05affrlr

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1 Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

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

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

2 [1]. Reading Data

2.1 [1.1] Loading the data

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

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

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

In [61]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from prettytable import PrettyTable
from matplotlib import mlab
```

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

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

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 1000

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

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (100000, 10)
```

Out[2]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      1  1303862400
1                     0                       0      0  1346976000
2                     1                       1      1  1219017600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
```

In [3]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
```

```
        HAVING COUNT(*)>1
        """, con)
```

```
In [4]: print(display.shape)
        display.head()
```

```
(80668, 7)
```

```
Out[4]:                  UserId   ProductId             ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
        3  #oc-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]: 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]: display['COUNT(*)'].sum()
```

```
Out[6]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

```
In [7]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
```

```
Out[7]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
        1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
        2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
        3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
        4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2

           HelpfulnessDenominator  Score        Time  \
        0                       2      5  1199577600
        1                       2      5  1199577600
        2                       2      5  1199577600
        3                       2      5  1199577600
        4                       2      5  1199577600

                                     Summary  \
        0  LOACKER QUADRATINI VANILLA WAFERS
        1  LOACKER QUADRATINI VANILLA WAFERS
        2  LOACKER QUADRATINI VANILLA WAFERS
        3  LOACKER QUADRATINI VANILLA WAFERS
        4  LOACKER QUADRATINI VANILLA WAFERS

                                                        Text
        0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

```
In [8]: #Sorting data according to ProductId in ascending order
        sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

```
In [9]: #Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
        final.shape
```

Out[9]: (87775, 10)

In [10]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[10]: 87.775

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[11]:
```
      Id   ProductId          UserId              ProfileName  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     3                       1      5  1224892800
1                     3                       2      4  1212883200

                                 Summary  \
0            Bought This for My Son at College
1  Pure cocoa taste with crunchy almonds inside

                                          Text
0  My son loves spaghetti so I didn't hesitate or...
1  It was almost a 'love at first bite' - the per...
```

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(87773, 10)
```

Out[13]:
```
1    73592
0    14181
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

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

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

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

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

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

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

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

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

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

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

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

        print(sent_0)
```

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

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

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

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

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

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

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

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

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

            # general
            phrase = re.sub(r"n\'t", " not", phrase)
```

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

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

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

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

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

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

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

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

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

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

```
In [22]: # 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%|| 87773/87773 [00:28<00:00, 3093.88it/s]
```

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

```
Out[23]: 'way hot blood took bite jig lol'
```

5 [4] Splitting the data

```
In [23]: X = preprocessed_reviews
         Y = final['Score'].values
```

```
In [24]: #from sklearn.model_selection import train_test_split

         # Here we are splitting the data(X ,Y) into train, cross-validation and test data
         # X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, shuffle=F
         X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.30) # this is r
         X_train, X_cv, Y_train, Y_cv     = train_test_split(X_train, Y_train, test_size=0.30)
```

6 [4] Featurization

6.1 [4.1] BAG OF WORDS

```
In [25]: #BoW
         vectorizerb = CountVectorizer(min_df = 10)
         vectorizerb.fit(X_train) # fit has to happen only on train data
         print(vectorizerb.get_feature_names()[:20])# printing some feature names
         print("="*50)

         # we use the fitted CountVectorizer to convert the text to vector
```

```
X_train_bow = vectorizerb.transform(X_train)
X_cv_bow = vectorizerb.transform(X_cv)
X_test_bow = vectorizerb.transform(X_test)


print("After vectorizations")
print(X_train_bow.shape, Y_train.shape)
print(X_cv_bow.shape, Y_cv.shape)
print(X_test_bow.shape, Y_test.shape)
print("="*100)

print("the type of count vectorizer ")
print(type(X_train_bow))
print(type(X_cv_bow))
print(type(X_test_bow))
```

```
['aa', 'aafco', 'ability', 'able', 'absence', 'absent', 'absolute', 'absolutely', 'absolutly',
==================================================
After vectorizations
(43008, 8101) (43008,)
(18433, 8101) (18433,)
(26332, 8101) (26332,)
==========================================================================================
the type of count vectorizer
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
```

6.2 [4.3] TF-IDF

In [26]:
```
tfidf_vect = TfidfVectorizer(min_df=10)
tfidf_vect.fit(X_train)
print("some sample features ",tfidf_vect.get_feature_names()[0:10])
print('='*50)

# we use the fitted CountVectorizer to convert the text to vector
X_train_tfidf = tfidf_vect.transform(X_train)
X_cv_tfidf = tfidf_vect.transform(X_cv)
X_test_tfidf = tfidf_vect.transform(X_test)

print("After vectorizations")
print(X_train_tfidf.shape, Y_train.shape)
print(X_cv_tfidf.shape, Y_cv.shape)
print(X_test_tfidf.shape, Y_test.shape)
print("="*100)

print("the type of count vectorizer ")
```

```
print(type(X_train_tfidf))
print(type(X_cv_tfidf))
print(type(X_test_tfidf))
```

```
some sample features  ['aa', 'aafco', 'ability', 'able', 'absence', 'absent', 'absolute', 'abso
==================================================
After vectorizations
(43008, 8101) (43008,)
(18433, 8101) (18433,)
(26332, 8101) (26332,)
====================================================================================================
the type of count vectorizer
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
```

6.3 [4.4] Word2Vec

In [83]:
```
# Train your own Word2Vec model using your own text corpus
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
```

In [84]:
```
# this line of code trains your w2v model on the give list of sentances, fitting the 
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=-1)
```

In [85]:
```
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  12469
sample words  ['beagles', 'love', 'food', 'little', 'worried', 'reading', 'reviews', 'weight',
```

6.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

6.4.1 Converting Train data text

In [86]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this lis
for sent in tqdm(list_of_sentance_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
        sent_vectors_train.append(sent_vec)
    sent_vectors_train = np.array(sent_vectors_train)
    print(sent_vectors_train.shape)
    print(sent_vectors_train[0])
```

```
100%|| 43008/43008 [01:51<00:00, 386.52it/s]


(43008, 50)
[-9.20977168e-04 -2.62901402e-04 -1.24378716e-03 -1.57319791e-04
  5.98810116e-05  1.08551165e-03 -5.28792135e-04 -8.77466923e-04
 -1.53270885e-03  8.66955069e-05 -2.46861111e-04  1.87352263e-04
  5.59329896e-04 -7.12459862e-04 -3.87754817e-04  8.75376305e-04
 -2.40781712e-04 -9.24346357e-04  6.34178550e-04 -9.28385325e-04
 -1.84821904e-05 -1.13730007e-03  8.22906492e-04  1.83632819e-03
 -7.27313156e-04 -1.01738588e-04 -6.70573247e-04 -1.83118674e-03
  1.19111032e-03 -1.50023999e-03  4.39717542e-04 -2.23893134e-03
  1.09100041e-03  5.31805423e-05 -8.47370467e-04 -3.36606106e-04
 -1.57798268e-03 -2.20810941e-04  7.00341833e-05 -1.75991464e-04
  9.68675361e-04  1.88565005e-03  8.69625657e-04  8.12293115e-05
 -5.80354220e-04  1.80386371e-04  8.15080039e-04 -1.95798032e-03
 -6.17218626e-04 -5.33464381e-04]
```

6.4.2 Converting CV data set

```
In [87]: list_of_sentance_cv=[]
         for sentance in X_cv:
             list_of_sentance_cv.append(sentance.split())
```

```
In [88]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(list_of_sentance_cv): # 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
             sent_vectors_cv.append(sent_vec)
```

```
sent_vectors_cv = np.array(sent_vectors_cv)
print(sent_vectors_cv.shape)
print(sent_vectors_cv[0])
```

```
100%|| 18433/18433 [00:48<00:00, 380.27it/s]


(18433, 50)
[ 6.36758921e-04 -3.22297540e-03 -3.52984840e-03 -8.19505138e-04
 -5.37860698e-04  5.59060294e-04 -1.40478836e-03 -2.10203056e-04
  1.65505802e-04  1.95176308e-04 -1.99217785e-03 -6.27172298e-05
  6.06064506e-04  7.52241529e-04  1.34496103e-04 -7.23200499e-04
  1.08443266e-03 -1.43231591e-04  2.71784125e-03 -1.54025779e-03
 -1.16689521e-03  1.96472277e-03  1.71092739e-03  2.44592261e-04
  1.33712294e-03 -8.94514981e-05 -3.93841068e-05  7.96984482e-04
  7.66680040e-04  1.85681255e-03  2.97937979e-03 -7.53948775e-04
 -1.52100524e-03  6.65586482e-04  8.65623346e-04  1.00250211e-03
  5.97029392e-04 -1.18704038e-03  1.19535701e-03  1.35434439e-03
  5.34404951e-05 -8.11878755e-04  5.40677252e-04 -9.82659950e-04
  5.69844500e-04 -8.92694997e-04  2.87000999e-04  1.42793218e-03
 -1.45332540e-03 -1.10055001e-03]
```

6.4.3 Converting Test data set

```
In [89]: list_of_sentance_test=[]
         for sentance in X_test:
             list_of_sentance_test.append(sentance.split())
```

```
In [90]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(list_of_sentance_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
             sent_vectors_test.append(sent_vec)
         sent_vectors_test = np.array(sent_vectors_test)
         print(sent_vectors_test.shape)
         print(sent_vectors_test[0])
```

```
100%|| 26332/26332 [01:09<00:00, 378.46it/s]
```

```
(26332, 50)
[-1.59844072e-03  7.58379172e-04 -1.78729943e-04  1.23153026e-04
 -1.23894293e-04  2.01177212e-03  8.48205265e-04  2.20336647e-03
  2.67048531e-04 -1.20540381e-03  2.70881126e-03 -3.35108475e-04
  2.67536770e-03  5.54078483e-04  3.45815244e-05 -9.58713987e-04
 -2.51264600e-04  2.01500967e-04 -4.45649266e-04 -8.65552607e-04
  6.89085869e-04  8.47349834e-04  1.91838075e-03  1.57579691e-03
  1.82565583e-03  1.62166423e-04  7.36111102e-04  2.71051938e-04
  4.74309934e-04  1.71959211e-03  2.41457570e-04  1.48060523e-03
 -3.15647163e-04 -9.15031543e-05  1.75016316e-03 -3.26641760e-04
  9.33087640e-04  9.84536942e-04 -5.69839848e-04  7.45966225e-04
  6.92062489e-04  2.53437213e-04 -1.72437280e-03 -5.73539320e-04
 -1.41352436e-04 -1.04494459e-03 -5.86548941e-04 -1.26160682e-03
  2.51154052e-03 -1.11418288e-03]
```

[4.4.1.2] TFIDF weighted W2v

6.4.4 Converting train data set

In [91]:
```python
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix_train = 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_)))
```

In [92]:
```python
# 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_train = []; # the tfidf-w2v for each sentence/review is stored in
row=0;
for sent in tqdm(list_of_sentance_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
```

```
        tfidf_sent_vectors_train.append(sent_vec)
        row += 1
```

```
100%|| 43008/43008 [19:37<00:00, 32.03it/s]
```

6.4.5 Converting CV data set

```
In [93]: # 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_cv = []; # the tfidf-w2v for each sentence/review is stored in thi
         row=0;
         for sent in tqdm(list_of_sentance_cv): # 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_cv.append(sent_vec)
             row += 1
```

```
100%|| 18433/18433 [05:06<00:00, 60.07it/s]
```

6.4.6 Converting Test data set

```
In [94]: # 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_test = []; # the tfidf-w2v for each sentence/review is stored in th
         row=0;
         for sent in tqdm(list_of_sentance_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
        tfidf_sent_vectors_test.append(sent_vec)
        row += 1
```

```
100%|| 26332/26332 [05:42<00:00, 76.98it/s]
```

7 [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.

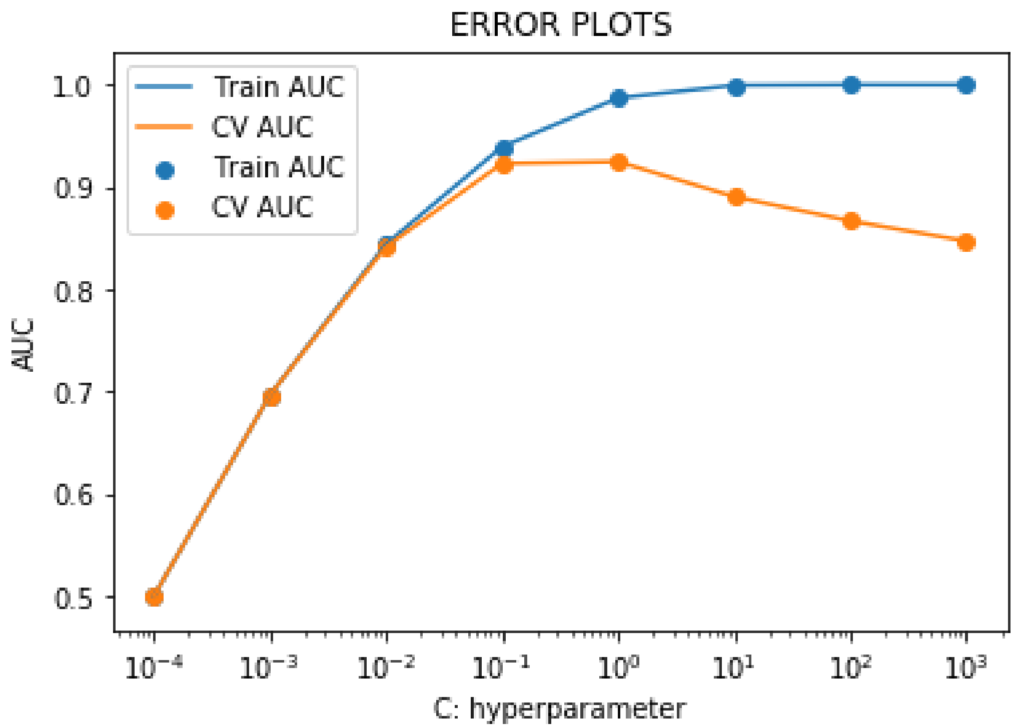
8 Applying Logistic Regression

8.1 [5.1] Logistic Regression on BOW, SET 1

8.1.1 [5.1.1] Applying Logistic Regression with L1 regularization on BOW, SET 1

8.2 Hyperparameter tuning using GridSearch

In [27]:
```
#clf = LogisticRegression()
C = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
parameters = {'C':[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
grid = GridSearchCV(LogisticRegression(penalty = 'l1'), parameters, cv=3, scoring='ro
grid.fit(X_train_bow, Y_train)

#a = grid.best_params_
best_c = grid.best_params_.get('C')

train_auc_bow = grid.cv_results_['mean_train_score']
cv_auc_bow = grid.cv_results_['mean_test_score']

plt.plot(C, train_auc_bow, label='Train AUC')
plt.scatter(C, train_auc_bow, label='Train AUC')
plt.plot(C, cv_auc_bow, label='CV AUC')
plt.scatter(C, cv_auc_bow, label='CV AUC')

plt.legend()
plt.xscale('log')
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [28]:
```
print(best_c)
```

1

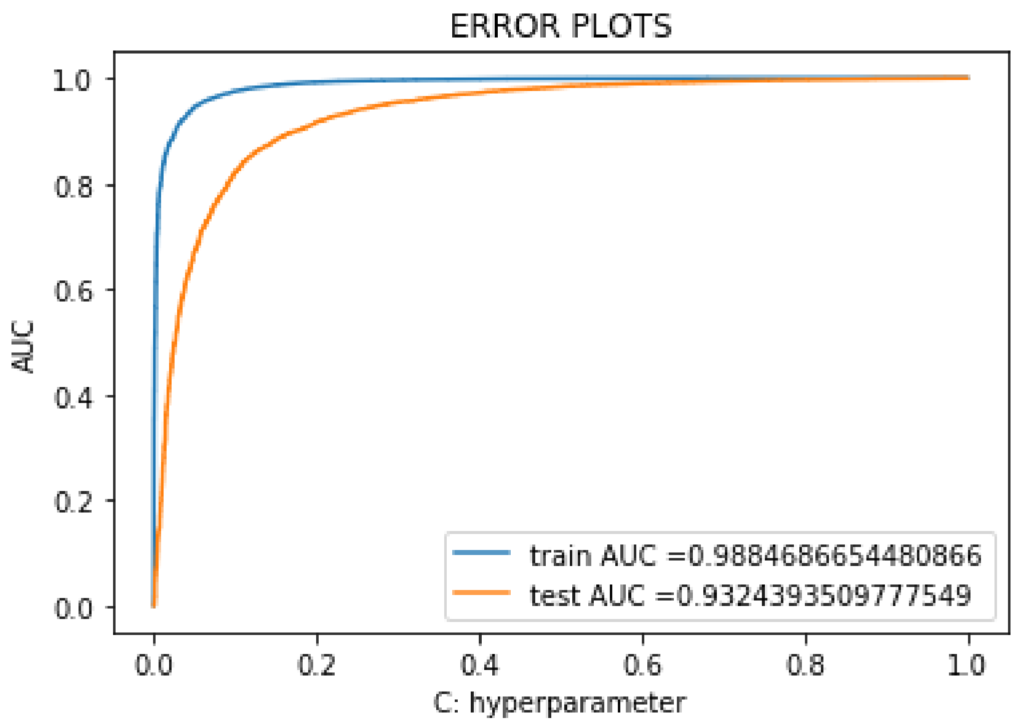
In [29]:
```
print(grid.best_estimator_)
```

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

8.3 Testing with Testing data

In [30]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sk

clf = LogisticRegression()
clf.fit(X_train_bow, Y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
# not the predicted outputs

train_fpr_bow, train_tpr_bow, thresholds_bow = roc_curve(Y_train, clf.predict_proba(X_
test_fpr_bow, test_tpr_bow, thresholds_bow = roc_curve(Y_test, clf.predict_proba(X_tes
```

```
plt.plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, trai
plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tp
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



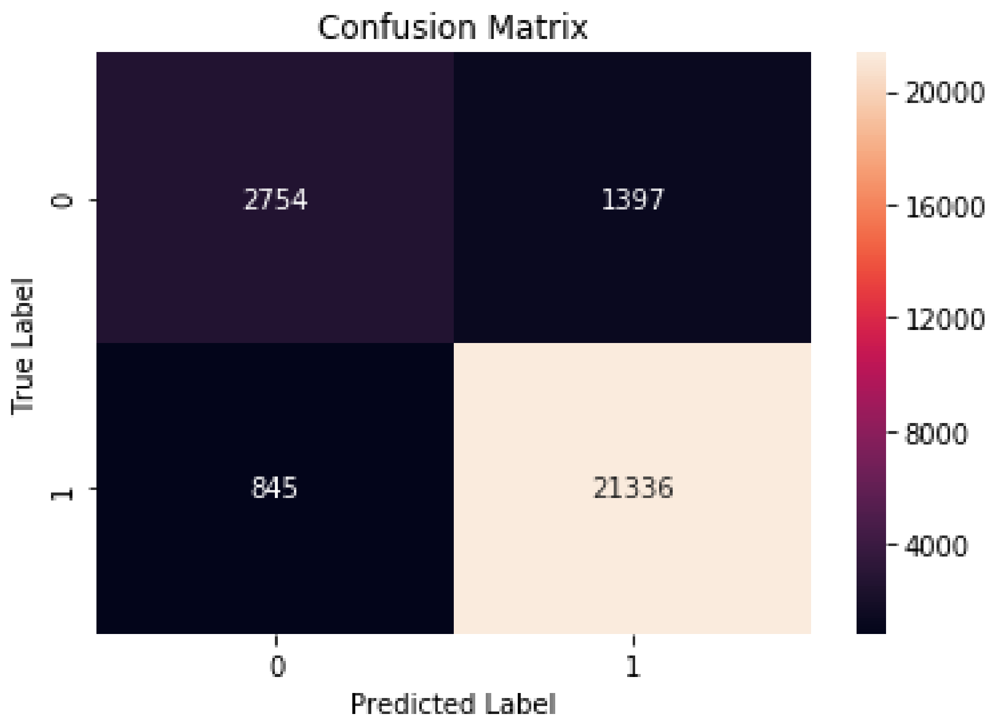
8.3.1 Calculating Accuracy, Precision, Recall & F1

```
In [76]: #L1 Regularizer
         clf = LogisticRegression(C = 1, penalty='l1')

         clf.fit(X_train_bow,Y_train)

         predl1 = clf.predict(X_test_bow)

         accb1 = accuracy_score(Y_test, predl1) * 100
         preb1 = precision_score(Y_test, predl1) * 100
         recb1 = recall_score(Y_test, predl1) * 100
         f1b1 = f1_score(Y_test, predl1) * 100
```

```
print("Accuracy : " + str(accb1))
print("Precision : " + str(preb1))
print("Recall : "+ str(recb1))
print("F1 : " + str(f1b1))
```

```
Accuracy : 91.4818471821358
Precision : 93.85062021641593
Recall : 96.1904332536856
F1 : 95.00612267616609
```

```
In [32]: cm = confusion_matrix(Y_test,predl1)
         sns.heatmap(cm, annot=True,fmt='d')
         plt.title('Confusion Matrix')
         plt.ylabel('True Label')
         plt.xlabel('Predicted Label')
         plt.show()
```



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

```
In [33]: # Please write all the code with proper documentation
         clf = LogisticRegression(C=100, penalty='l1')
         clf.fit(X_train_bow, Y_train)
```

```
s1 = np.count_nonzero(clf.coef_)
print(np.count_nonzero(clf.coef_))
print(clf.coef_)
```

```
7063
[[ 0.          0.          0.         ...  7.58361217 -1.80794967
   0.        ]]
```

```
In [34]: clf = LogisticRegression(C=0.1, penalty='l1')
         clf.fit(X_train_bow, Y_train)

         s2 = np.count_nonzero(clf.coef_)
         print(np.count_nonzero(clf.coef_))
         print(clf.coef_)
```

```
728
[[0. 0. 0. ... 0. 0. 0.]]
```

```
In [35]: clf = LogisticRegression(C=0.01, penalty='l1')
         clf.fit(X_train_bow, Y_train)

         s3 = np.count_nonzero(clf.coef_)
         print(np.count_nonzero(clf.coef_))
         print(clf.coef_)
```

```
91
[[0. 0. 0. ... 0. 0. 0.]]
```

```
In [36]: clf = LogisticRegression(C=0.001, penalty='l1')
         clf.fit(X_train_bow, Y_train)

         s4 = np.count_nonzero(clf.coef_)
         print(np.count_nonzero(clf.coef_))
         print(clf.coef_)
```

```
3
[[0. 0. 0. ... 0. 0. 0.]]
```

```
In [100]: name= ["GRID", "GRID"]
          c= [100,0.1,0.01,0.001]
          s=[s1,s2,s3,s4]


          #Initialize Prettytable
          ptable = PrettyTable()
```

```
ptable.add_column("C", c)
ptable.add_column("Sparsity", s)


print(ptable)
```

```
+--------+----------+
|   C    | Sparsity |
+--------+----------+
|  100   |   7063   |
|  0.1   |   728    |
|  0.01  |    91    |
| 0.001  |    3     |
+--------+----------+
```

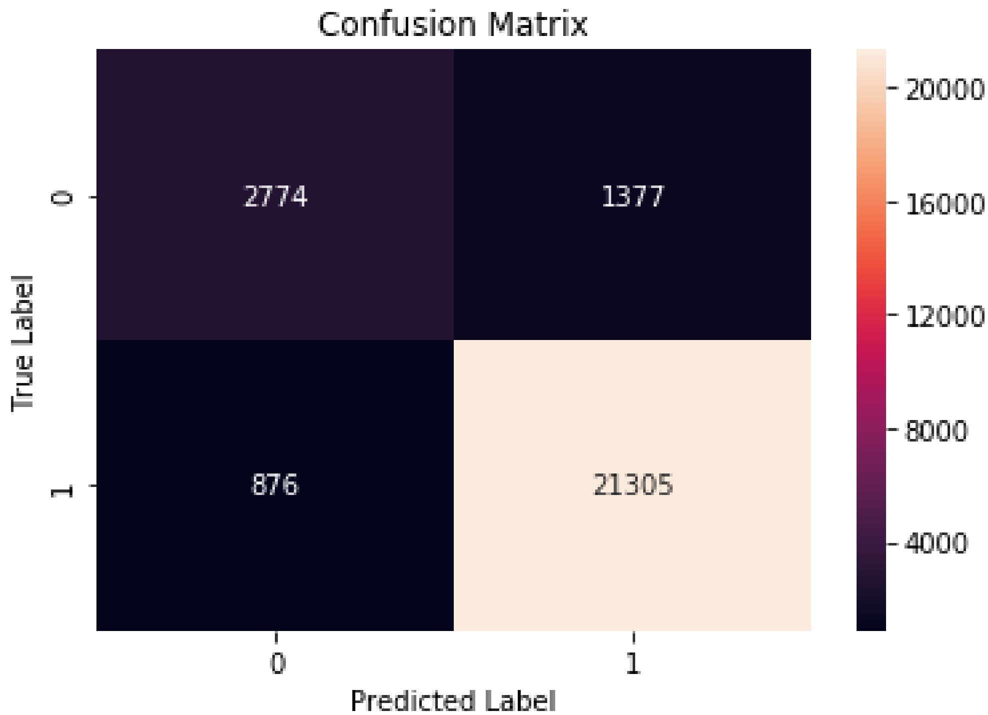
8.3.2 [5.1.2] Applying Logistic Regression with L2 regularization on BOW, SET 1

8.3.3 Calculating Accuracy, Precision, Recall & F1

```
In [77]: # L2 Regularizer
         clf = LogisticRegression(C = 1, penalty='l2')

         clf.fit(X_train_bow,Y_train)

         predl2 = clf.predict(X_test_bow)

         accb2 = accuracy_score(Y_test, predl2) * 100
         preb2 = precision_score(Y_test, predl2) * 100
         recb2 = recall_score(Y_test, predl2) * 100
         f1b2 = f1_score(Y_test, predl2) * 100


         print("Accuracy : " + str(accb2))
         print("Precision : " + str(preb2))
         print("Recall : "+ str(recb2))
         print("F1 : " + str(f1b2))
```

```
Accuracy : 91.44387057572536
Precision : 93.92910678070717
Recall : 96.0506740002705
F1 : 94.97804426810511
```

```
In [39]: cm = confusion_matrix(Y_test,predl2)
         sns.heatmap(cm, annot=True,fmt='d')
         plt.title('Confusion Matrix')
         plt.ylabel('True Label')
         plt.xlabel('Predicted Label')
         plt.show()
```




```
In [78]: # Please compare all your models using Prettytable library
         name= ["GRID", "GRID"]
         reg= ["L1","L2"]
         acc= [accb1,accb2]
         pre= [preb1,preb2]
         rec= [recb1,recb2]
         f1= [f1b1,f1b2]


         #Initialize Prettytable
         ptable = PrettyTable()
         ptable.add_column("Hyperparameter", name)
         ptable.add_column("Regularizer", reg)
         ptable.add_column("Accuracy%", acc)
         ptable.add_column("Precision%", pre)
         ptable.add_column("Recall%", rec)
         ptable.add_column("F1%", f1)

         print(ptable)
```

```
+----------------+-------------+-------------------+-------------------+-------------------+---
| Hyperparameter | Regularizer |     Accuracy%     |     Precision%    |      Recall%      |
+----------------+-------------+-------------------+-------------------+-------------------+---
|      GRID      |      L1     | 91.4818471821358  | 93.85062021641593 | 96.1904332536856  | 95
```

```
|      GRID       |      L2      | 91.44387057572536 | 93.92910678070717 | 96.0506740002705 | 94
+----------------+-------------+--------------------+--------------------+------------------+---
```

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

```
In [41]: #Weights before adding noise
         old_weg = clf.coef_[0]
         print(old_weg)

         X_train_noise = X_train_bow.todense()

         #Adding noise
         X_train_noise_t = X_train_noise.astype('float64')
         X_train_noise_t += 0.01
         print(X_train_noise_t)

         #Training model with noisy data
         clf = LogisticRegression(C = 1 , penalty='l2')
         clf.fit(X_train_noise_t,Y_train)

         #Weights after adding noise
         new_weg = clf.coef_[0]
         print(new_weg)
         print(new_weg.size)
```

```
[-0.12452753  0.01725924  0.52043825 ...  0.18088959  0.28956795
  0.10230405]
[[0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 ...
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]
 [0.01 0.01 0.01 ... 0.01 0.01 0.01]]
[-0.12769705  0.01579193  0.521005   ...  0.17928473  0.2892642
  0.10011302]
8101
```

```
In [54]: difference = (abs((old_weg-new_weg)/old_weg))*100
         print(difference)
```

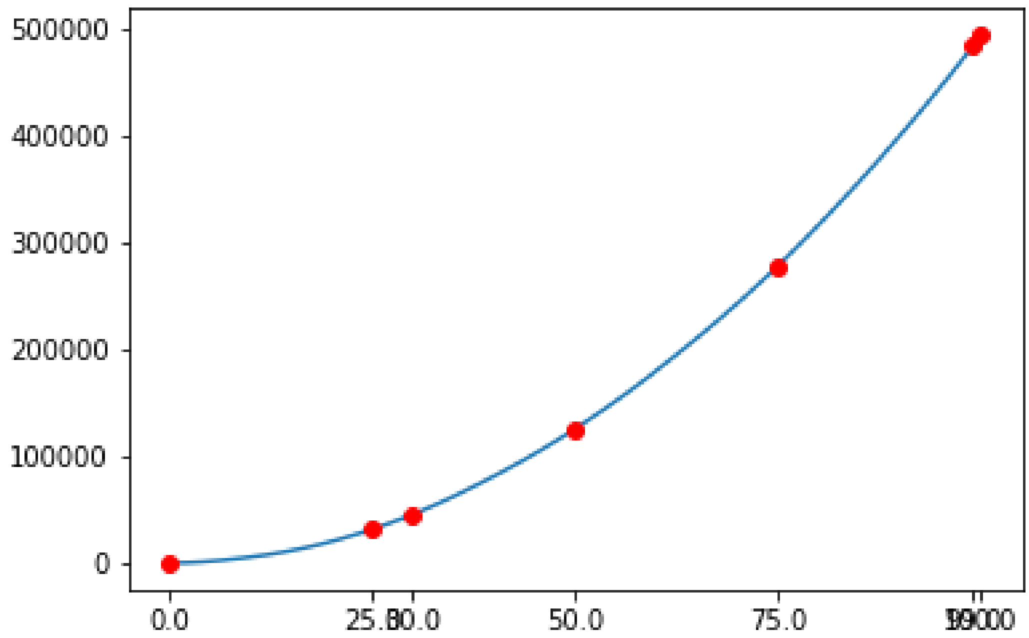
```
[2.54523744 8.50157227 0.10889994 ... 0.88720407 0.10489762 2.14168657]
```

```
In [53]: print(np.percentile(difference,90))
         print(np.percentile(difference,91))
         print(np.percentile(difference,94))
```

```
print(np.percentile(difference,97))
print(np.percentile(difference,98))
print(np.percentile(difference,99))
print(np.percentile(difference,99.1))
print(np.percentile(difference,99.2))
print(np.percentile(difference,99.4))
print(np.percentile(difference,99.6))
print(np.percentile(difference,99.7))
print(np.percentile(difference,99.8))
print(np.percentile(difference,99.9))
print(np.percentile(difference,100))
```

```
1.5665473336487306
1.73154770944275
2.603184161110672
4.817723279901305
7.992467002853713
14.665209613473754
16.674836319685518
17.759561807037173
26.070037505553437
45.25995779992553
60.87161889762165
100.6723207907454
254.11791579732613
9242.726249068579
```

In [66]:
```
#https://stackoverflow.com/questions/18153054/percentiles-on-x-axis-with-matplotlib
d = np.sort(np.random.randint(0,1000,1000)).cumsum()

# Percentile values
p = np.array([0.0, 25.0, 30.0, 50.0, 75.0, 99.0, 100.0])

perc = mlab.prctile(d, p=p)

plt.plot(d)
# Place red dots on the percentiles
plt.plot((len(d)-1) * p/100., perc, 'ro')

# Set tick locations and labels
plt.xticks((len(d)-1) * p/100., map(str, p))

plt.show()
```




```
In [69]: print(difference[np.where(difference > 25)].size)
```

```
51
```

8.3.4 [5.1.3] Feature Importance on BOW, SET 1

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

```
In [132]: # this code is copied from here:https://stackoverflow.com/questions/26976362/how-to-

          def most_informative_feature_for_binary_classification(vectorizer, classifier, n=10)
              class_labels = classifier.classes_
              feature_names = vectorizer.get_feature_names()
              topn_class1 = sorted(zip(classifier.coef_[0], feature_names))[-n:]


              for coef, feat in reversed(topn_class1):
                  print (class_labels[1], coef, feat)


          most_informative_feature_for_binary_classification(vectorizerb, clf)
```

```
1 2.8687310535917736 pleasantly
1 2.4082679631154256 satisfied
1 2.210133552371643 hooked
```

```
1 2.146384676901295 amazing
1 2.076545491015456 excellent
1 2.051208688613232 delicious
1 1.9052016062453565 yummy
1 1.8874359671304837 amazed
1 1.86098552839777 compares
1 1.7975113044415867 beat
```

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

```
In [133]: # this code is copied from here:https://stackoverflow.com/questions/26976362/how-to-

          def most_informative_feature_for_binary_classification(vectorizer, classifier, n=10)
              class_labels = classifier.classes_
              feature_names = vectorizer.get_feature_names()
              topn_class2 = sorted(zip(classifier.coef_[0], feature_names))[:n]

              for coef, feat in topn_class2:
                  print( class_labels[0], coef, feat)


          most_informative_feature_for_binary_classification(vectorizerb, clf)
```

```
0 -3.0923685890351136 worst
0 -2.4625352214614304 disappointment
0 -2.405131771995396 closely
0 -2.398231395243532 sounded
0 -2.3886624782949277 cancelled
0 -2.378952400379236 awful
0 -2.350115053095102 disappointing
0 -2.2960626229124586 hopes
0 -2.2693369354015647 terrible
0 -2.236787074732326 undrinkable
```

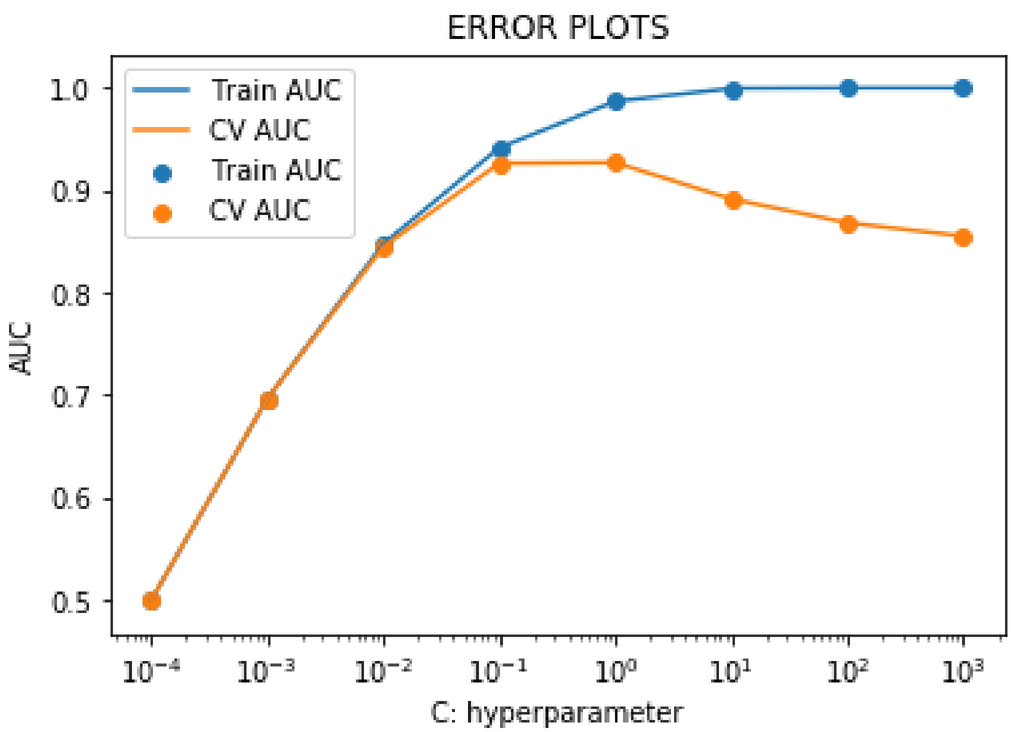
8.4 [5.2] Logistic Regression on TFIDF, SET 2

8.4.1 [5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

8.4.2 Hyperparameter tuning using GridSearch

```
In [134]: #clf = LogisticRegression()
          C = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
          parameters = {'C':[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
          grid = GridSearchCV(LogisticRegression(penalty = 'l1'), parameters, cv=3, scoring='r
          grid.fit(X_train_bow, Y_train)

          #a = grid.best_params_
```

```
best_c = grid.best_params_.get('C')

train_auc_tfidf = grid.cv_results_['mean_train_score']
cv_auc_tfidf = grid.cv_results_['mean_test_score']

plt.plot(C, train_auc_tfidf, label='Train AUC')
plt.scatter(C, train_auc_tfidf, label='Train AUC')
plt.plot(C, cv_auc_tfidf, label='CV AUC')
plt.scatter(C, cv_auc_tfidf, label='CV AUC')

plt.legend()
plt.xscale('log')
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```




```
In [135]: print(best_c)
```

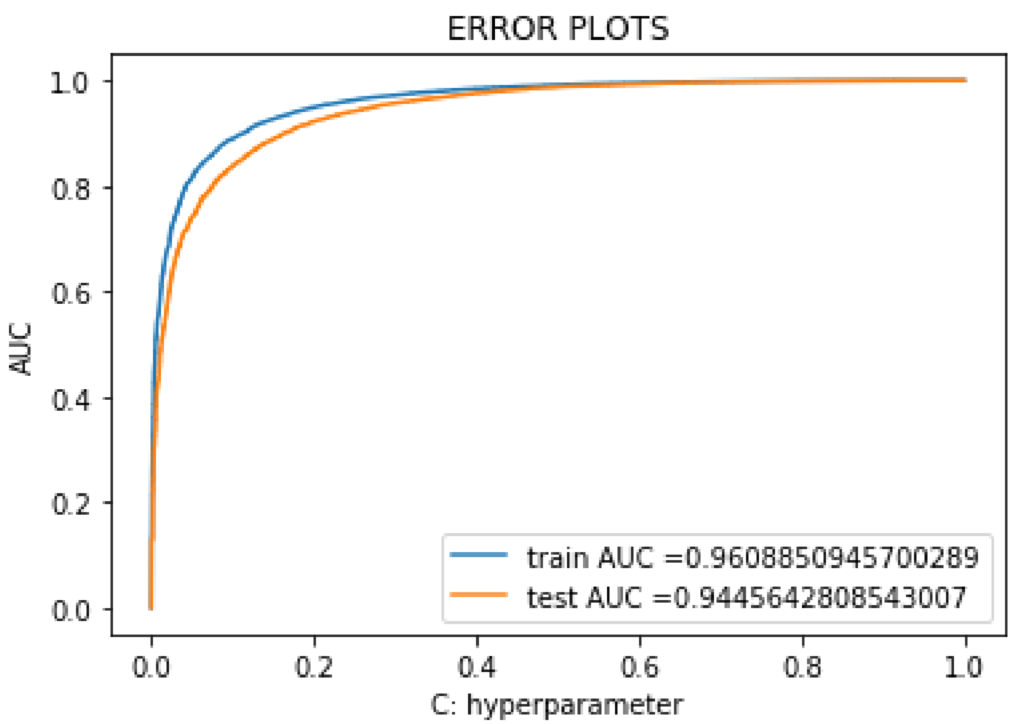
```
1
```

```
In [136]: print(grid.best_estimator_)
```

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

8.5 Testing with Test data

```
In [138]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#s

          clf = LogisticRegression(penalty='l1')
          clf.fit(X_train_tfidf, Y_train)
          # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates o
          # not the predicted outputs

          train_fpr_tfidf, train_tpr_tfidf, thresholds_tfidf = roc_curve(Y_train, clf.predict_
          test_fpr_tfidf, test_tpr_tfidf, thresholds_tfidf = roc_curve(Y_test, clf.predict_pro

          plt.plot(train_fpr_tfidf, train_tpr_tfidf, label="train AUC ="+str(auc(train_fpr_tfi
          plt.plot(test_fpr_tfidf, test_tpr_tfidf, label="test AUC ="+str(auc(test_fpr_tfidf,
          plt.legend()
          plt.xlabel("C: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```

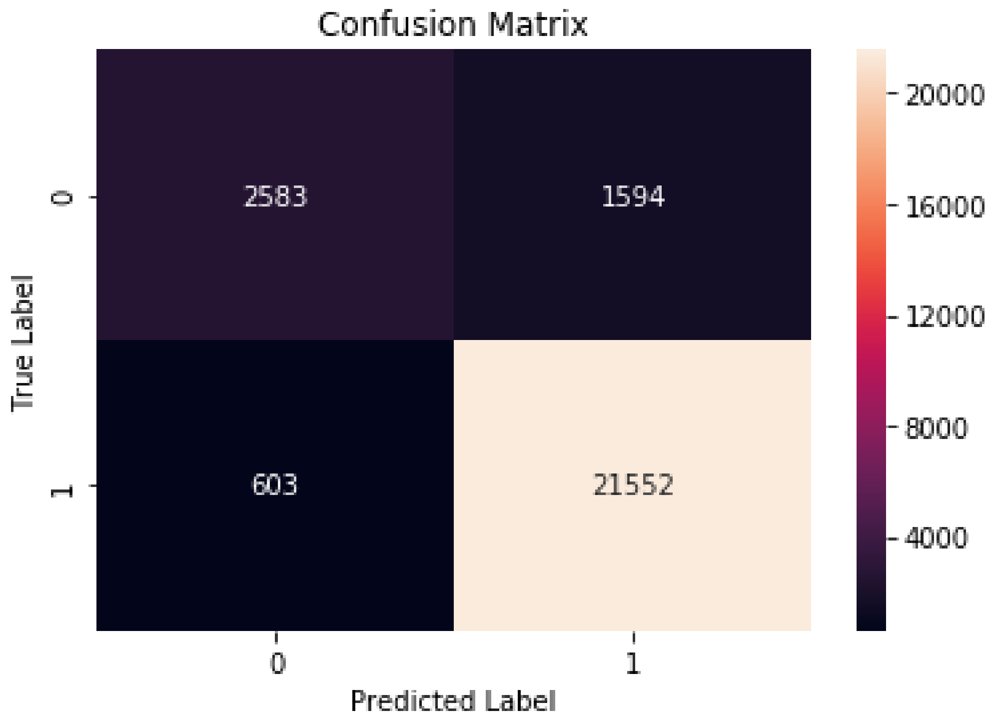


8.5.1 Calculating Accuracy, Precision, Recall & F1

```
In [79]: #L1 Regularizer
         clf = LogisticRegression(C = 1, penalty='l1')

         clf.fit(X_train_tfidf,Y_train)

         predt1 = clf.predict(X_test_tfidf)

         acct1 = accuracy_score(Y_test, predt1) * 100
         pret1 = precision_score(Y_test, predt1) * 100
         rect1 = recall_score(Y_test, predt1) * 100
         f1t1 = f1_score(Y_test, predt1) * 100


         print("Accuracy : " + str(acct1))
         print("Precision : " + str(pret1))
         print("Recall : "+ str(rect1))
         print("F1 : " + str(f1t1))
```

```
Accuracy : 91.77426705149628
Precision : 93.24575428892442
Recall : 97.28145710292593
F1 : 95.2208640395393
```

```
In [140]: cm = confusion_matrix(Y_test,predt1)
          sns.heatmap(cm, annot=True,fmt='d')
          plt.title('Confusion Matrix')
          plt.ylabel('True Label')
          plt.xlabel('Predicted Label')
          plt.show()
```



8.5.2 [5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

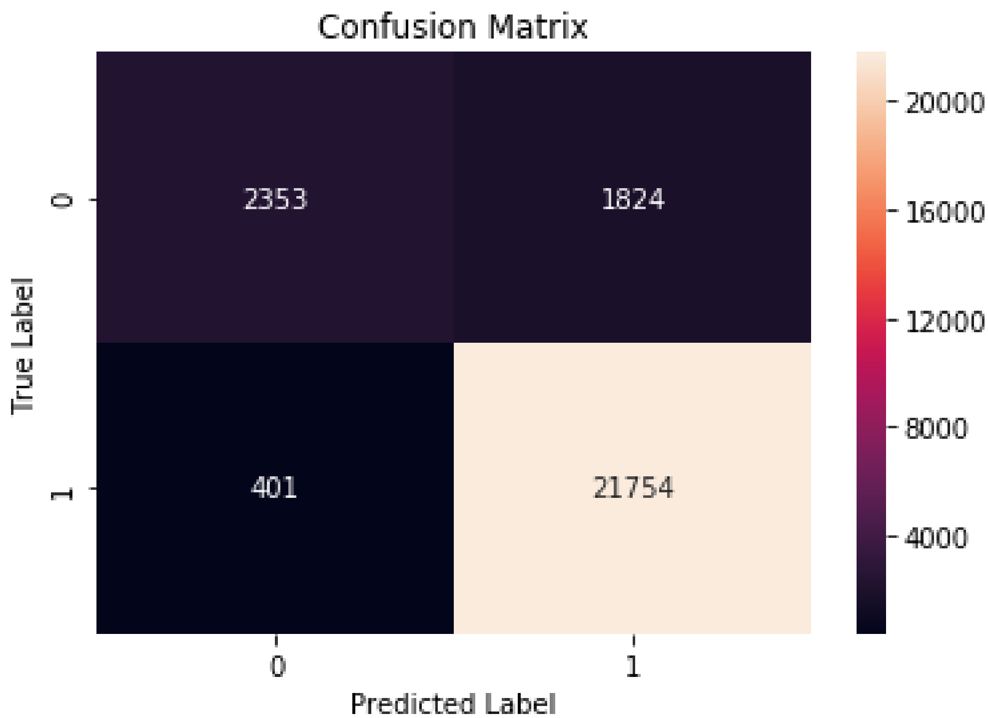
8.5.3 Calculating Accuracy, Precision, Recall & F1

```
In [80]: # L2 Regularizer
         clf = LogisticRegression(C = 1, penalty='l2')

         clf.fit(X_train_tfidf,Y_train)

         predt2 = clf.predict(X_test_tfidf)

         acct2 = accuracy_score(Y_test, predt2) * 100
         pret2 = precision_score(Y_test, predt2) * 100
         rect2 = recall_score(Y_test, predt2) * 100
         f1t2 = f1_score(Y_test, predt2) * 100


         print("Accuracy : " + str(acct2))
         print("Precision : " + str(pret2))
         print("Recall : "+ str(rect2))
         print("F1 : " + str(f1t2))
```

```
Accuracy : 91.69831383867538
Precision : 92.3928253402875
```

```
Recall : 98.23272169875118
F1 : 95.22331963989161
```

```
In [142]: cm = confusion_matrix(Y_test,predt2)
          sns.heatmap(cm, annot=True,fmt='d')
          plt.title('Confusion Matrix')
          plt.ylabel('True Label')
          plt.xlabel('Predicted Label')
          plt.show()
```



8.5.4 [5.2.3] Feature Importance on TFIDF, SET 2

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

```
In [144]: # this code is copied from here:https://stackoverflow.com/questions/26976362/how-to-

          def most_informative_feature_for_binary_classification(vectorizer, classifier, n=10)
              class_labels = classifier.classes_
              feature_names = vectorizer.get_feature_names()
              topn_class1 = sorted(zip(classifier.coef_[0], feature_names))[-n:]


              for coef, feat in reversed(topn_class1):
```

```
                print (class_labels[1], coef, feat)


        most_informative_feature_for_binary_classification(tfidf_vect, clf)
```

```
1 9.704297214578249 great
1 7.987935765742484 best
1 7.3283042837775545 delicious
1 6.192219042721783 perfect
1 5.780201538715221 nice
1 5.763099509902627 loves
1 5.755635831789511 good
1 5.719272092890176 excellent
1 5.457260900783352 love
1 5.2232073193425235 wonderful
```

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

In [143]:
```
# this code is copied from here:https://stackoverflow.com/questions/26976362/how-to-

def most_informative_feature_for_binary_classification(vectorizer, classifier, n=10)
    class_labels = classifier.classes_
    feature_names = vectorizer.get_feature_names()
    topn_class2 = sorted(zip(classifier.coef_[0], feature_names))[:n]

    for coef, feat in topn_class2:
        print( class_labels[0], coef, feat)


most_informative_feature_for_binary_classification(tfidf_vect, clf)
```

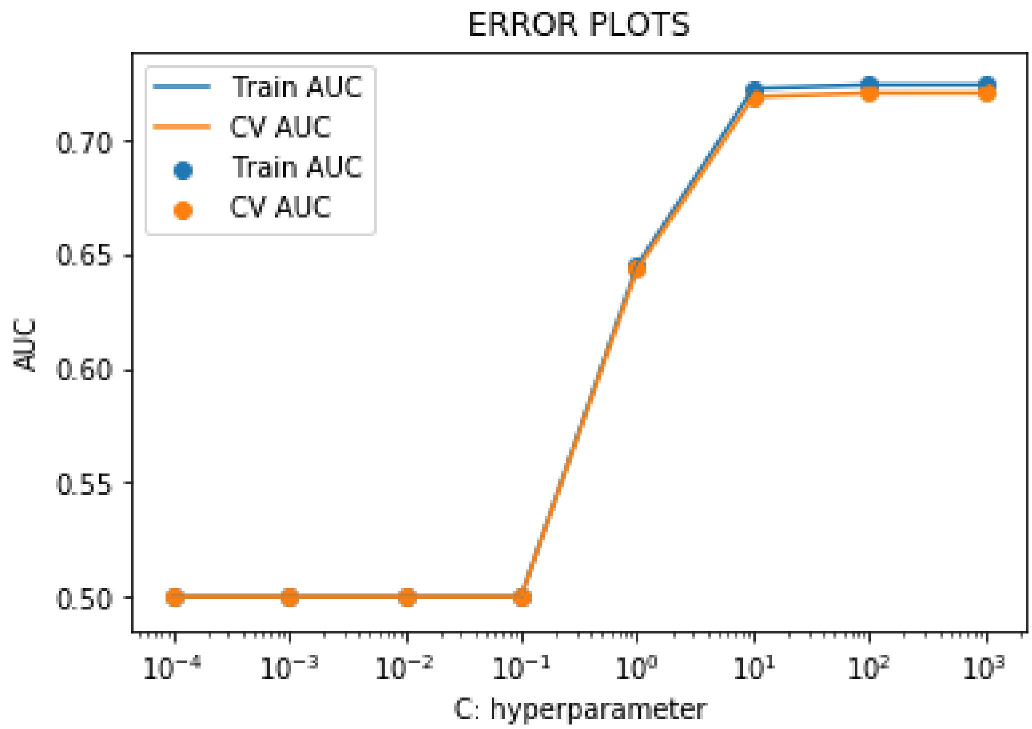
```
0 -6.985364410392888 not
0 -6.580207768799396 worst
0 -6.236374144075262 disappointed
0 -5.564541474219999 awful
0 -5.232906116688167 terrible
0 -5.152253527463616 horrible
0 -4.9229359910569634 disappointing
0 -4.788835329559626 disappointment
0 -4.547341320639886 unfortunately
0 -4.331842626836214 return
```

8.6 [5.3] Logistic Regression on AVG W2V, SET 3

8.6.1 [5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

8.7 Hyperparameter tuning with Train data

```
In [168]: #clf = LogisticRegression()
          C = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
          parameters = {'C':[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
          grid = GridSearchCV(LogisticRegression(penalty = 'l1'), parameters, cv=3, scoring='ro
          grid.fit(sent_vectors_train, Y_train)

          #a = grid.best_params_
          best_c = grid.best_params_.get('C')

          train_auc_aw2v = grid.cv_results_['mean_train_score']
          cv_auc_aw2v = grid.cv_results_['mean_test_score']

          plt.plot(C, train_auc_aw2v, label='Train AUC')
          plt.scatter(C, train_auc_aw2v, label='Train AUC')
          plt.plot(C, cv_auc_aw2v, label='CV AUC')
          plt.scatter(C, cv_auc_aw2v, label='CV AUC')

          plt.legend()
          plt.xscale('log')
          plt.xlabel("C: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```




```
In [170]: print(best_c)
```

```
1000
```

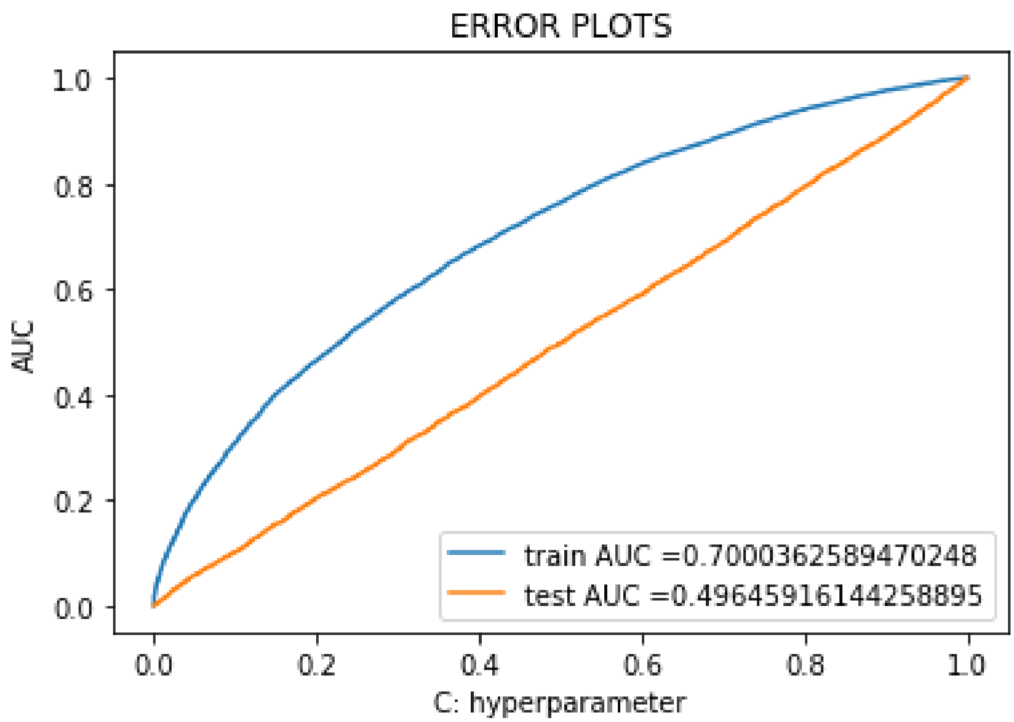
```
In [171]: print(grid.best_estimator_)
```

```
LogisticRegression(C=1000, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

8.8 Testing with Test data

```
In [176]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#s

          clf = LogisticRegression()
          clf.fit(sent_vectors_train, Y_train)
          # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates o
          # not the predicted outputs

          train_fpr_aw2v, train_tpr_aw2v, thresholds_aw2v = roc_curve(Y_train, clf.predict_prol
          test_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(Y_test, clf.predict_proba(s
```

```
plt.plot(train_fpr_aw2v, train_tpr_aw2v, label="train AUC ="+str(auc(train_fpr_aw2v,
plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, tes
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



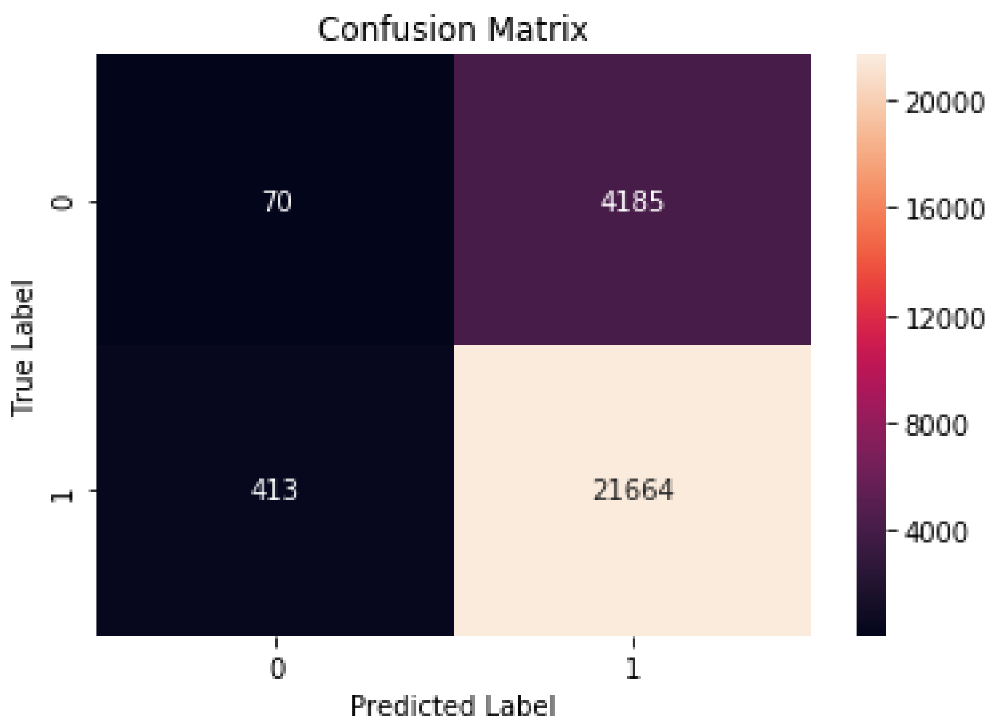
8.8.1 Calculating Accuracy, Precision, Recall & F1

```
In [95]: #L1 Regularizer
         clf = LogisticRegression(C = 1000, penalty='l1')

         clf.fit(sent_vectors_train,Y_train)

         predw1 = clf.predict(sent_vectors_test)

         acca1 = accuracy_score(Y_test, predw1) * 100
         prea1 = precision_score(Y_test, predw1) * 100
         reca1 = recall_score(Y_test, predw1) * 100
         f1a1 = f1_score(Y_test, predw1) * 100
```

```
print("Accuracy : " + str(acca1))
print("Precision : " + str(prea1))
print("Recall : "+ str(reca1))
print("F1 : " + str(f1a1))
```

```
Accuracy : 84.34984049825309
Precision : 84.92419554455446
Recall : 98.99463504801406
F1 : 91.42119616129234
```

```
In [178]: cm = confusion_matrix(Y_test,predw1)
          sns.heatmap(cm, annot=True,fmt='d')
          plt.title('Confusion Matrix')
          plt.ylabel('True Label')
          plt.xlabel('Predicted Label')
          plt.show()
```



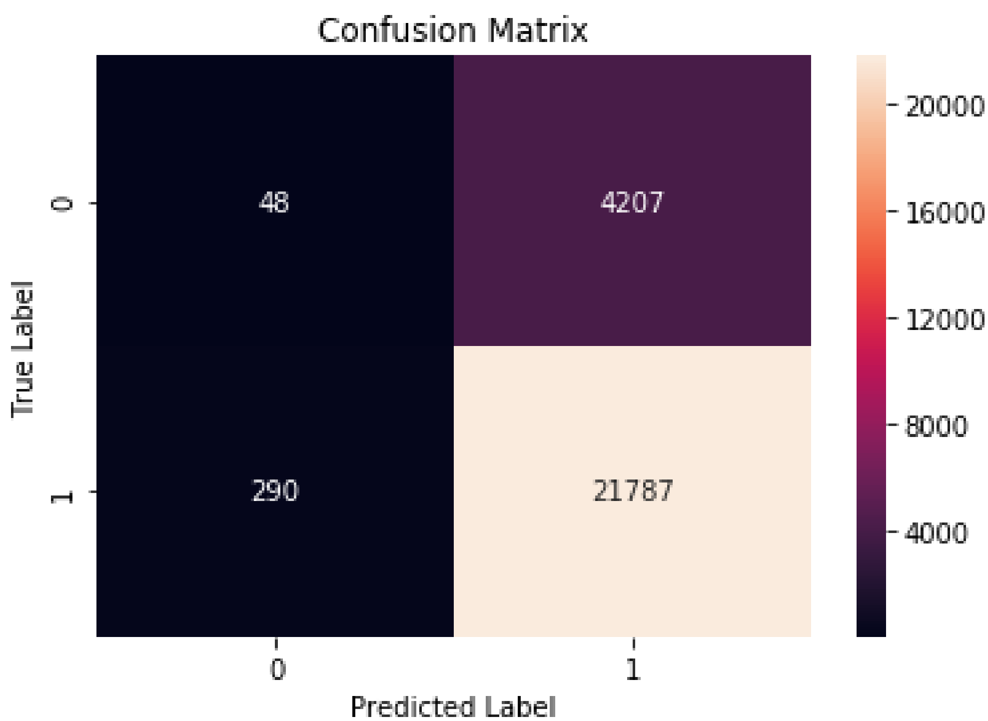
8.8.2 [5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

```
In [96]: #L1 Regularizer
         clf = LogisticRegression(C = 1000, penalty='l2')

         clf.fit(sent_vectors_train,Y_train)
```

```
predw2 = clf.predict(sent_vectors_test)

acca2 = accuracy_score(Y_test, predw2) * 100
prea2 = precision_score(Y_test, predw2) * 100
reca2 = recall_score(Y_test, predw2) * 100
f1a2 = f1_score(Y_test, predw2) * 100


print("Accuracy : " + str(acca2))
print("Precision : " + str(prea2))
print("Recall : "+ str(reca2))
print("F1 : " + str(f1a2))
```

```
Accuracy : 84.37262646209935
Precision : 84.76102516739783
Recall : 99.30120373292456
F1 : 91.45680652729047
```

```
In [181]: cm = confusion_matrix(Y_test,predw2)
          sns.heatmap(cm, annot=True,fmt='d')
          plt.title('Confusion Matrix')
          plt.ylabel('True Label')
          plt.xlabel('Predicted Label')
          plt.show()
```

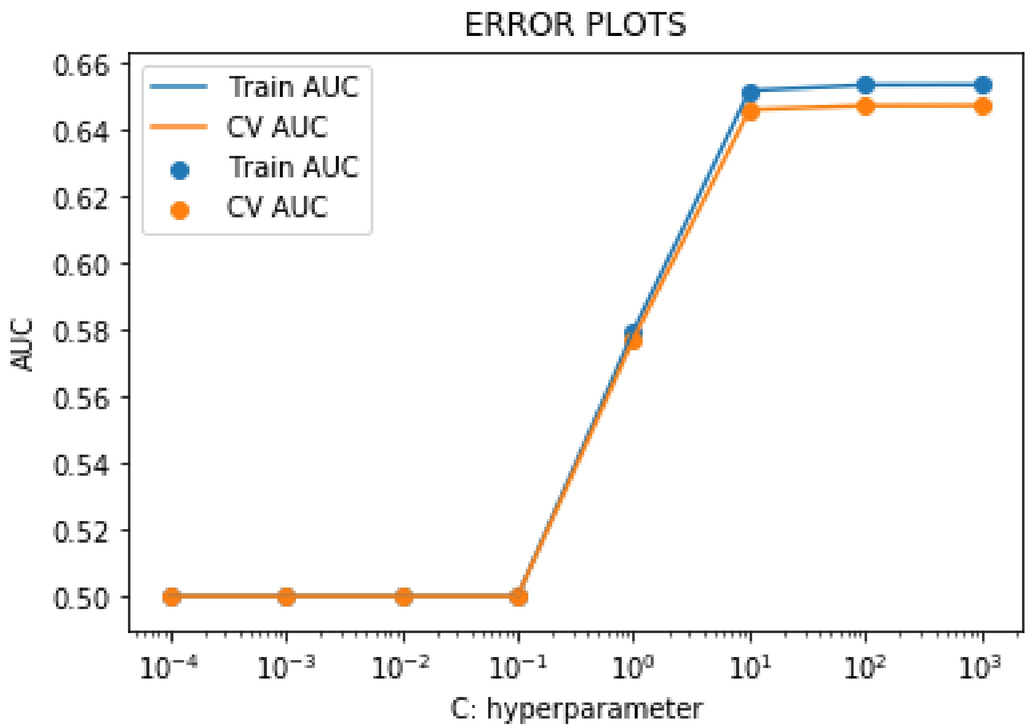


8.9 [5.4] Logistic Regression on TFIDF W2V, SET 4

8.9.1 [5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

8.10 Hyperparameter tuning with Train data

In [185]:
```
#clf = LogisticRegression()
C = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
parameters = {'C':[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]}
grid = GridSearchCV(LogisticRegression(penalty = 'l1'), parameters, cv=3, scoring='r
grid.fit(tfidf_sent_vectors_train, Y_train)

#a = grid.best_params_
best_c = grid.best_params_.get('C')

train_auc_tfw2v = grid.cv_results_['mean_train_score']
cv_auc_tfw2v = grid.cv_results_['mean_test_score']

plt.plot(C, train_auc_tfw2v, label='Train AUC')
plt.scatter(C, train_auc_tfw2v, label='Train AUC')
plt.plot(C, cv_auc_tfw2v, label='CV AUC')
plt.scatter(C, cv_auc_tfw2v, label='CV AUC')

plt.legend()
plt.xscale('log')
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```




```
In [186]: print(best_c)
```

```
1000
```

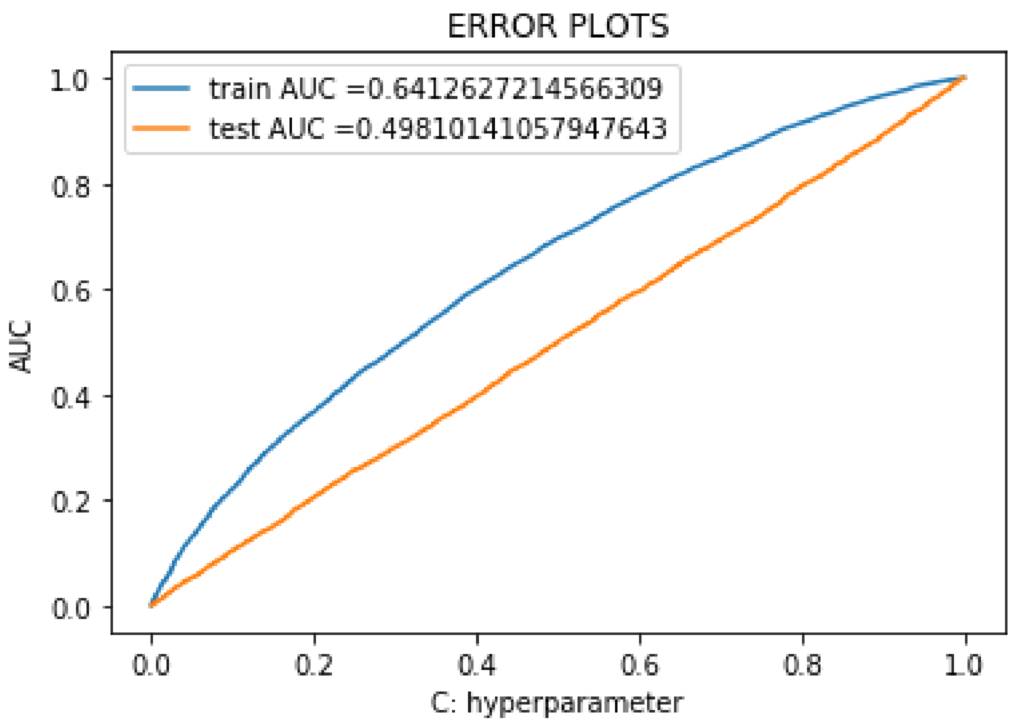
```
In [187]: print(grid.best_estimator_)
```

```
LogisticRegression(C=1000, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

8.11 Testing with Test Data

```
In [188]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#s

          clf = LogisticRegression()
          clf.fit(tfidf_sent_vectors_train, Y_train)
          # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates o
          # not the predicted outputs

          train_fpr_tfw2v, train_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_train, clf.predict_
          test_fpr_tfw2v, test_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_test, clf.predict_pro
```

```
plt.plot(train_fpr_tfw2v, train_tpr_tfw2v, label="train AUC ="+str(auc(train_fpr_tfw2
plt.plot(test_fpr_tfw2v, test_tpr_tfw2v, label="test AUC ="+str(auc(test_fpr_tfw2v, t
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



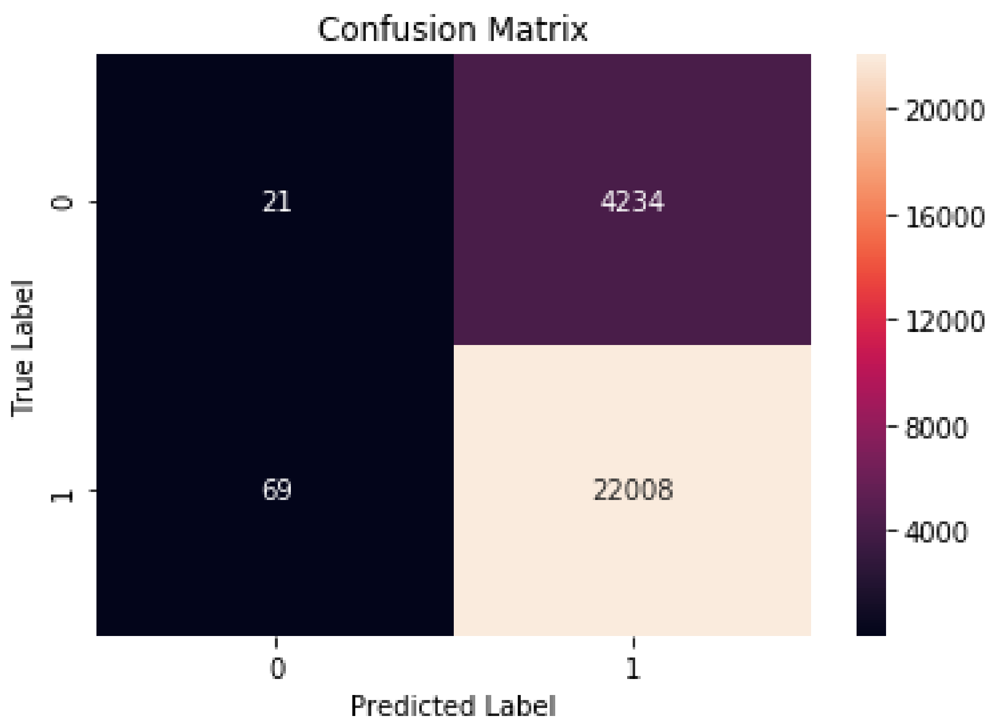
8.11.1 Calculating Accuracy, Precision, Recall & F1

```
In [97]: #L1 Regularizer
         clf = LogisticRegression(C = 1000, penalty='l1')

         clf.fit(tfidf_sent_vectors_train,Y_train)

         predf1 = clf.predict(tfidf_sent_vectors_test)

         accw1 = accuracy_score(Y_test, predf1) * 100
         prew1 = precision_score(Y_test, predf1) * 100
         recw1 = recall_score(Y_test, predf1) * 100
         f1w1 = f1_score(Y_test, predf1) * 100
```

```
print("Accuracy : " + str(accw1))
print("Precision : " + str(prew1))
print("Recall : "+ str(recw1))
print("F1 : " + str(f1w1))
```

```
Accuracy : 84.20552939389336
Precision : 84.33023468454739
Recall : 99.79261530138407
F1 : 91.41217039377231
```

In [190]:
```
cm = confusion_matrix(Y_test,predf1)
sns.heatmap(cm, annot=True,fmt='d')
plt.title('Confusion Matrix')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```



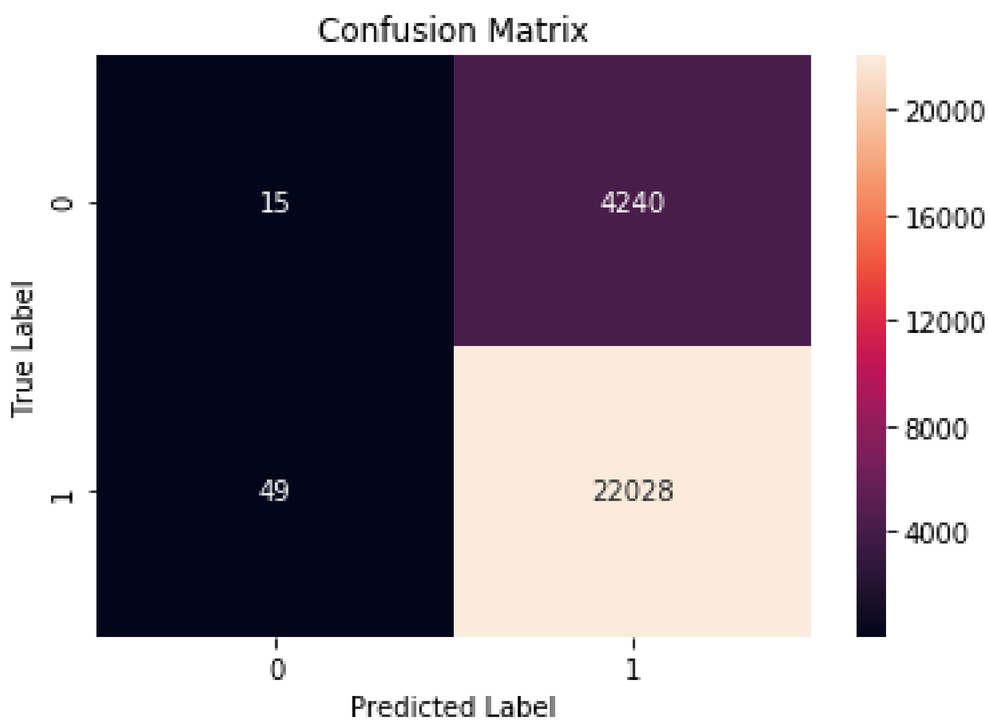
8.11.2 [5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

In [98]:
```
#L1 Regularizer
clf = LogisticRegression(C = 1000, penalty='l2')

clf.fit(tfidf_sent_vectors_train,Y_train)
```

```
predf2 = clf.predict(tfidf_sent_vectors_test)

accw2 = accuracy_score(Y_test, predf2) * 100
prew2 = precision_score(Y_test, predf2) * 100
recw2 = recall_score(Y_test, predf2) * 100
f1w2 = f1_score(Y_test, predf2) * 100


print("Accuracy : " + str(accw2))
print("Precision : " + str(prew2))
print("Recall : "+ str(recw2))
print("F1 : " + str(f1w2))
```

```
Accuracy : 84.22451769709859
Precision : 84.31230728234802
Recall : 99.85122402055813
F1 : 91.42621259029929
```

```
In [192]: cm = confusion_matrix(Y_test,predf2)
          sns.heatmap(cm, annot=True,fmt='d')
          plt.title('Confusion Matrix')
          plt.ylabel('True Label')
          plt.xlabel('Predicted Label')
          plt.show()
```



9 [6] Conclusions

```
In [99]: # Please compare all your models using Prettytable library
         number= [1,2,3,4,5,6,7,8]
         name= ["Bow", "Bow", "Tfidf", "Tfidf", "Avg W2v", "Avg W2v", "Tfidf W2v", "Tfidf W2v"]
         reg= ["L1","L2", "L1", "L2", "L1", "L2", "L1", "L2"]
         acc= [accb1,accb2,acct1,acct2,acca1,acca2,accw1,accw2]
         pre= [preb1,preb2,pret1,pret2,prea1,pret2,prew1,prew2]
         rec= [recb1,recb2,rect1,rect2,reca1,reca2,recw1,recw2]
         f1= [f1b1,f1b2,f1t1,f1t2,f1a1,f1a2,f1w1,f1w2]


         #Initialize Prettytable
         ptable = PrettyTable()
         ptable.add_column("Index", number)
         ptable.add_column("Model", name)
         ptable.add_column("Regularizer", reg)
         ptable.add_column("Accuracy%", acc)
         ptable.add_column("Precision%", pre)
         ptable.add_column("Recall%", rec)
         ptable.add_column("F1%", f1)

         print(ptable)
```

Index	Model	Regularizer	Accuracy%	Precision%	Recall%
1	Bow	L1	91.4818471821358	93.85062021641593	96.1904332536856
2	Bow	L2	91.44387057572536	93.92910678070717	96.0506740002705
3	Tfidf	L1	91.77426705149628	93.24575428892442	97.28145710292593
4	Tfidf	L2	91.69831383867538	92.3928253402875	98.23272169875118
5	Avg W2v	L1	84.34984049825309	84.92419554455446	98.99463504801406
6	Avg W2v	L2	84.37262646209935	92.3928253402875	99.30120373292456
7	Tfidf W2v	L1	84.20552939389336	84.33023468454739	99.79261530138407
8	Tfidf W2v	L2	84.22451769709859	84.31230728234802	99.85122402055813

1. We have taken 100000 data points.
2. Accuracy percentage is more in Bow and Tfidf.
3. Sparsity(non-zero weights) increases as value of C decreases in L1 reguralization.
4. Features are multicollinear.