array[0]
#     print(percentage_change_array)
#     print(sorted(percentage_change_array))
#     print('='*100)

    threshold = [x for x in range(0,105,5)]

    threshold_pts = []

    for thr in threshold:
        pts = sum(i > thr for i in percentage_change_array)
        threshold_pts.append(pts)

    print('threshold_pts: ', threshold_pts)
    print('threshold_pts sum: ', sum(threshold_pts))

    # Plotting the graph for elbow point
    plt.plot(threshold, threshold_pts)

    plt.legend()
    plt.xlabel("Threshold")
    plt.ylabel("No.of points")
    plt.title("Percentiles")
    plt.show()

    # After obtaining the elbow point from the plot, getting the features which are
    indexes = []
    for change in percentage_change_array:
        if change > elbow_point:
            indexes.append(percentage_change_array.index(change))

#     print(indexes)
    indexes = set(indexes)
    indexes = list(indexes)
    # Get feature names
    print('='*100)
    print('Multicollinear Features')
    feat=count_vect.get_feature_names()
    for ind in indexes:
```

```
                print(feat[ind])
```

```
In [140]: def sparsity_of_matrix(log_reg_optimal, c_values, train_vect, y_train):
              sparsity_val = []
              for c_val in c_values:
                  log_reg_optimal = LogisticRegression(penalty='l1', dual=False, C=c_val)
                  log_reg_optimal.fit(train_vect, y_train)
                  weight_vec = log_reg_optimal.coef_
                  non_zero = np.count_nonzero(weight_vec)
                  total_val = np.product(weight_vec.shape)
                  sparsity = (total_val - non_zero) / total_val
                  sparsity_val.append(sparsity)

              sparsities = pd.DataFrame({'C(=1\lambda)':c_values, '% sparsity':sparsity_val})
              return sparsities
```

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 [141]: X = np.array(final['Text_Summary'])
          y = np.array(final['Score'])
          data_split(X,y)
          X_train = frompicklefile('X_train')
          X_test = frompicklefile('X_test')
          y_train = frompicklefile('y_train')
          y_test = frompicklefile('y_test')
          count_vect = apply_vectorizers_train_test('BOW', X_train, X_test)
```

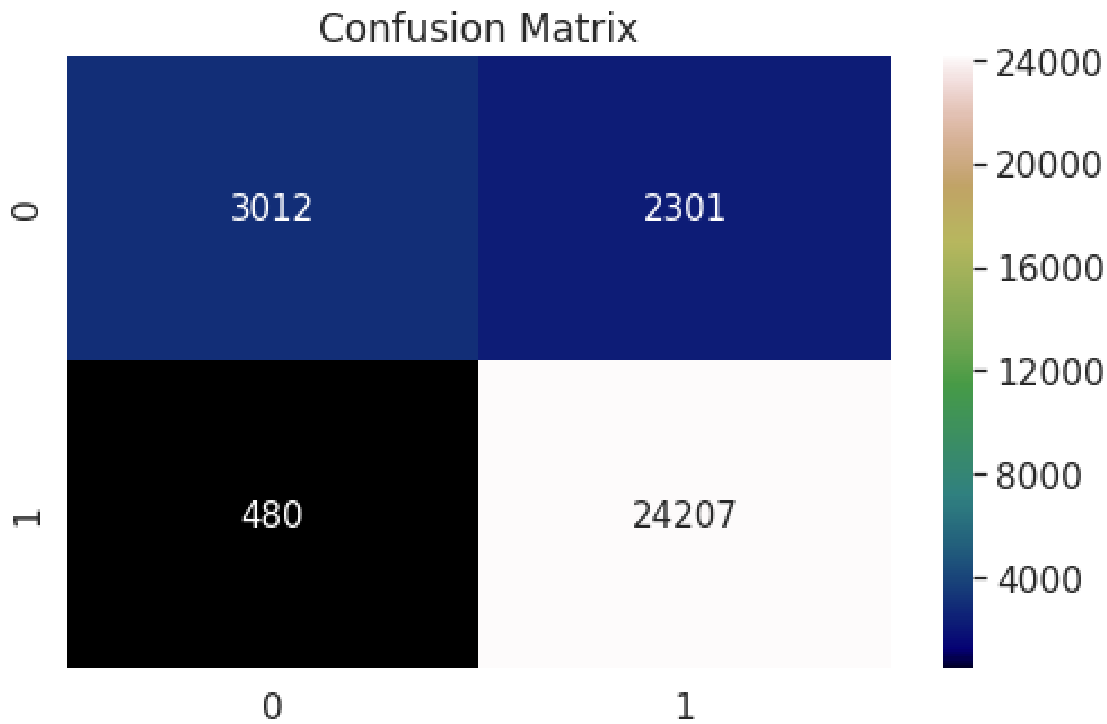
```
'train_vect' and 'test_vect' are the pickle files.
```

```
In [142]: train_vect = frompicklefile('train_vect')
          test_vect = frompicklefile('test_vect')
          y_train = frompicklefile('y_train')
          y_test = frompicklefile('y_test')
```

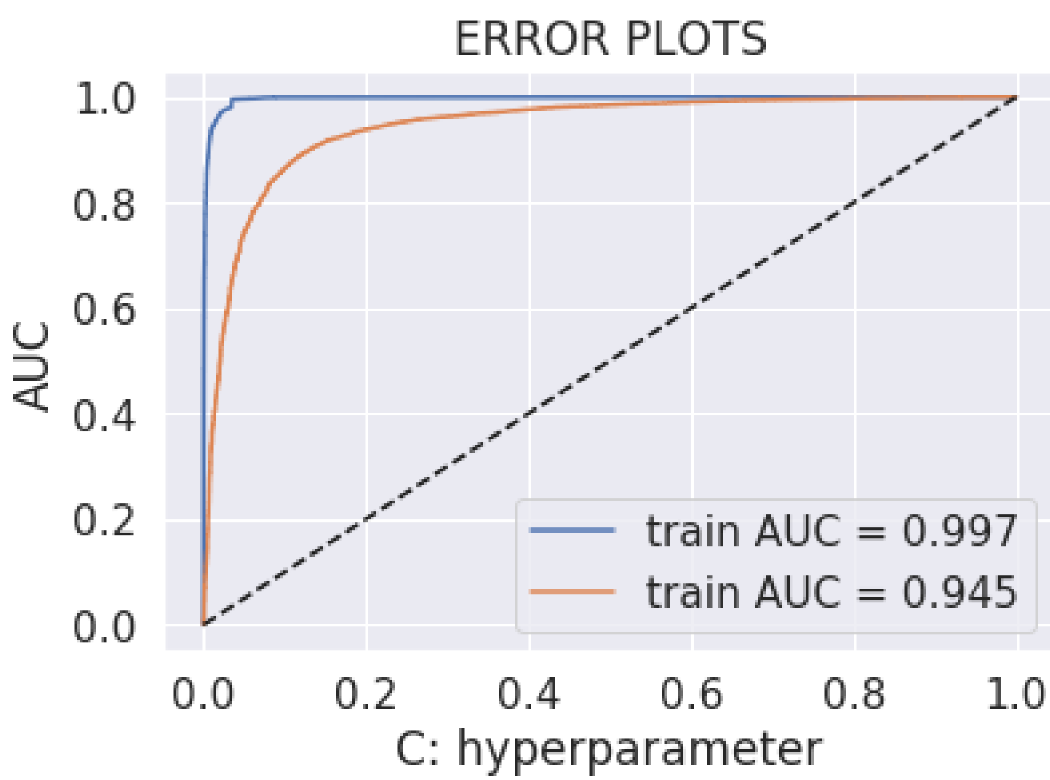
```
In [143]: c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
          clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_reg

          optimal_c_bow1 = optimal_c

          print('The optimal C is {}' .format(optimal_c))

          train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

          # log_reg_optimal = log_reg_optimal('l1', False, optimal_c)
```

```
log_reg_optimal = LogisticRegression(penalty='l1', dual=False, C=optimal_c)

retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.01
```




```
In [144]: bow_auc1 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```



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

```
In [145]: sparsities_obtained = sparsity_of_matrix(log_reg_optimal, c_values, train_vect, y_tra
          sparsities_obtained
```

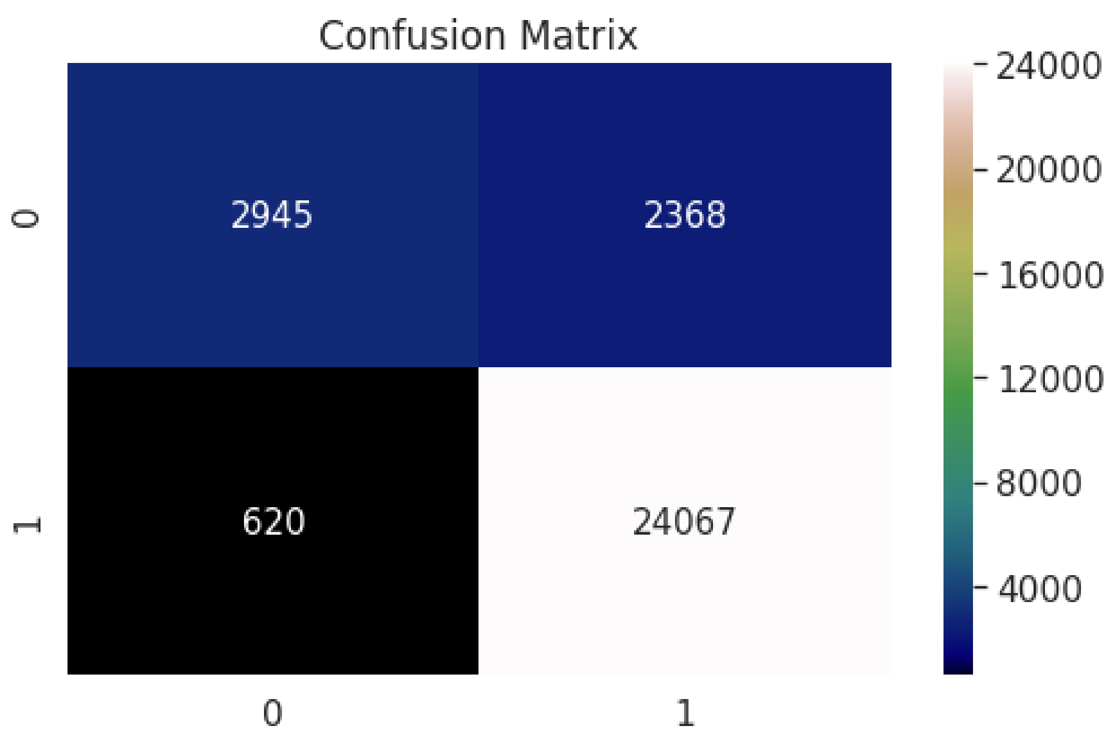
```
Out[145]:     C(=1\lambda)  % sparsity
          0        0.00001    1.000000
          1        0.00010    1.000000
          2        0.00100    0.999301
          3        0.01000    0.914996
          4        0.10000    0.856442
          5        1.00000    0.832671
          6       10.00000    0.788915
          7      100.00000    0.641080
          8     1000.00000    0.358820
          9    10000.00000    0.097084
          10  100000.00000    0.027658
```

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

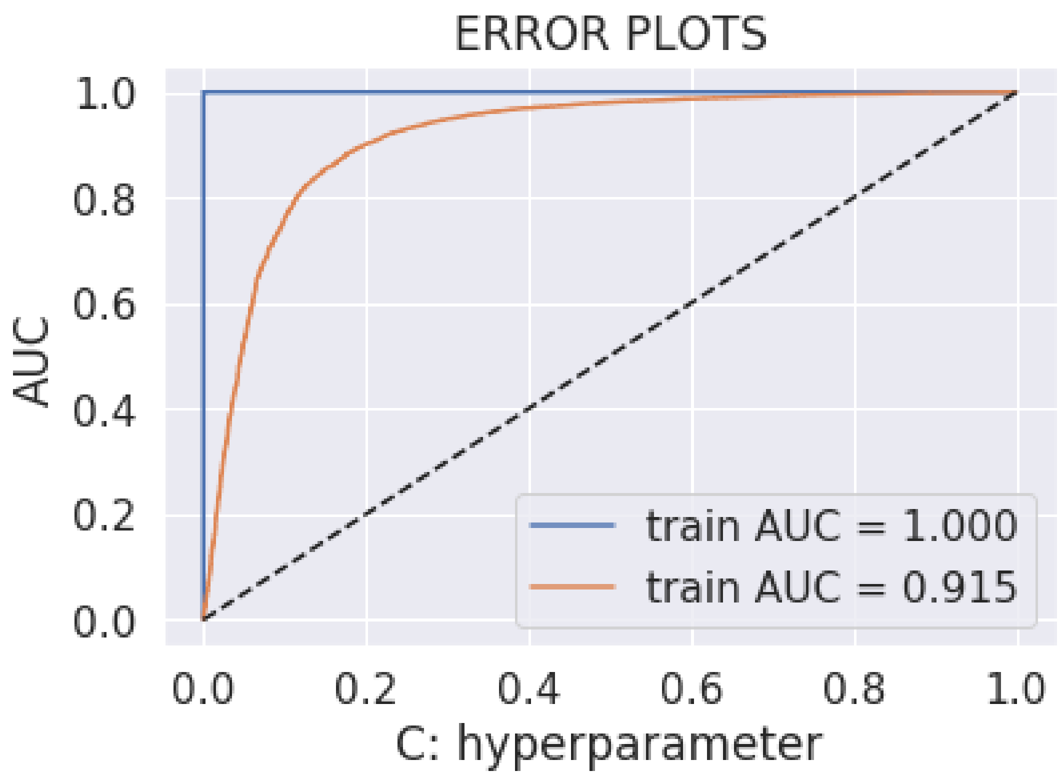
```
In [146]: c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
          clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_reg

          optimal_c_bow1 = optimal_c

          print('The optimal C is {}' .format(optimal_c))

          train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

          # log_reg_optimal = log_reg_optimal(optimal_c, 'l2', True)

          log_reg_optimal = LogisticRegression(penalty='l2', dual=True, C=optimal_c)

          retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

          cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.01
```


ERROR PLOTS
1.00
0.95
0.90
0.85
0.80
AUC
Train AUC
CV AUC
0
20000
40000
60000
80000
100000
C: hyperparameter


Confusion Matrix
2945
2368
620
24067
0
1
0
1
24000
20000
16000
12000
8000
4000

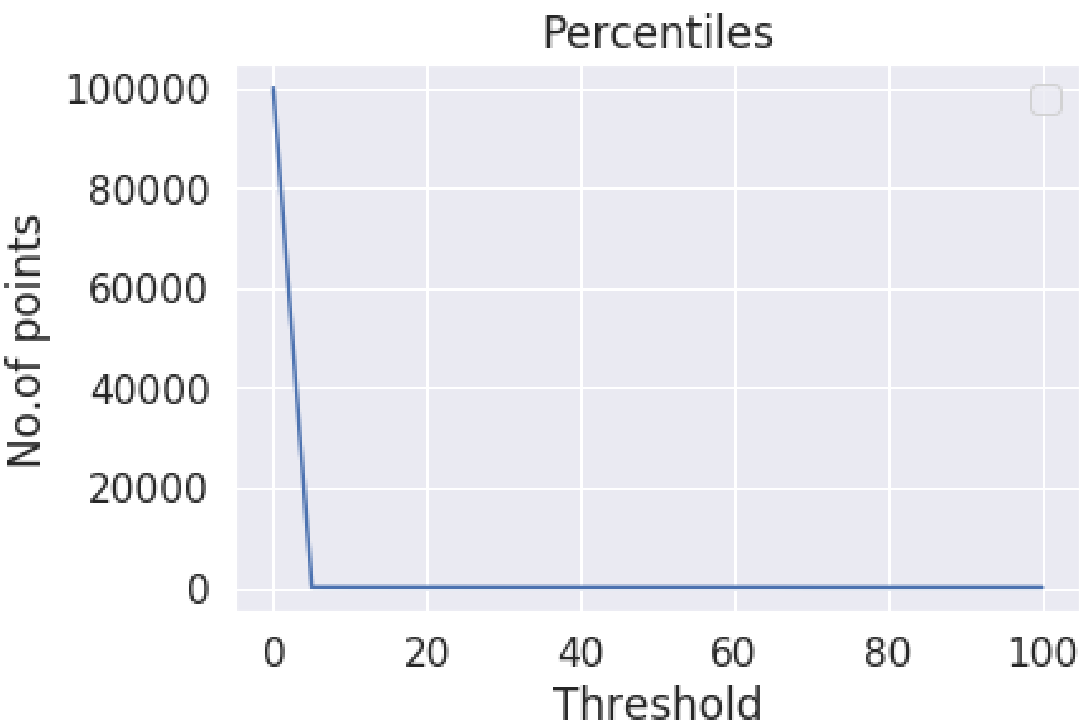
```
In [147]: bow_auc2 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```



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

```
In [148]: pertubation_test(log_reg_optimal, train_vect, y_train, 5, count_vect)
```

```
(1, 100078)


No handles with labels found to put in legend.


threshold_pts:  [100078, 76, 63, 60, 60, 59, 56, 56, 56, 56, 56, 56, 56, 56, 45, 45, 45, 45, 4
threshold_pts sum:  101159
```




```
=================================================================================================
Multicollinear Features
slips
pricingprice
parent
schnauzers
godsconsider
bircherm
godseven
oknot
shop
stirfry
mgo
aicr
keys
lifestyles
lifetaken
deteriorates
emerging
thread
older
evaluated
antioxidantstea
```

```
invasions
flavortea
```

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 [149]: positive_features, negative_features = get_features_top(count_vect, log_reg_optimal)
          positive_features
```

```
Out[149]:         features  probabilities
          40187      great       0.599256
          7441        best       0.379616
          38890       good       0.362875
          52056       love       0.303995
          23205  delicious       0.278825
          30964  excellent       0.263939
          52607      loves       0.246569
          64751    perfect       0.223891
          87309      tasty       0.215951
          59056       nice       0.210098
          32891   favorite       0.206770
```

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

```
In [150]: negative_features
```

```
Out[150]:             features  probabilities
          89512          thought      -0.148003
          57062            money      -0.152467
          95936             weak      -0.158847
          44051         horrible      -0.165708
          25598    disappointing      -0.171483
          88577         terrible      -0.184638
          66811             poor      -0.195334
          5066             awful      -0.200570
          97807            worst      -0.216595
          25490     disappointed      -0.219960
          59633              not      -0.400503
```

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

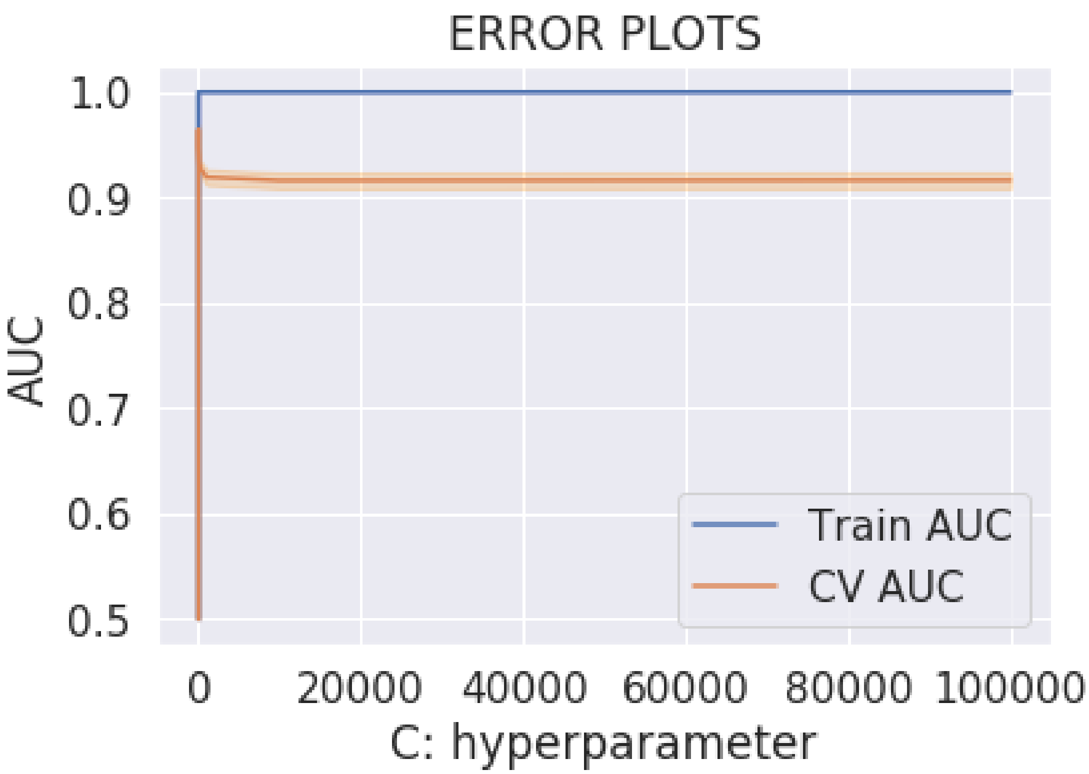
```
In [175]: X = np.array(final['Text_Summary'])
          y = np.array(final['Score'])
          data_split(X,y)
          X_train = frompicklefile('X_train')
          X_test = frompicklefile('X_test')
          count_vect = apply_vectorizers_train_test('TF-IDF', X_train, X_test)
```

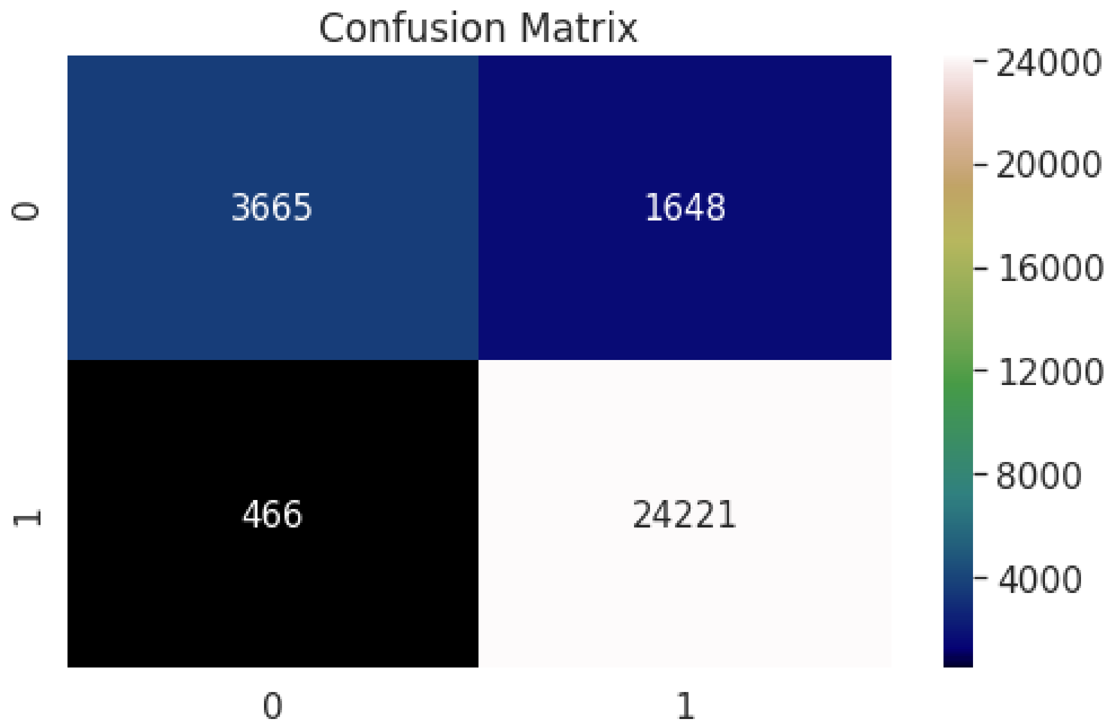
'train_vect' and 'test_vect' are the pickle files.

```
In [176]: train_vect = frompicklefile('train_vect')
          test_vect = frompicklefile('test_vect')
          y_train = frompicklefile('y_train')
          y_test = frompicklefile('y_test')
```

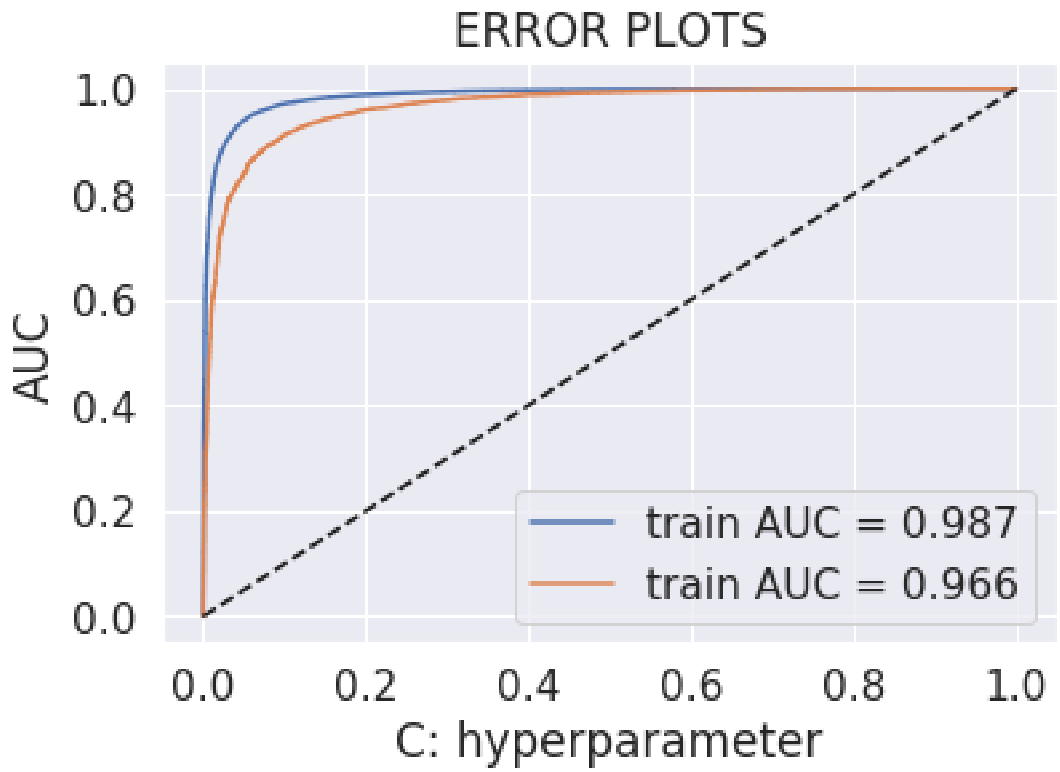
```
In [177]: c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
          clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_reg

          optimal_c_bow1 = optimal_c

          print('The optimal C is {}' .format(optimal_c))

          train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

          # log_reg_optimal = log_reg_optimal(optimal_c, 'l1', False)

          log_reg_optimal = LogisticRegression(penalty='l1', dual=False, C=optimal_c)

          retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

          cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.01
```






```
In [178]: tfidf_auc1 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```



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

In [179]:
```
sparsities_obtained = sparsity_of_matrix(log_reg_optimal, c_values, train_vect, y_tra
sparsities_obtained
```

Out[179]:

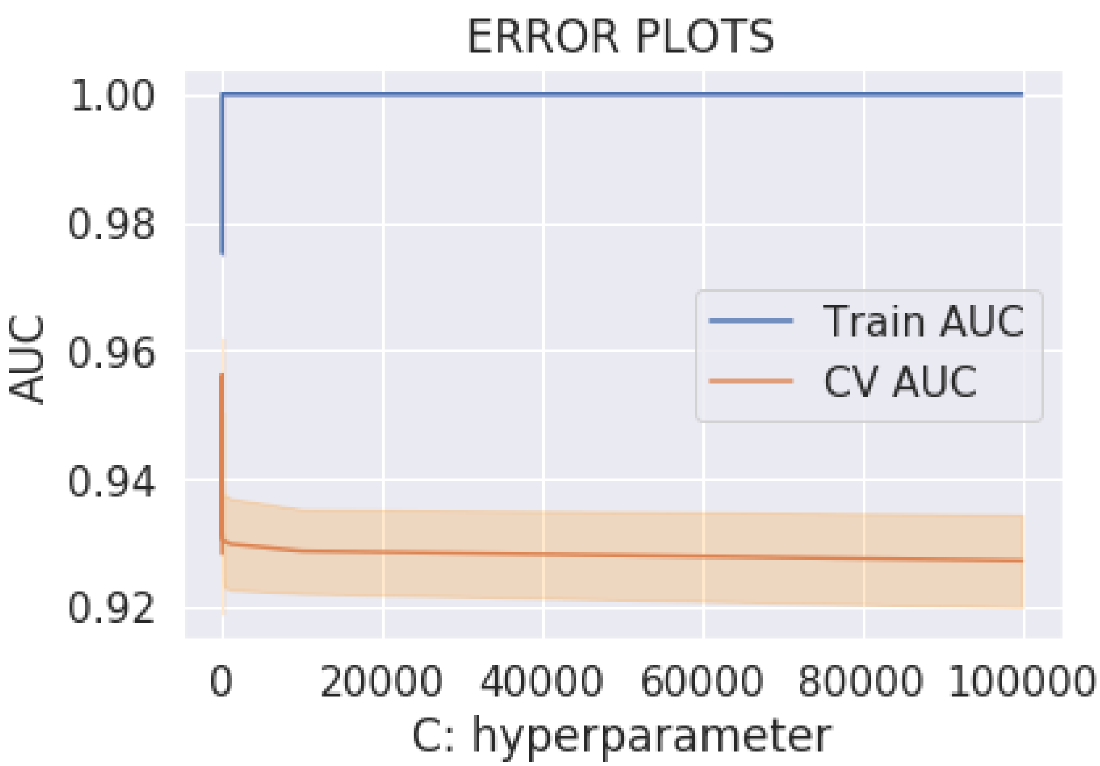
	C(=1\lambda)	% sparsity
0	0.00001	1.000000
1	0.00010	1.000000
2	0.00100	0.997809
3	0.01000	0.911538
4	0.10000	0.717235
5	1.00000	0.667965
6	10.00000	0.560711
7	100.00000	0.200073
8	1000.00000	0.025925
9	10000.00000	0.001728
10	100000.00000	0.000195

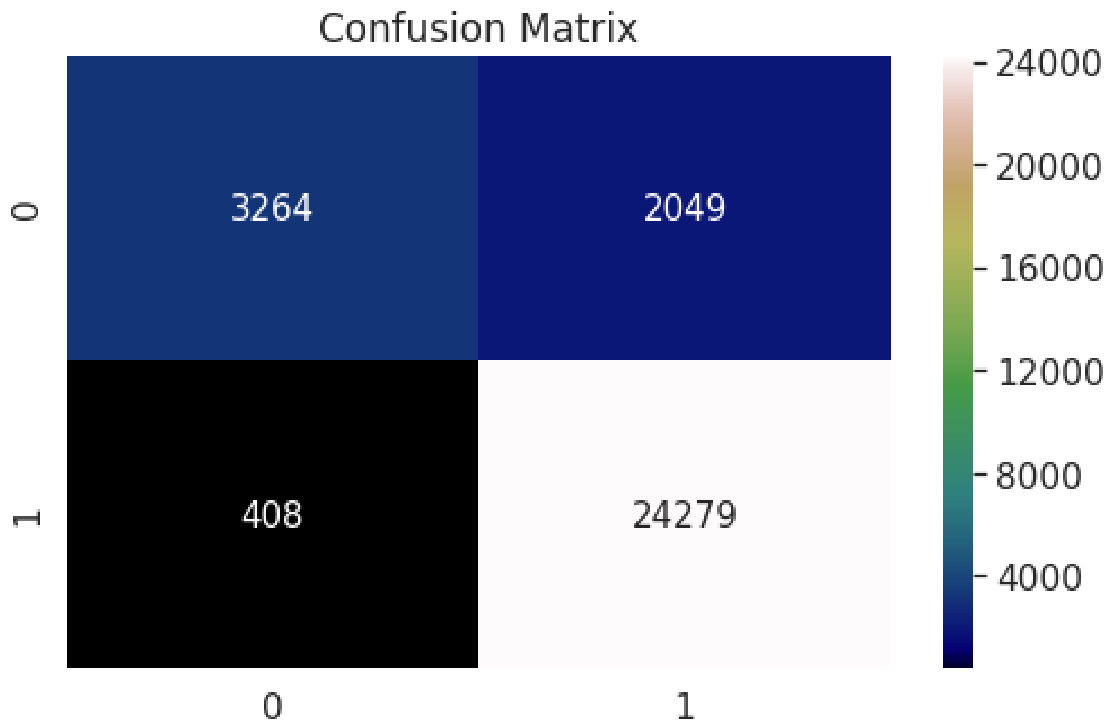
7.2.2 [5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [180]:
```
c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_reg
```

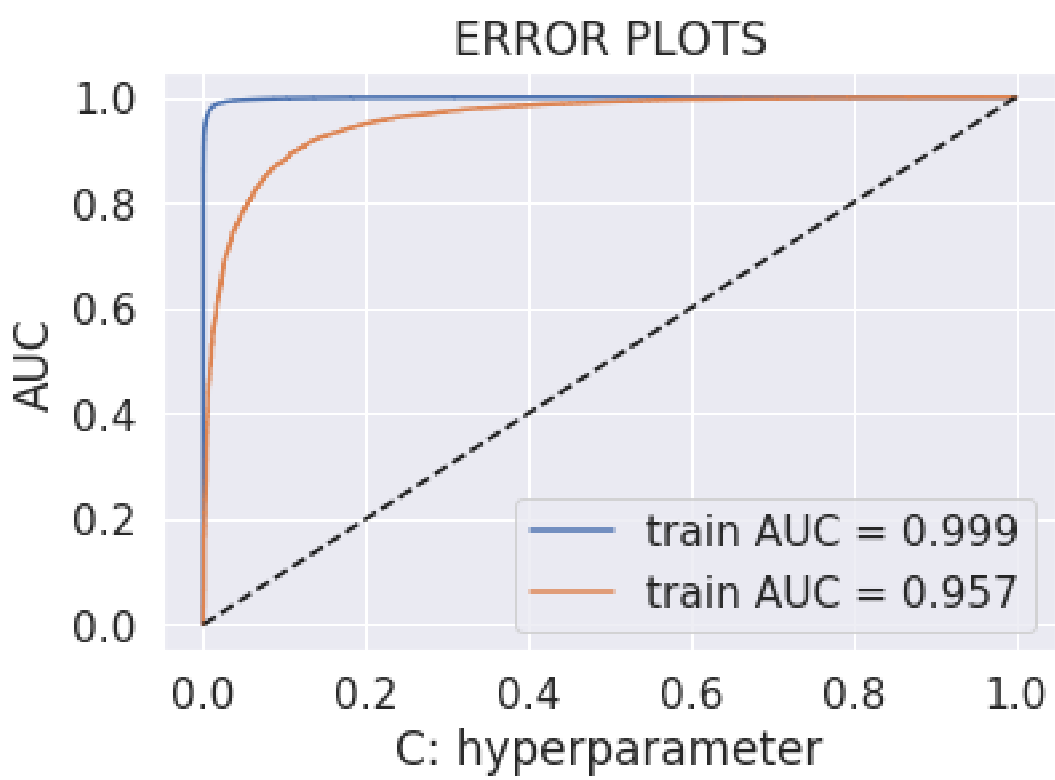
```
optimal_c_bow1 = optimal_c

print('The optimal C is {}' .format(optimal_c))

train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

# log_reg_optimal = log_reg_optimal(optimal_c, 'l2', True)
log_reg_optimal = LogisticRegression(penalty='l2', dual=True, C=optimal_c)

retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.0001
```





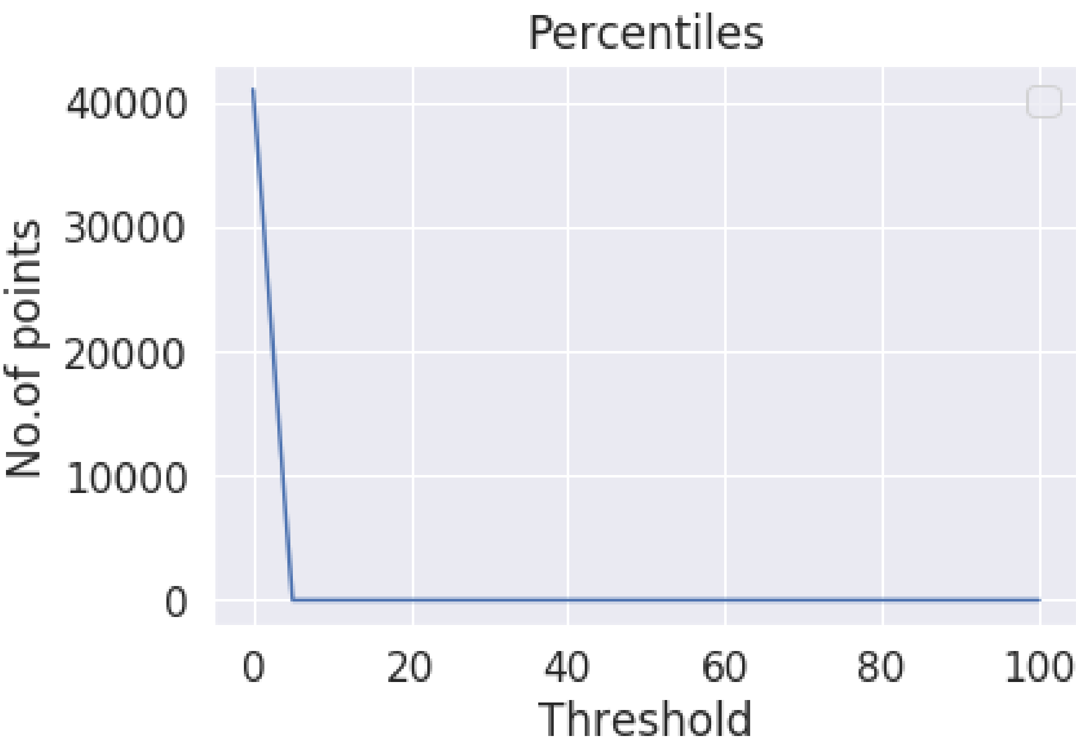

```
In [181]: tfidf_auc2 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```



[5.2.2.1] Performing pertubation test (multicollinearity check) on TF-IDF, SET 2

In [182]:
```
pertubation_test(log_reg_optimal, train_vect, y_train, 3, count_vect)
```

```
(1, 41080)


No handles with labels found to put in legend.


threshold_pts:  [41080, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
threshold_pts sum:  41080
```




```
==========================================================================================
Multicollinear Features
```

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 [159]:
```
positive_features, negative_features = get_features_top(count_vect, log_reg_optimal)
positive_features
```

Out[159]:

	features	probabilities
15880	great	0.131472
15190	good	0.093207
2859	best	0.092064
20686	love	0.077836
8742	delicious	0.072187
11330	excellent	0.059990
20971	loves	0.058857
26979	perfect	0.056689
11937	favorite	0.051851
35785	tasty	0.050544
40293	wonderful	0.049112

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

In [160]:
```
negative_features
```

Out[160]:

	features	probabilities
17343	horrible	-0.044422
9326	disappointing	-0.047418
24144	not buy	-0.049733
24898	not worth	-0.051299
24670	not recommend	-0.052525
2055	awful	-0.052873
36383	terrible	-0.053355
9301	disappointed	-0.053717
24382	not good	-0.056202
40481	worst	-0.056947
24056	not	-0.060473

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 [161]:
```
X = np.array(final['Text_Summary'])
y = np.array(final['Score'])
data_split(X,y)
X_train = frompicklefile('X_train')
X_test = frompicklefile('X_test')
apply_vectorizers_train_test('AvgW2V', X_train, X_test)
```

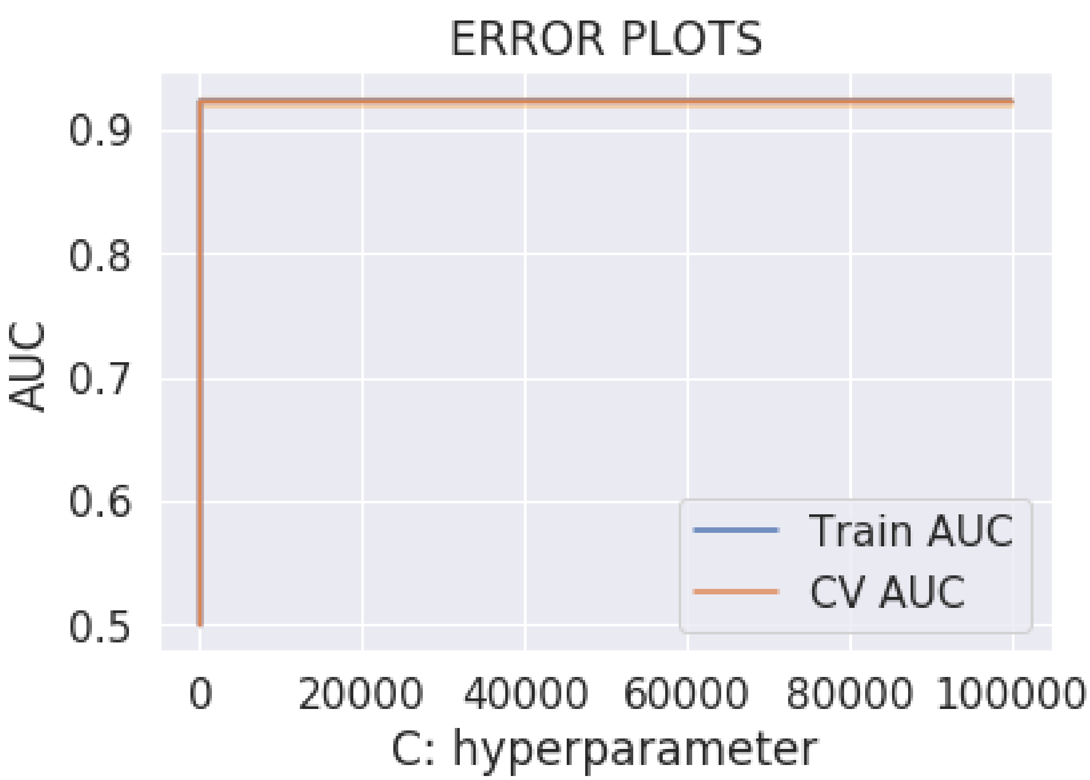
```
100%|| 70000/70000 [04:19<00:00, 259.99it/s]
100%|| 30000/30000 [01:55<00:00, 259.93it/s]
```

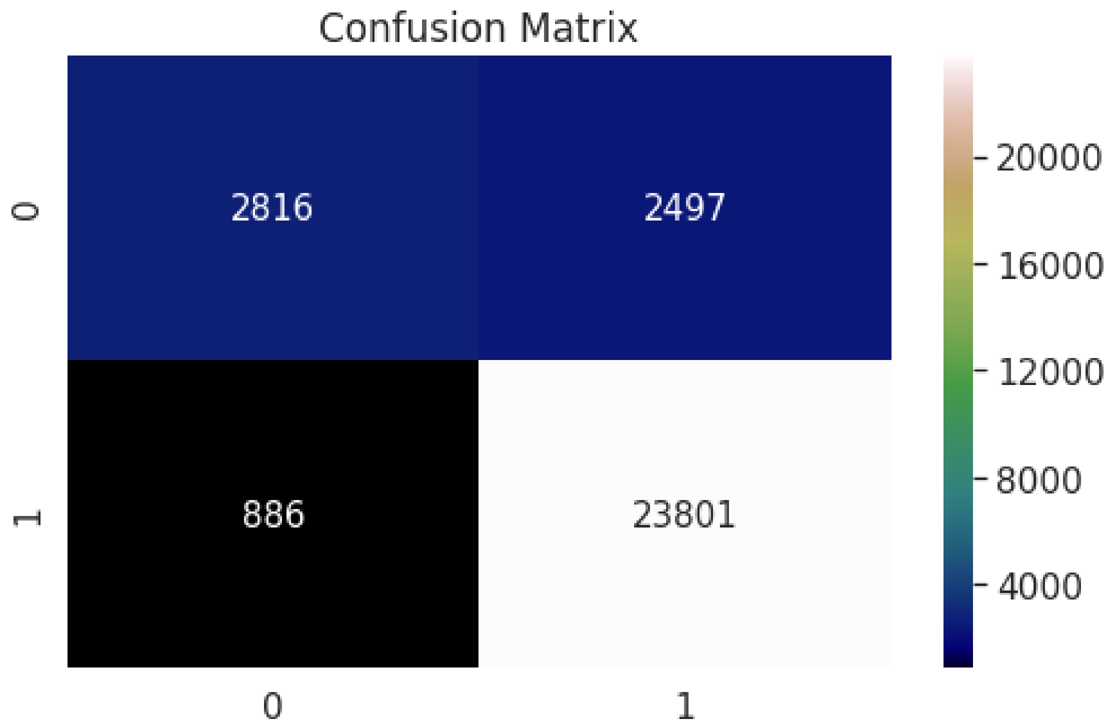
'train_vect' and 'test_vect' are the pickle files.

```
In [162]: train_vect = frompicklefile('train_vect')
          test_vect = frompicklefile('test_vect')
          y_train = frompicklefile('y_train')
          y_test = frompicklefile('y_test')
```

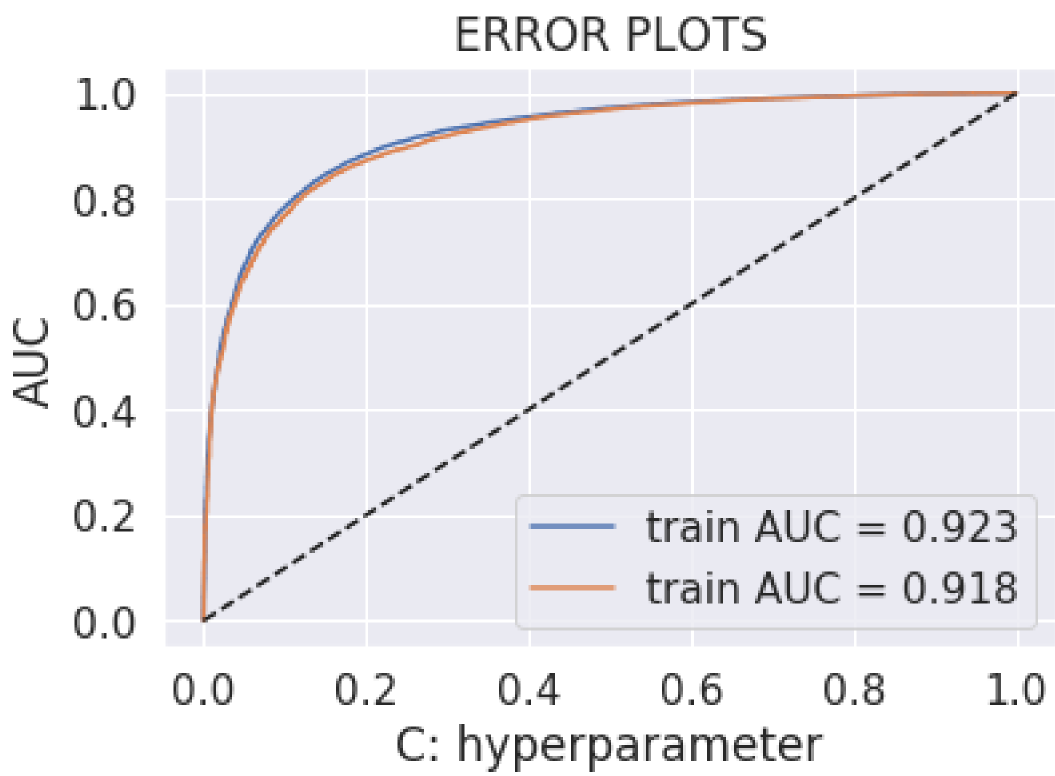
```
In [163]: c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
          clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_reg

          optimal_c_bow1 = optimal_c

          print('The optimal C is {}' .format(optimal_c))

          train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

          # log_reg_optimal = log_reg_optimal(optimal_c, 'l1', False)
          log_reg_optimal = LogisticRegression(penalty='l1', dual=False, C=optimal_c)

          retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

          cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 1
```





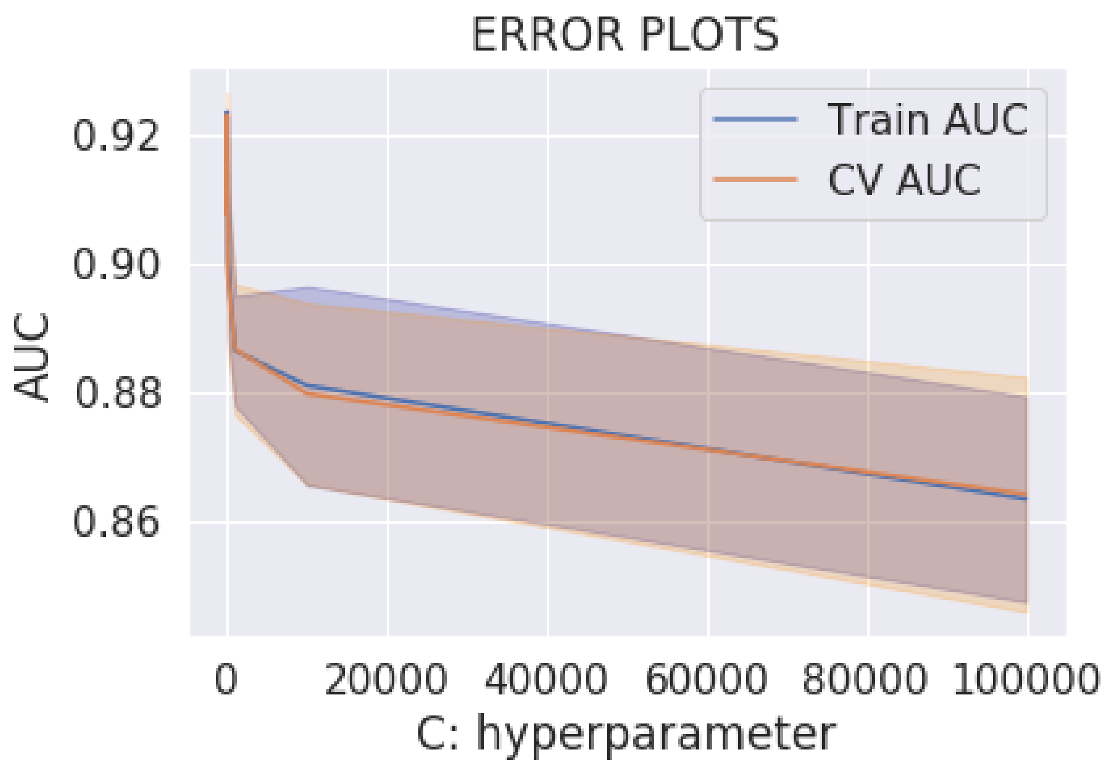

```
In [164]: avgw2v_auc1 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```

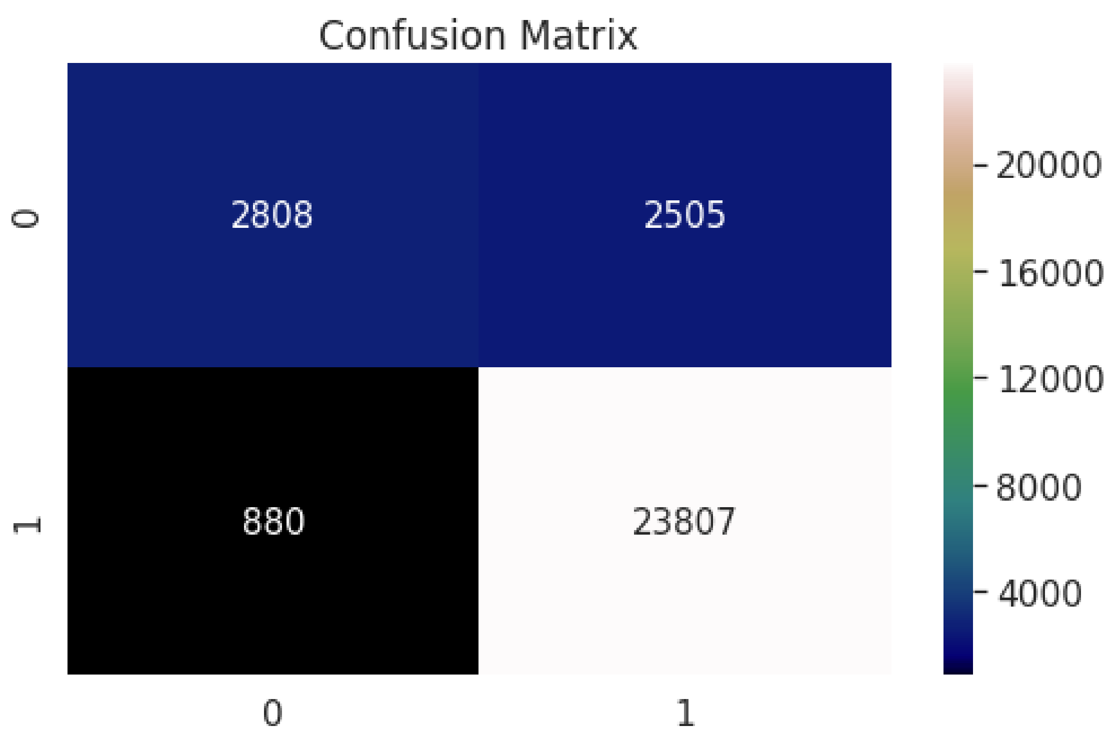


7.3.2 [5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

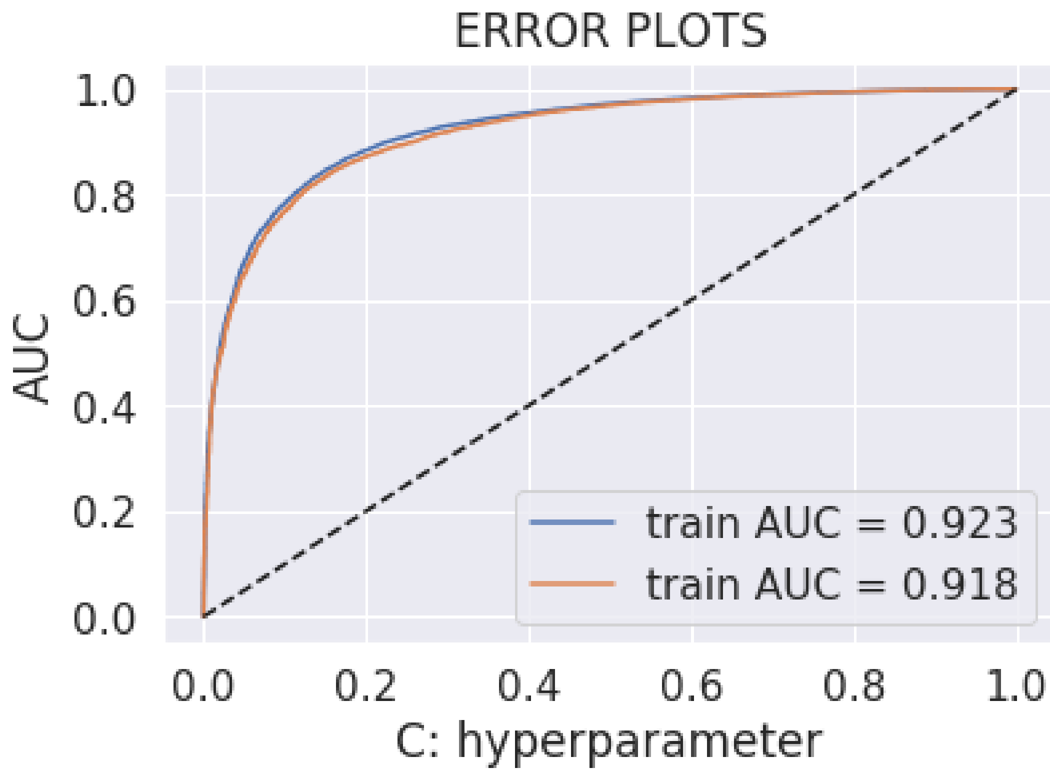
In [165]:
```
c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_regr

optimal_c_bow1 = optimal_c

print('The optimal C is {}' .format(optimal_c))

train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

# log_reg_optimal = log_reg_optimal(optimal_c, 'l2', True)
log_reg_optimal = LogisticRegression(penalty='l2', dual=True, C=optimal_c)

retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.1
```


ERROR PLOTS
Train AUC
CV AUC
0.92
0.90
0.88
0.86
AUC
0
20000
40000
60000
80000
100000
C: hyperparameter


Confusion Matrix
2808
2505
880
23807
0
1
0
1
20000
16000
12000
8000
4000

```
In [166]: avgw2v_auc2 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```



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 [167]: X = np.array(final['Text_Summary'])
          y = np.array(final['Score'])
          data_split(X,y)
          X_train = frompicklefile('X_train')
          X_test = frompicklefile('X_test')
          apply_vectorizers_train_test('TF-IDF W2V', X_train, X_test)
```

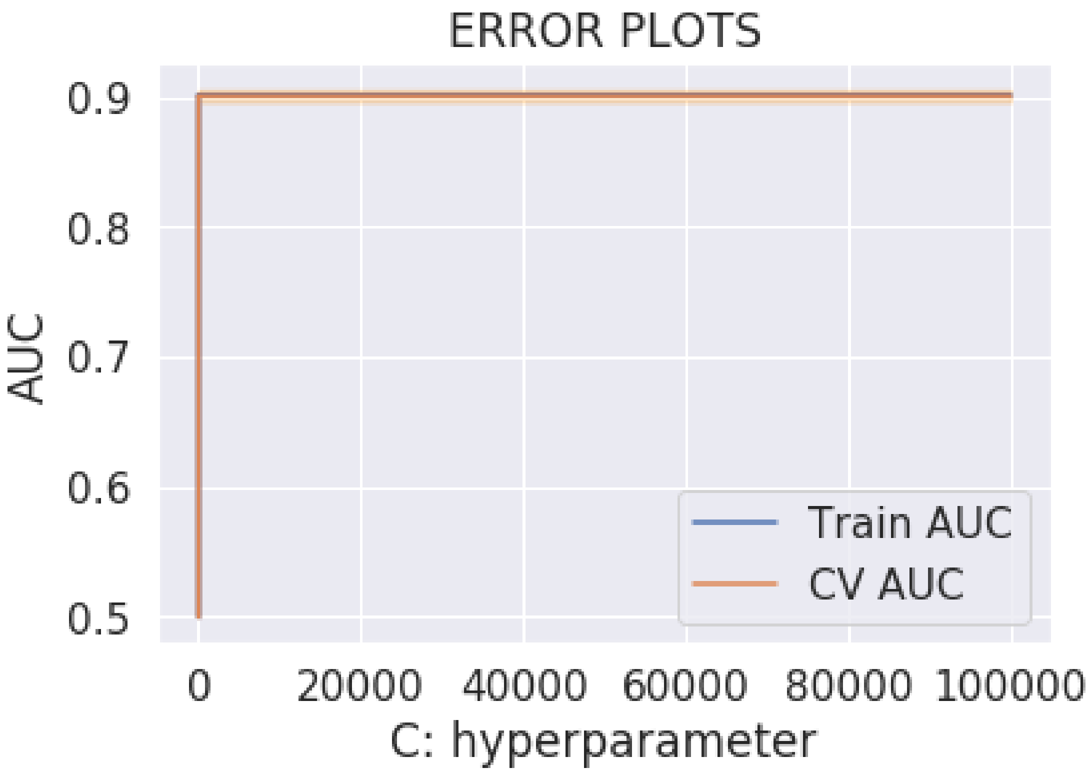
```
100%|| 70000/70000 [2:02:00<00:00,  6.40it/s]
100%|| 30000/30000 [56:18<00:00, 13.76it/s]
```

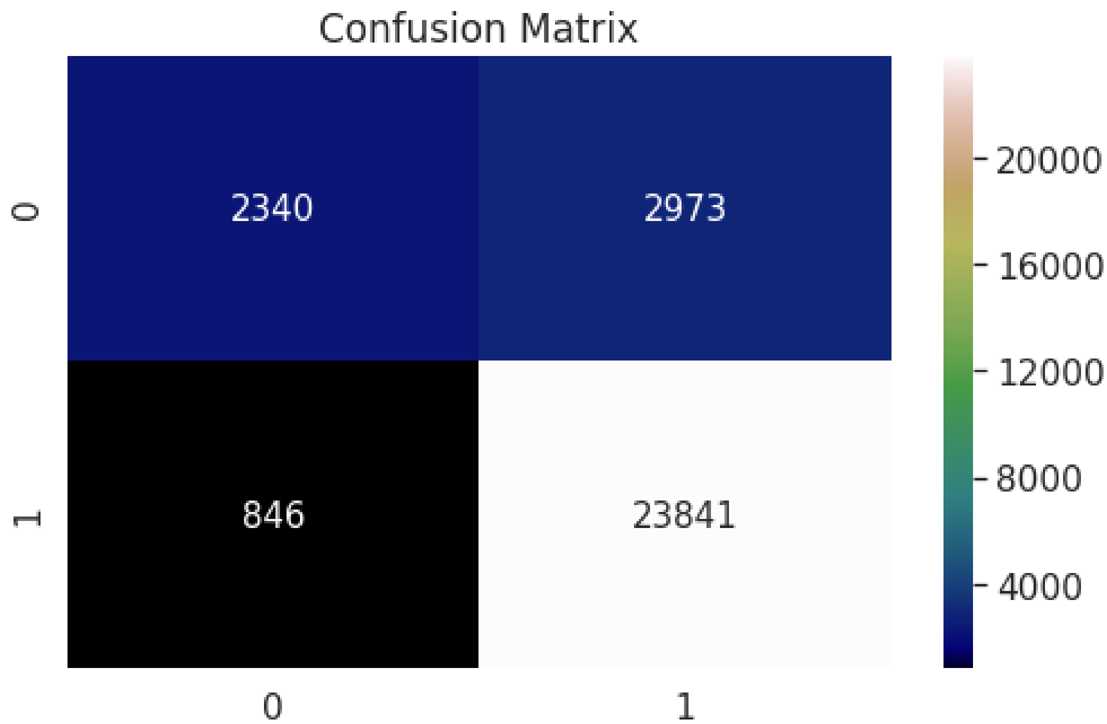
```
'train_vect' and 'test_vect' are the pickle files.
```

```
In [168]: train_vect = frompicklefile('train_vect')
          test_vect = frompicklefile('test_vect')
          y_train = frompicklefile('y_train')
          y_test = frompicklefile('y_test')
```

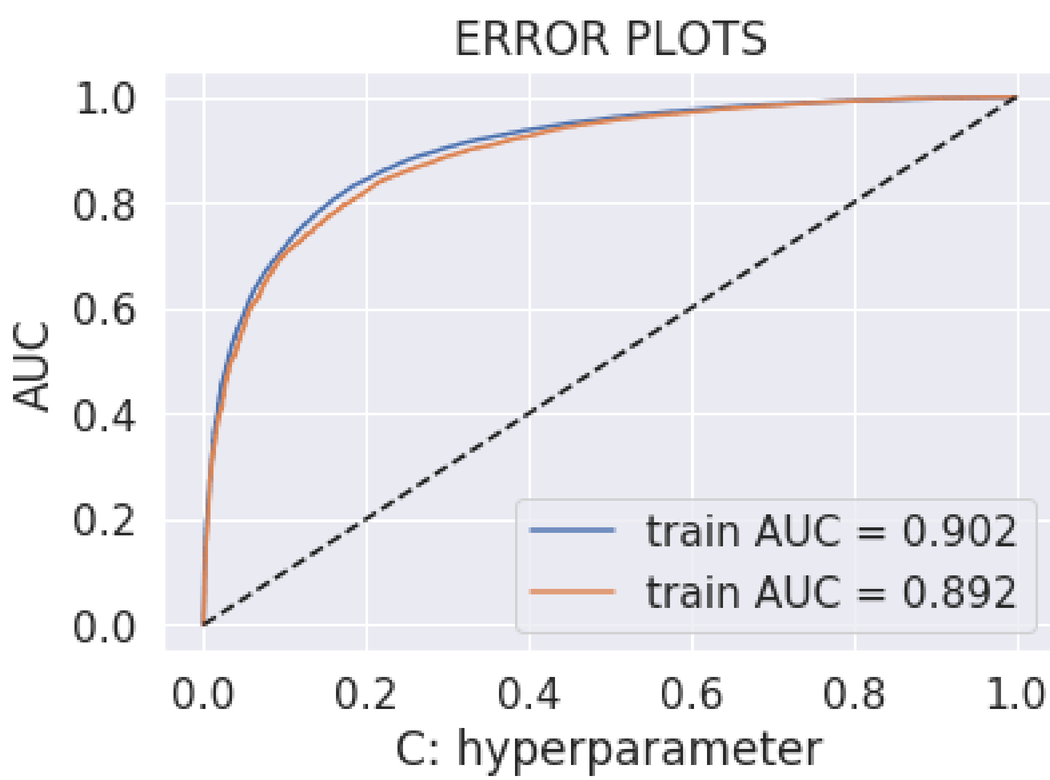
In [169]:
```
c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_regr

optimal_c_bow1 = optimal_c

print('The optimal C is {}' .format(optimal_c))

train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

# log_reg_optimal = log_reg_optimal(optimal_c, 'l1', False)
log_reg_optimal = LogisticRegression(penalty='l1', dual=False, C=optimal_c)


retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.1
```






```
In [170]: tfidfw2v_auc1 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```

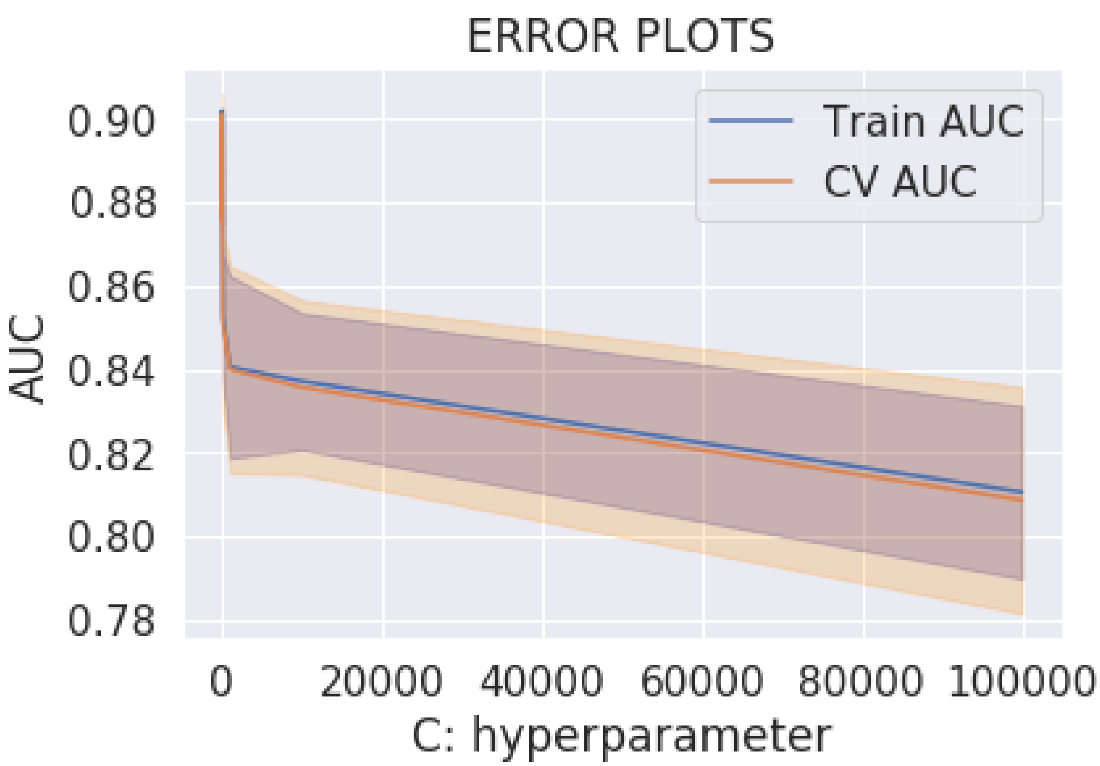


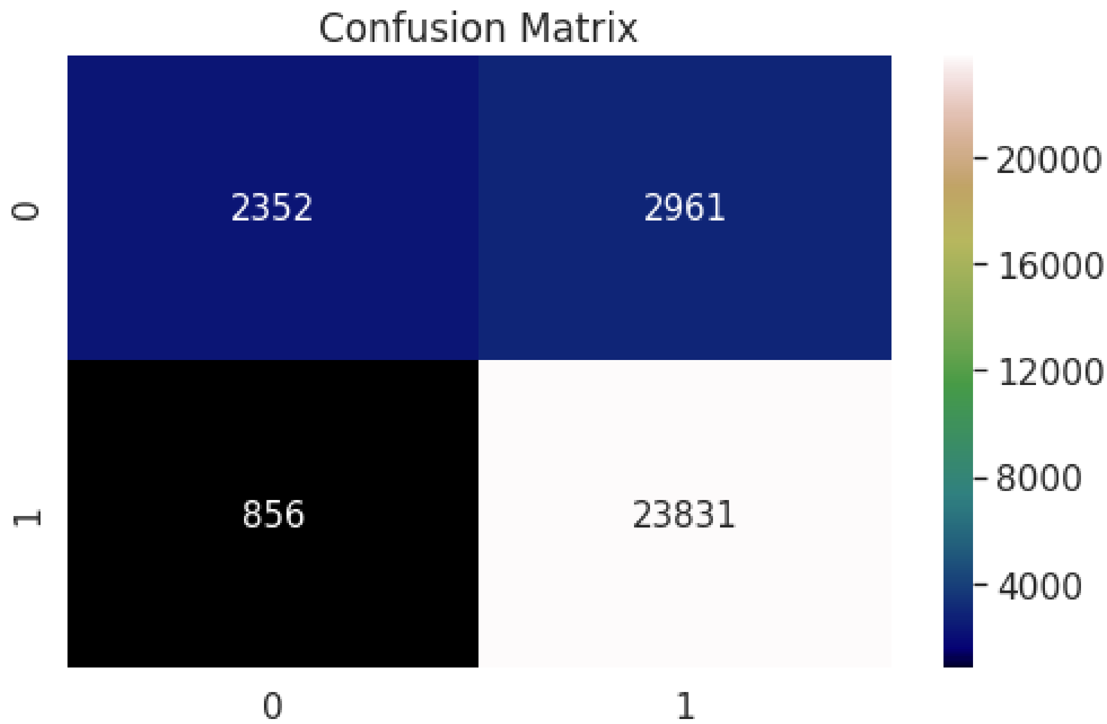
7.4.2 [5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

```
In [171]: # Please write all the code with proper documentation
```

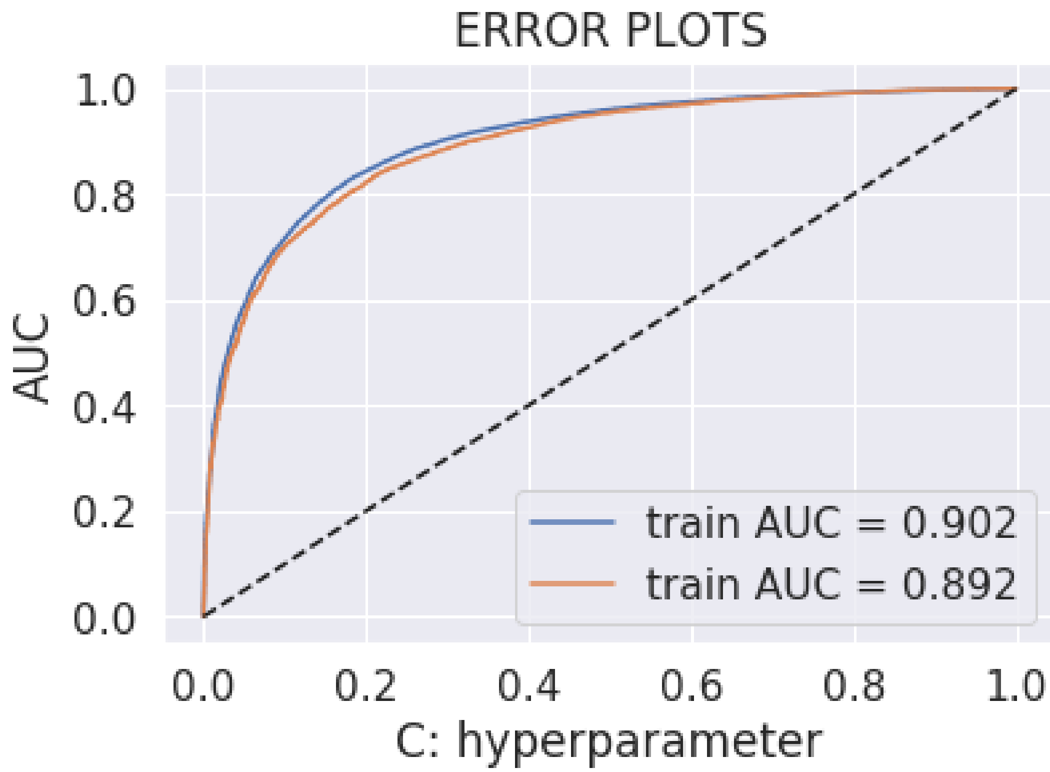
```
In [172]: c_values = [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4,10**
          clf, optimal_c, train_auc, train_auc_std, cv_auc, cv_auc_std = applying_logistic_reg

          optimal_c_bow1 = optimal_c

          print('The optimal C is {}' .format(optimal_c))

          train_cv_error_plot(train_auc, train_auc_std, cv_auc, cv_auc_std)

          # log_reg_optimal = log_reg_optimal(optimal_c, 'l2', True)
          log_reg_optimal = LogisticRegression(penalty='l2', dual=True, C=optimal_c)


          retrain_log_reg(log_reg_optimal, train_vect, y_train, test_vect, y_test)

          cm_fig(log_reg_optimal, y_test, test_vect)
```

```
The optimal C is 0.1
```






```
In [173]: tfidfw2v_auc2 = error_plot(log_reg_optimal, train_vect, y_train, test_vect, y_test)
```



8 [6] Conclusions

```
In [174]: # Please compare all your models using Prettytable library
```