Edited_05 Amazon Fine Food Reviews Analysis_Logistic Regression

April 4, 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 [198]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os
```

In [199]:
```
# 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 poi
# 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 LIMIT 20

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negat
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 (200000, 10)
```

```
Out[199]:    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 [200]: display = pd.read_sql_query("""
          SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
          FROM Reviews
          GROUP BY UserId
          HAVING COUNT(*)>1
          """, con)
```

```
In [201]: print(display.shape)
          display.head()
```

```
(80668, 7)
```

```
Out[201]:                 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-R11O5J5ZVQE25C  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 [202]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[202]:               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 [203]: display['COUNT(*)'].sum()
```

```
Out[203]: 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 [204]: display= pd.read_sql_query("""
          SELECT *
          FROM Reviews
          WHERE Score != 3 AND UserId="AR5J8UI46CURR"
          ORDER BY ProductID
          """, con)
          display.head()
```

```
Out[204]:        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 [205]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fa
```

In [206]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep
final.shape
```

Out[206]: (160178, 10)

In [207]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[207]: 80.089

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 [208]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[208]:
```
      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 [209]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [210]:
```
#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()
```

```
(160176, 10)
```

Out[210]:
```
1    134799
0     25377
Name: Score, dtype: int64
```

In [211]:
```
##Sorting data for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, 


final = time_sorted_data.take(np.random.permutation(len(final))[:100000])
print(final.shape)
final.head()
```

```
(100000, 10)
```

```
Out[211]:          Id   ProductId          UserId               ProfileName  \
          10291  11237  B001KVPC0G   AY74M03WTAOMB                   Nut Nut
          79814  86781  B002DHBT7Q  A1CHKAWX7FAOM4        L. Kirk "Crabseye"
          76651  83391  B005ZBZLT4  A2QOYXPT6POXQS               Tony Barnes
          40580  44095  B00168ACG2   AO26QTL5I5JRF             Suzanne Davis
          64314  69846  B002B8ODPW  A2ZE8BSZ5MMEOP  Jasmine "Uniquely Yours"

                 HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
          10291                     0                       0      1  1226534400
          79814                     2                       2      1  1317600000
          76651                     0                       0      1  1349049600
          40580                     0                       0      1  1346112000
          64314                     0                       0      1  1343520000

                                      Summary  \
          10291           Best Roasted Almonds
          79814      One of my favorite cookies
          76651                    Great deal!
          40580  THIS IS THE BEST CORNBREAD!!!!
          64314           Convenient and tasty

                                                              Text
          10291  I've tried several other brands of roasted sal...
          79814  A cookie a day (or 2, depending on serving siz...
          76651  This coffee is a great deal!  All the coffee d...
          40580  I have been eating this cornbread for years an...
          64314  Not my favorite, but for the price great produ...
```

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 [212]: # 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)
```

```
I've tried several other brands of roasted salted almonds available via the Internet and in sto
==================================================
The stigma of decafs, in general, has vanished! Emeril's Jazzed Up Decaf is, by far, the riches
==================================================
This is not a traditional cookie!  However, it is a good thing: it is its own little niche of y
==================================================
Bought these for my grandbabies and they love them. I love them because they are organic. Only
==================================================
```

```
In [213]: # 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)
```

```
I've tried several other brands of roasted salted almonds available via the Internet and in sto
```

```
In [214]: # 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)
```

```
I've tried several other brands of roasted salted almonds available via the Internet and in sto
==================================================
The stigma of decafs, in general, has vanished! Emeril's Jazzed Up Decaf is, by far, the riches
==================================================
This is not a traditional cookie!  However, it is a good thing: it is its own little niche of y
==================================================
Bought these for my grandbabies and they love them. I love them because they are organic. Only
```

In [215]:

```
# 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 [216]:

```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
This is not a traditional cookie!  However, it is a good thing: it is its own little niche of y
==================================================
```

In [217]:

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

```
I've tried several other brands of roasted salted almonds available via the Internet and in sto
```

```
In [218]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
          sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
          print(sent_1500)
```

```
This is not a traditional cookie However it is a good thing it is its own little niche of yummi
```

```
In [219]: # 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', 'ourselv
                      "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 [220]: # Combining all the above stundents
          from tqdm import tqdm
          prepr_rev = []
          # 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
              prepr_rev.append(sentance.strip())
```

```
100%|| 100000/100000 [00:46<00:00, 2145.59it/s]
```

In [221]:
```
print(len(prepr_rev))
final.shape
```

```
100000
```

Out[221]:
```
(100000, 10)
```

In [222]:
```
prepr_rev[1500]
```

Out[222]:
```
'not traditional cookie however good thing little niche yumminess fig flavor subtle
```

In [223]:
```
final ['prepr_rev']= prepr_rev
final.head(5)
```

Out[223]:
```
          Id   ProductId          UserId              ProfileName  \
10291  11237  B001KVPC0G   AY74M03WTA0MB                  Nut Nut
79814  86781  B002DHBT7Q  A1CHKAWX7FA0M4       L. Kirk "Crabseye"
76651  83391  B005ZBZLT4  A2Q0YXPT6P0XQS              Tony Barnes
40580  44095  B00168ACG2   A026QTL5I5JRF             Suzanne Davis
64314  69846  B002B8ODPW  A2ZE8BSZ5MME0P  Jasmine "Uniquely Yours"

       HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
10291                     0                       0      1  1226534400
79814                     2                       2      1  1317600000
76651                     0                       0      1  1349049600
40580                     0                       0      1  1346112000
64314                     0                       0      1  1343520000

                             Summary  \
10291            Best Roasted Almonds
79814      One of my favorite cookies
76651                     Great deal!
40580  THIS IS THE BEST CORNBREAD!!!!
64314            Convenient and tasty

                                                    Text  \
10291  I've tried several other brands of roasted sal...
79814  A cookie a day (or 2, depending on serving siz...
76651  This coffee is a great deal!  All the coffee d...
40580  I have been eating this cornbread for years an...
64314  Not my favorite, but for the price great produ...

                                               prepr_rev
10291  tried several brands roasted salted almonds av...
79814  cookie day depending serving size one indulgen...
76651  coffee great deal coffee drinkers house enjoy ...
40580  eating cornbread years could not find locally ...
64314  not favorite price great product handy stores ...
```

[3.2] Preprocessing Review Summary

```
In [224]: ## Similartly you can do preprocessing for review summary also.

          preprocessed_summary = []
          # tqdm is for printing the status bar
          for summary in tqdm(final['Summary'].values):
              summary = re.sub(r"http\S+", "", summary) # remove urls from text python: https:/
              summary = BeautifulSoup(summary, 'lxml').get_text() # https://stackoverflow.com/
              summary = decontracted(summary)
              summary = re.sub("\S*\d\S*", "", summary).strip() #remove words with numbers pyt
              summary = re.sub('[^A-Za-z]+', ' ', summary) #remove spacial character: https://
              # 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 [00:29<00:00, 3428.23it/s]
```

```
In [225]: prepr_rev = [i + ' ' + j for i, j in zip(prepr_rev,preprocessed_summary)]
          print(prepr_rev[1500])
```

```
not traditional cookie however good thing little niche yumminess fig flavor subtle want full f
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [226]: X = np.array(prepr_rev)
          y = np.array(final['Score'])
```

```
In [227]: from sklearn.model_selection import train_test_split
          #splitting data into Train, C.V and Test
          X_train, X_test, y_train, y_test = train_test_split(final ['prepr_rev'], final['Score
          X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33)
          print("Train:",X_train.shape,y_train.shape)
          print("CV:",X_cv.shape,y_cv.shape)
          print("Test:",X_test.shape,y_test.shape)
```

```
Train: (44890,) (44890,)
CV: (22110,) (22110,)
Test: (33000,) (33000,)
```

```
In [228]: vectorizer = CountVectorizer(min_df=10, max_features=500)
          vectorizer.fit(X_train)
          #vectorizer.fit(X_train) # fit has to happen only on train data
          # we use the fitted CountVectorizer to convert the text to vector
```

```
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.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)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

5.2 [4.3] TF-IDF

```
In [229]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
          tf_idf_vect.fit(X_train)
          # we use the fitted CountVectorizer to convert the text to vector
          X_train_tfidf = tf_idf_vect.transform(X_train)
          X_cv_tfidf = tf_idf_vect.transform(X_cv)
          X_test_tfidf = tf_idf_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)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

5.3 [4.4] Word2Vec

```
In [230]: # List of sentence in X_train text
          sent_of_train=[]
          for sent in X_train:
              sent_of_train.append(sent.split())

          # List of sentence in X_test text
          sent_of_test=[]
          for sent in X_test:
              sent_of_test.append(sent.split())

          # Train your own Word2Vec model using your own train text corpus
          # min_count = 5 considers only words that occured atleast 5 times
          w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)
```

```
print(w2v_model.wv.most_similar('great'))
print('='*50)
print(w2v_model.wv.most_similar('worst'))

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
[('fantastic', 0.8478500843048096), ('good', 0.8255733251571655), ('awesome', 0.81360322237014
==================================================
[('best', 0.7517200708389282), ('nastiest', 0.7383694648742676), ('greatest', 0.71207940578460
number of words that occured minimum 5 times  12960
```

```
In [231]: 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  12960
sample words  ['tea', 'go', 'everyday', 'nearly', 'indestructible', 'forgotten', 'steeped', 'mi
```

5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

```
In [166]: i=0
          sent_of_test_cv=[]
          for sentance in X_cv:
              sent_of_test_cv.append(sentance.split())
```

```
In [167]: # 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(sent_of_test_cv): # for each review/sentence
              sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need
              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%|| 22110/22110 [01:05<00:00, 336.99it/s]
```

```
(22110, 50)
[-0.52553881 -0.56571381  0.63142397  0.43928345  0.59151121  0.34461575
  0.18870962  0.45058656 -0.82038542 -0.29991521  0.56942672 -0.67313881
 -0.71965228 -0.07363756  0.2739284   0.0503723   0.52536564  0.63691369
  0.18458937  0.23666228 -0.32867154 -0.15568994  0.09874957 -0.01075351
  0.33511867  1.14519034  0.29567677 -0.0468841  -0.03616501  0.08883335
 -0.36886215 -0.42454403 -0.57793536  0.37274055 -0.06555429  0.18378313
  0.30609365 -0.04986344  0.03503402  0.93081964 -0.07000684 -0.54992588
  0.2967225   0.18228281  0.0962322   0.48645934 -0.23933173  0.25615076
  0.29496165 -0.3852263 ]
```

In [168]:
```python
# compute average word2vec for X_test .
test_vectors = [];
for sent in tqdm(sent_of_test):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    test_vectors.append(sent_vec)

test_vectors = np.array(test_vectors)

print(test_vectors.shape)
print(test_vectors[0])
```

```
100%|| 33000/33000 [01:37<00:00, 338.26it/s]


(33000, 50)
[-0.19294365 -0.66535483  0.49491829  0.61472203  0.43786552 -0.2212762
  0.63726501 -0.09604544 -1.01787599 -0.38894434 -0.02899949 -0.36255753
 -0.46169367 -0.24737216 -0.55879127  0.22363069  0.50083397  0.24539507
 -0.0535983   0.33607479  0.03222066 -0.15921549  0.32272275  0.31025571
  0.21540802  0.19478748 -0.61918377 -0.0017801  -0.71217188 -0.46075358
 -0.54823264 -0.17418158 -0.12233295 -0.03316205 -0.08219504  0.14051325
 -0.26644893  0.27429939 -0.4835991   0.73440272  0.55616765 -0.06391602
 -0.40270575 -0.12931861 -0.24423024  0.236344    0.26991326  0.16444251
 -0.22399055  0.54960559]
```

In [169]:
```
# compute average word2vec for X_train .
train_vectors = [];
for sent in tqdm(sent_of_train):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_vectors.append(sent_vec)

train_vectors = np.array(train_vectors)

print(train_vectors.shape)
print(train_vectors[0])
```

```
100%|| 44890/44890 [02:09<00:00, 346.49it/s]

(44890, 50)
[-0.14060537 -0.72614364  0.32810215  1.11755044  0.23384139  0.28288134
 -0.01866034 -0.04290673 -0.52098112 -0.01752026 -0.01945195  0.15767466
 -0.07230324 -0.01717835 -0.27854393  0.05381443  0.73443291  0.75394678
  0.93170925  0.04095242 -0.49682882 -0.20451759  0.2238511   0.65370598
 -0.13699235 -0.40837955  0.57271826 -0.12713724 -0.59230489 -0.02618843
 -0.34113196 -0.33512895 -0.13026007 -0.22999276  0.30137488  0.37416903
  0.2087824   0.68820576  0.2217927   0.66206925  0.37959712  0.22534903
 -0.7366674  -0.62474787  0.04708067  0.12064839  0.31486852  0.38119362
  0.3194624  -0.3280405 ]
```

[4.4.1.2] TFIDF weighted W2v

In [170]:
```
tf_idf_vect = TfidfVectorizer()

# final_tf_idf1 is the sparse matrix with row= sentence, col=word and cell_val = tfi
final_tf_idf1 = tf_idf_vect.fit_transform(X_train)
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))

# tfidf words/col-names
tfidf_feat = tf_idf_vect.get_feature_names()

# compute TFIDF Weighted Word2Vec for X_test .
tfidf_test_vectors = [];
```

```
row=0;
for sent in tqdm(sent_of_test):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            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_test_vectors.append(sent_vec)

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

```
100%|| 33000/33000 [22:17<00:00, 24.67it/s]


(33000, 50)
[-0.16686663 -0.86323916  0.49690235  0.5184359   0.56615715 -0.54148702
  0.93596545 -0.25554939 -1.12918029 -0.77515194  0.04043236 -0.01329734
 -0.5751481  -0.6871599  -0.75427953  0.1534776   0.36420995  0.26531452
  0.08081806  0.42276238  0.15202629 -0.0840503   0.46600952  0.41430244
  0.26516221 -0.03617444 -0.87445306 -0.01075618 -0.63894613 -0.59917669
 -0.83022163 -0.19207686  0.0749336  -0.06149395 -0.1844047   0.28045885
 -0.81266072  0.22030619 -0.57452736  0.7226248   0.6758246   0.15453529
 -0.08191958  0.15770662 -0.32205749  0.08399961  0.39292019  0.16717439
 -0.39050156  0.80903407]
```

In [171]:
```
# compute TFIDF Weighted Word2Vec for X_train .
tfidf_train_vectors = [];
row=0;
for sent in tqdm(sent_of_train):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            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_train_vectors.append(sent_vec)
```

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

```
100%|| 44890/44890 [27:49<00:00, 26.89it/s]


(44890, 50)
[-0.29540099 -0.85954222 -0.18179773  0.88866737  0.38733377  0.07670469
 -0.08424611  0.12395096 -0.48383716 -0.07993022 -0.00500073  0.31535502
  0.06399823  0.02668346 -0.39874532 -0.19141424  0.41162859  0.67405128
  1.09345726  0.07239559 -0.44772274  0.12750844  0.26261354  0.38511071
 -0.16009767 -0.39785692  1.16591441 -0.4437846  -0.38423109  0.32179244
 -0.11075185 -0.21630509  0.073712   -0.27370394  0.21916168  0.2249126
 -0.02694394  0.95540116  0.0286596   0.38618412  0.51026674  0.42937773
 -0.9517379  -0.66895635  0.19392165 -0.37172587  0.3754621   0.14247962
  0.01241208 -0.48043844]
```

6 [5] Assignment 5: Apply Logistic Regression

```
<li><strong>Apply Logistic Regression on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vector
    </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.appliedaico
<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 t
    </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>
```


Note: Data Leakage

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

7 Applying Logistic Regression

7.1 [5.1] Logistic Regression on BOW, SET 1

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

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

In [232]:
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score

def lr_all (X_train,y_train,X_cv,penal):
    train_auc = []
    cv_auc = []
    hyper_param = [0.001, 0.01, 0.1, 1, 10, 100,1000]

    for i in tqdm(hyper_param):
        lr = LogisticRegression(C=i,penalty= penal)
        lr.fit(X_train_bow,y_train)



        y_train_pred =  lr.predict_proba(X_train_bow)[:,1]
        y_cv_pred = lr.predict_proba(X_cv_bow)[:,1]

        train_auc.append(roc_auc_score(y_train,y_train_pred))
        cv_auc.append(roc_auc_score(y_cv, y_cv_pred))

    #Plotting the AUC curve for train and test data

    #Print the graph

    # https://stackoverflow.com/questions/28077499/matplotlib-pyplot-plot-x-axis-tic

    plt.plot(np.log(hyper_param), train_auc, label='Train AUC-L1')
    plt.plot(np.log(hyper_param), cv_auc, label='CV AUC-L1')
```

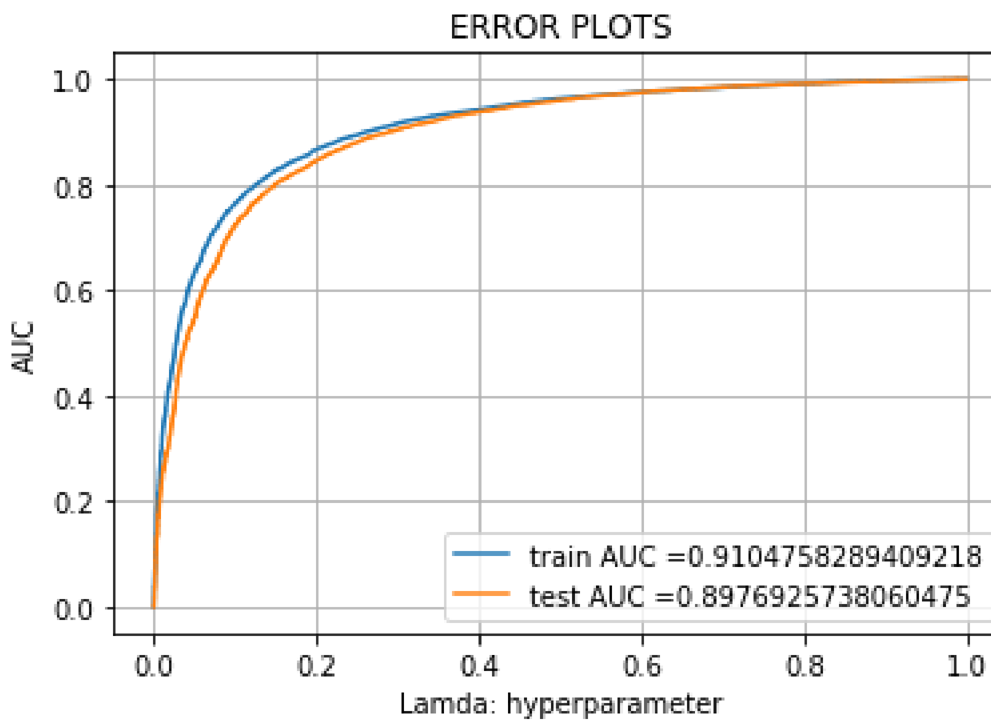
```
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.legend()
plt.xlabel("Lambda: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
#Cv-auc scores with penalty L1
print("--------------------------")
print("Cv auc scores with penalty L1")
print(cv_auc)
print("Maximun Auc value :",max(cv_auc))
print("Index",cv_auc.index(max(cv_auc)))

#Get lambda value for max auc in cv data
mx = 0
for i in range(len(cv_auc)):
    if(cv_auc[i]> cv_auc[mx]):
        mx = i
best = hyper_param[mx]
print("The optimal value of Lambda = ", best)



lr = LogisticRegression(C =best,penalty= 'l1', class_weight = 'balanced')
lr.fit(X_train_bow,y_train)



train_fpr, train_tpr, thresholds = roc_curve(y_train, lr.predict_proba(X_train_bo
test_fpr, test_tpr, thresholds = roc_curve(y_test, lr.predict_proba(X_test_bow)[

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))

plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.legend()
plt.xlabel("Lamda: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()


#Confusion Matrix

print("Train confusion matrix")
print(confusion_matrix(y_train, lr.predict(X_train_bow)))
```

```
print("Test confusion matrix")
print(confusion_matrix(y_test, lr.predict(X_test_bow)))

cm = confusion_matrix(y_train, lr.predict(X_train_bow))
cm = confusion_matrix(y_test, lr.predict(X_test_bow))
tn, fp, fn, tp = cm.ravel()
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
# Code for drawing seaborn heatmaps
class_names = ['0','1']
df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
fig = plt.figure(figsize=(5,3))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='rigl
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='rigl
plt.ylabel('True label',size=18)
plt.xlabel('Predict label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

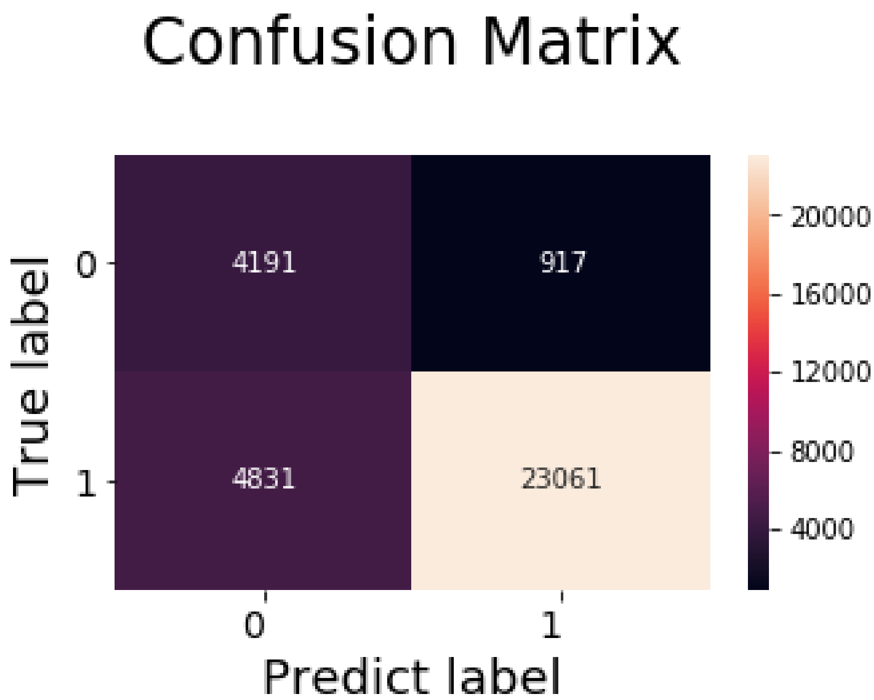
```
In [233]: lr_all(X_train_bow,y_train,X_cv_bow,'l1')
```

```
100%|| 7/7 [00:02<00:00,  2.96it/s]
```

```
--------------------------
Cv auc scores with penalty L1
[0.7149699199648194, 0.8623282056497347, 0.8972412121357145, 0.8963105754704795, 0.89600729675
Maximun Auc value : 0.8972412121357145
Index 2
The optimal value of Lambda =  0.1
```




```
Train confusion matrix
[[ 6174  1081]
 [ 6539 31096]]
Test confusion matrix
[[ 4191   917]
 [ 4831 23061]]
```



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

```
In [236]: def all_lr (X_train,y_train,X_cv,penal):
              train_auc_l2 = []
              cv_auc_l2 = []
              hyper_param = [0.001, 0.01, 0.1, 1, 10, 100,1000]

              for i in tqdm(hyper_param):
                  lr = LogisticRegression(C=i,penalty= penal)
                  lr.fit(X_train_bow,y_train)



                  y_train_pred =  lr.predict_proba(X_train_bow)[:,1]
                  y_cv_pred = lr.predict_proba(X_cv_bow)[:,1]

                  train_auc_l2.append(roc_auc_score(y_train,y_train_pred))
                  cv_auc_l2.append(roc_auc_score(y_cv, y_cv_pred))

              #Plotting the AUC curve for train and test data

              #Print the graph

              # https://stackoverflow.com/questions/28077499/matplotlib-pyplot-plot-x-axis-tic
```

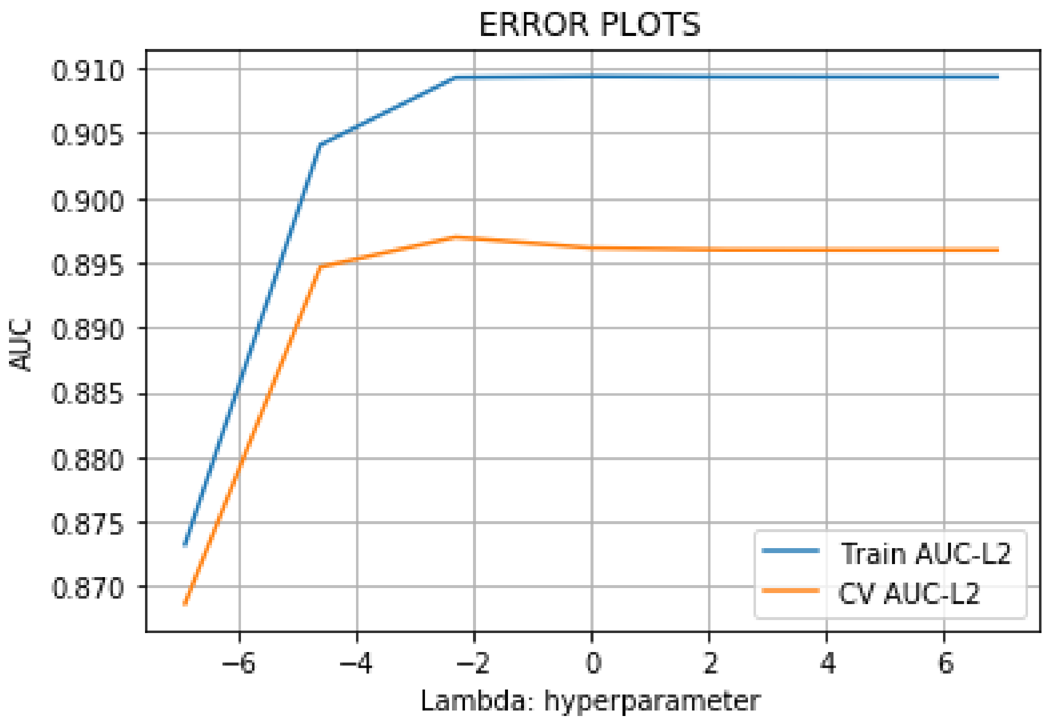
```
plt.plot(np.log(hyper_param), train_auc_l2, label='Train AUC-L2')
plt.plot(np.log(hyper_param), cv_auc_l2, label='CV AUC-L2')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.legend()
plt.xlabel("Lambda: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
#Cv auc scores with penalty L2
print("---------------------------")
print("Cv auc scores with penalty L2")
print(cv_auc_l2)
print("Maximun Auc value :",max(cv_auc_l2))
print("Index",cv_auc_l2.index(max(cv_auc_l2)))
```

```
#Get lambda value for max auc in cv data
mx = 0
for i in range(len(cv_auc_l2)):
    if(cv_auc_l2[i]> cv_auc_l2[mx]):
        mx = i
best = hyper_param[mx]
print("The optimal value of Lambda = ", best)


lr = LogisticRegression(C= best, penalty= 'l2', class_weight = 'balanced')
lr.fit(X_train_bow,y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, lr.predict_proba(X_train_bo
test_fpr, test_tpr, thresholds = roc_curve(y_test, lr.predict_proba(X_test_bow)[

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.legend()
plt.xlabel("Lamda: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

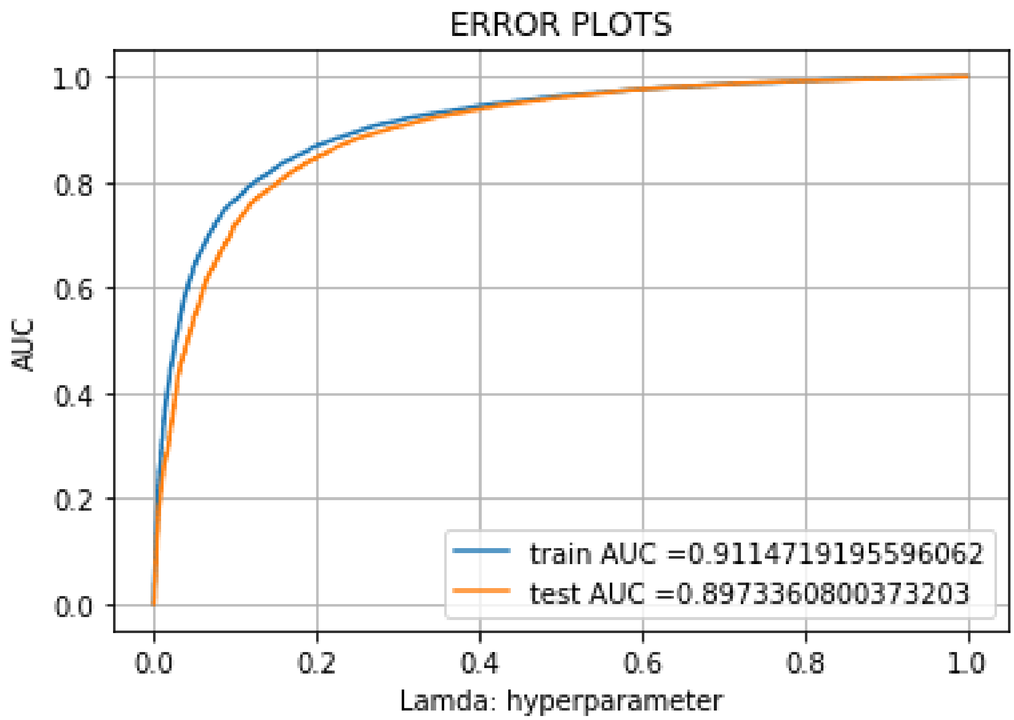
```
            #Confusion Matrix

            print("Train confusion matrix")
            print(confusion_matrix(y_train, lr.predict(X_train_bow)))
            print("Test confusion matrix")
            print(confusion_matrix(y_test, lr.predict(X_test_bow)))

            cm = confusion_matrix(y_train, lr.predict(X_train_bow))
            cm = confusion_matrix(y_test, lr.predict(X_test_bow))
            tn, fp, fn, tp = cm.ravel()
            # https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
            # Code for drawing seaborn heatmaps
            class_names = ['0','1']
            df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
            fig = plt.figure(figsize=(5,3))
            heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

        # Setting tick labels for heatmap
            heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='rig
            heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='rig
            plt.ylabel('True label',size=18)
            plt.xlabel('Predict label',size=18)
            plt.title("Confusion Matrix\n",size=24)
            plt.show()
```

```
In [237]: all_lr(X_train_bow,y_train,X_cv_bow,'l2')
```

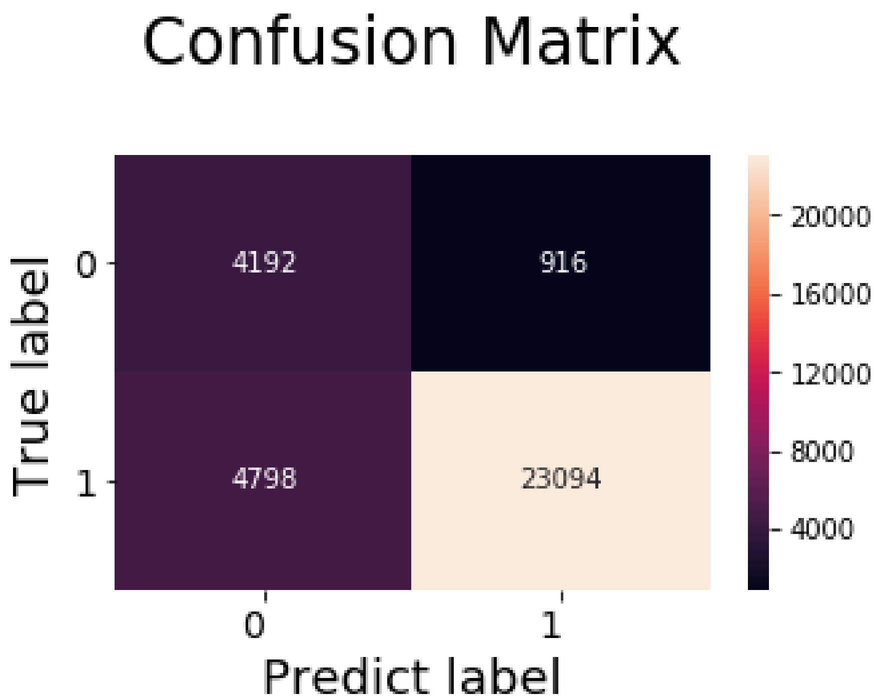
```
100%|| 7/7 [00:04<00:00,  1.47it/s]
```




```
--------------------------
Cv auc scores with penalty L2
[0.8686668268851596, 0.8946634880571093, 0.8969706221466804, 0.8961376090875506, 0.89598988413
Maximun Auc value : 0.8969706221466804
Index 2
The optimal value of Lambda =  0.1
```




```
Train confusion matrix
[[ 6162  1093]
 [ 6475 31160]]
Test confusion matrix
[[ 4192   916]
 [ 4798 23094]]
```




```
In [238]: from scipy.sparse import find
          #Weights before adding random noise
          weights1 = find(lr.coef_[0])[2]
          print(weights1[:10])
```

```
[ 0.15021456 -0.03929764 -0.05173317  0.43961426  0.05990978 -0.27028027
 -0.5902203  -0.13474628 -0.55136027  0.12501951]
```

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

```
In [239]: # Please write all the code with proper documentation

          lr = LogisticRegression(C=10,penalty='l2')
          lr.fit(X_train_bow,y_train)
          weight1 = lr.coef_ # the weight vector

          # New dataset by adding a small noise
          new_train = X_train_bow.astype(float)
          new_train.data += np.random.uniform(-0.0001,0.0001,1 )

          # Fit the model on new data
          lr = LogisticRegression(C=1,penalty='l2')
          lr.fit(X_train_bow,y_train)
```

```
weight2 =lr.coef_


weight1 += 10**-6
weight2 += 10**-6

percentage_change_vector = abs( (weight1-weight2) / (weight1) )*100
```

```
In [240]: #print weights difference
          print(percentage_change_vector.max())
          print(percentage_change_vector.min())
          print(percentage_change_vector.std())
```

```
82.51198275414353
0.013428872363584931
6.011225674585524
```

```
In [241]: percentage_change=[]
          collinear_features=[]

          for i in range(1,101):
              f=np.where(percentage_change_vector > i)[1].size
              percentage_change.append(i)
              collinear_features.append(f)
```

```
In [242]: feat = vectorizer.get_feature_names()
          print("No of features have weight changes greater than 30%: ", percentage_change_vec
          fe=[]
          print("\ncollinear features are  :")
          for i in np.where(percentage_change_vector > 1)[1]:
              fe.append(feat[i])
          print(fe)
```

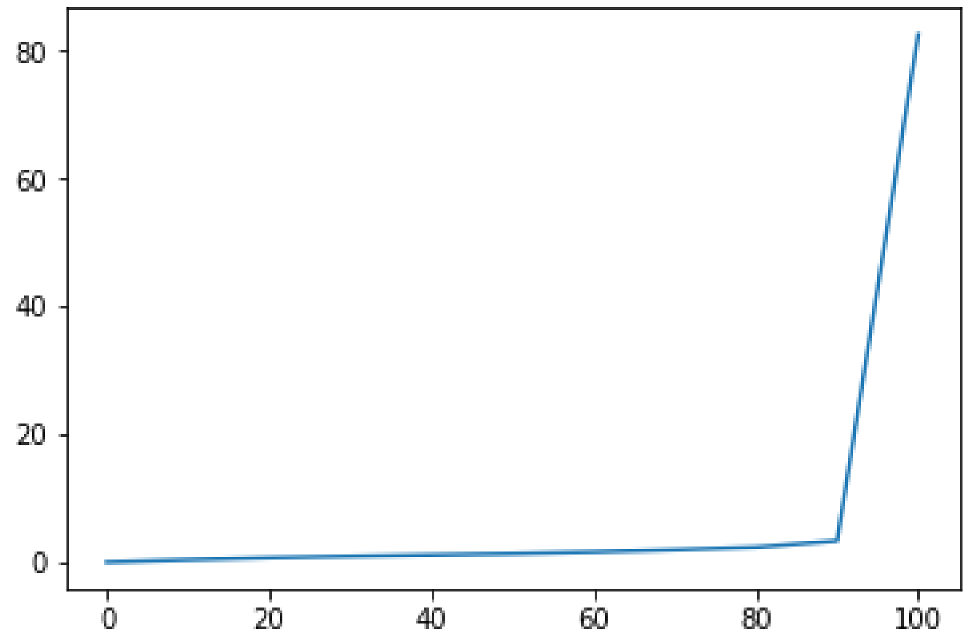
```
No of features have weight changes greater than 30%:  5

collinear features are  :
['able', 'actually', 'added', 'aftertaste', 'ago', 'almost', 'already', 'alternative', 'althou
```

```
In [243]: t = range(0,101,10)
          for i in t:
              print(i, "th percentile : ",np.percentile(percentage_change_vector,i))

          plt.plot(t,np.percentile(percentage_change_vector,t) )
```

```
0 th percentile :  0.013428872363584931
10 th percentile :  0.3774116085177026
```

```
20 th percentile :  0.697804242923374
30 th percentile :  0.9233637864705805
40 th percentile :  1.1362068754828873
50 th percentile :  1.3431337469014863
60 th percentile :  1.5986589368506539
70 th percentile :  1.9457369935720714
80 th percentile :  2.3428249702073187
90 th percentile :  3.313082637600024
100 th percentile :  82.51198275414353
```

Out[243]: [<matplotlib.lines.Line2D at 0x1a4742f0f0>]

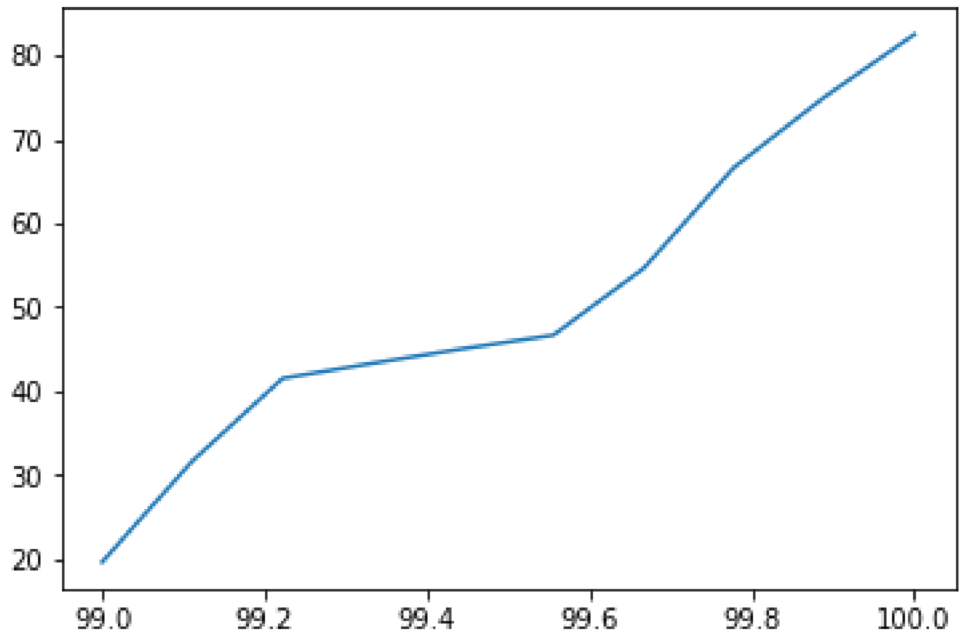


In [244]:
```
t = np.linspace(99,100,10)
for i in t:
    print(i, "th percentile : ",np.percentile(percentage_change_vector,i))

plt.plot(t,np.percentile(percentage_change_vector,t) )
```

```
99.0 th percentile :  19.63632149985406
99.11111111111111 th percentile :  31.68439678888494
99.22222222222223 th percentile :  41.535800817665084
99.33333333333333 th percentile :  43.339586771510895
99.44444444444444 th percentile :  45.06761464189339
99.55555555555556 th percentile :  46.68699433404016
99.66666666666667 th percentile :  54.62190417904557
```

```
99.77777777777777 th percentile :  66.64210745626136
99.88888888888889 th percentile :  75.02188514028092
100.0 th percentile :  82.51198275414353
```

Out[244]: [<matplotlib.lines.Line2D at 0x1a44599a20>]



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 [245]:
```
# Please write all the code with proper documentation
all_features = vectorizer.get_feature_names()

def most_informative_features(vectorizer, lr, n= 25):
    feature_names = all_features
    coefs_with_fns = sorted(zip(lr.coef_[0], feature_names))
    top = zip(coefs_with_fns[:(n + 1): -1], coefs_with_fns[:n])
    print("\t\tPositive\t\t\t\t\tNegative")
    print("________________________________________________________________________________
    for (coef_1, fn_2), (coef_2, fn_1) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_2, coef_2, fn_1))
```

In [246]:
```
most_informative_features(X_train_bow,lr)
```

```
                Positive                                                Negative
--------------------------------------------------------------------------------

        1.8518          amazing                                         -1.5299         disappointe
        1.6625          perfect                                         -1.2900         money
        1.6435          excellent                                       -1.0010         stick
        1.5841          delicious                                       -0.7998         away
        1.5318          pleased                                         -0.7797         thought
        1.4619          highly                                          -0.7468         nothing
        1.4241          smooth                                          -0.7252         guess
        1.3956          wonderful                                       -0.6910         bad
        1.2573          yummy                                           -0.6908         rather
        1.2346          awesome                                         -0.6460         opened
        1.2338          loves                                           -0.6136         reviews
        1.2224          glad                                            -0.6096         tasted
        1.2101          great                                           -0.5683         received
        1.1767          surprised                                       -0.5632         left
        1.1650          best                                            -0.5628         service
        1.1544          thank                                           -0.5375         looked
        1.0184          tasty                                           -0.5335         cannot
        1.0117          exactly                                         -0.5204         maybe
        1.0067          nice                                            -0.5130         instead
        0.9683          stores                                          -0.5098         bought
        0.9572          thanks                                          -0.5019         bitter
        0.9096          definitely                                      -0.4868         gave
        0.9057          happy                                           -0.4864         even
        0.8527          easy                                            -0.4828         aftertaste
        0.8428          works                                           -0.4777         ingredient
```

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

In [247]:
```
# Please write all the code with proper documentation
most_informative_features(X_train_bow,lr)
```

```
                Positive                                                Negative
--------------------------------------------------------------------------------

        1.8518          amazing                                         -1.5299         disappointe
        1.6625          perfect                                         -1.2900         money
        1.6435          excellent                                       -1.0010         stick
        1.5841          delicious                                       -0.7998         away
        1.5318          pleased                                         -0.7797         thought
        1.4619          highly                                          -0.7468         nothing
        1.4241          smooth                                          -0.7252         guess
        1.3956          wonderful                                       -0.6910         bad
        1.2573          yummy                                           -0.6908         rather
        1.2346          awesome                                         -0.6460         opened
```

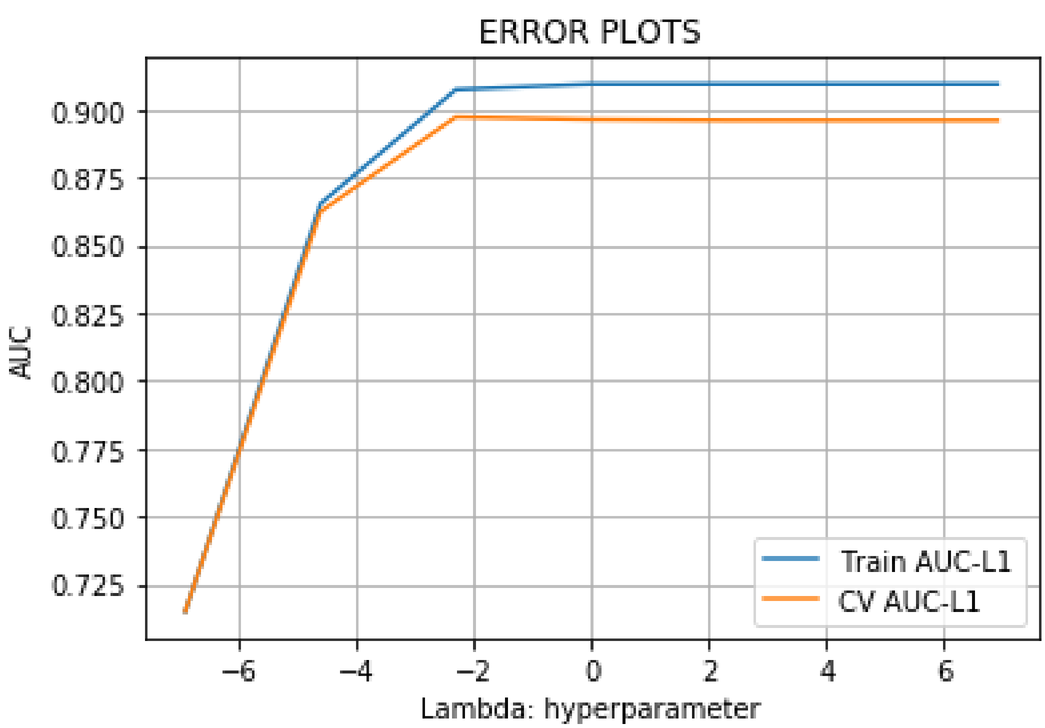
1.2338	loves	-0.6136	reviews
1.2224	glad	-0.6096	tasted
1.2101	great	-0.5683	received
1.1767	surprised	-0.5632	left
1.1650	best	-0.5628	service
1.1544	thank	-0.5375	looked
1.0184	tasty	-0.5335	cannot
1.0117	exactly	-0.5204	maybe
1.0067	nice	-0.5130	instead
0.9683	stores	-0.5098	bought
0.9572	thanks	-0.5019	bitter
0.9096	definitely	-0.4868	gave
0.9057	happy	-0.4864	even
0.8527	easy	-0.4828	aftertaste
0.8428	works	-0.4777	ingredient

7.2 [5.2] Logistic Regression on TFIDF, SET 2

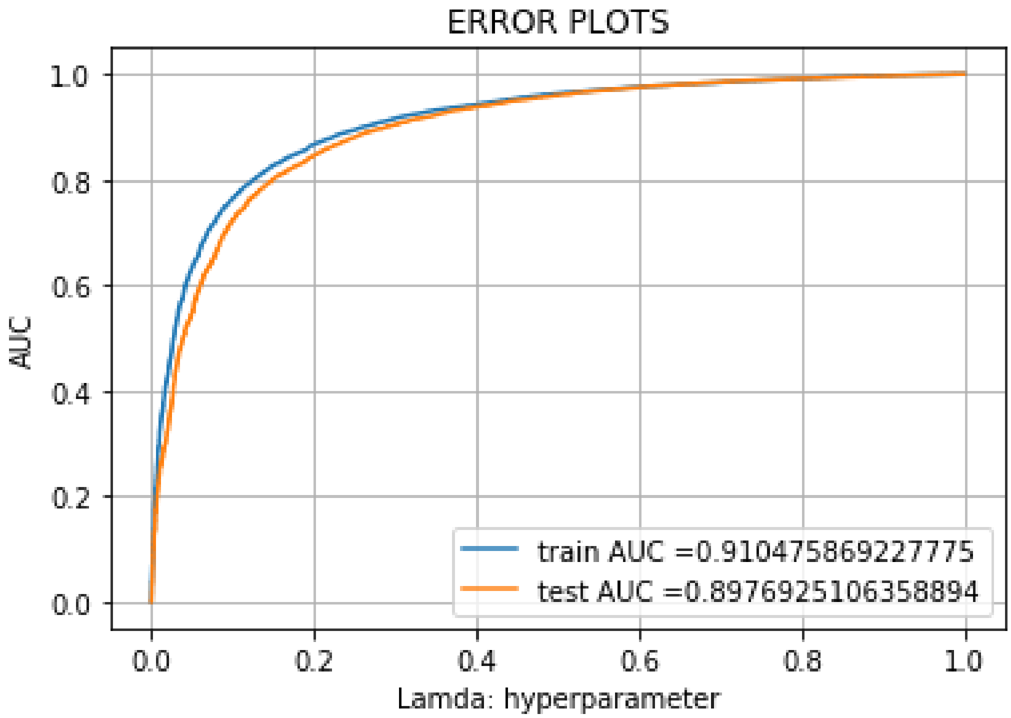
7.2.1 [5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

```
In [248]: lr_all(X_train_tfidf,y_train,X_cv_tfidf,'l1')
```

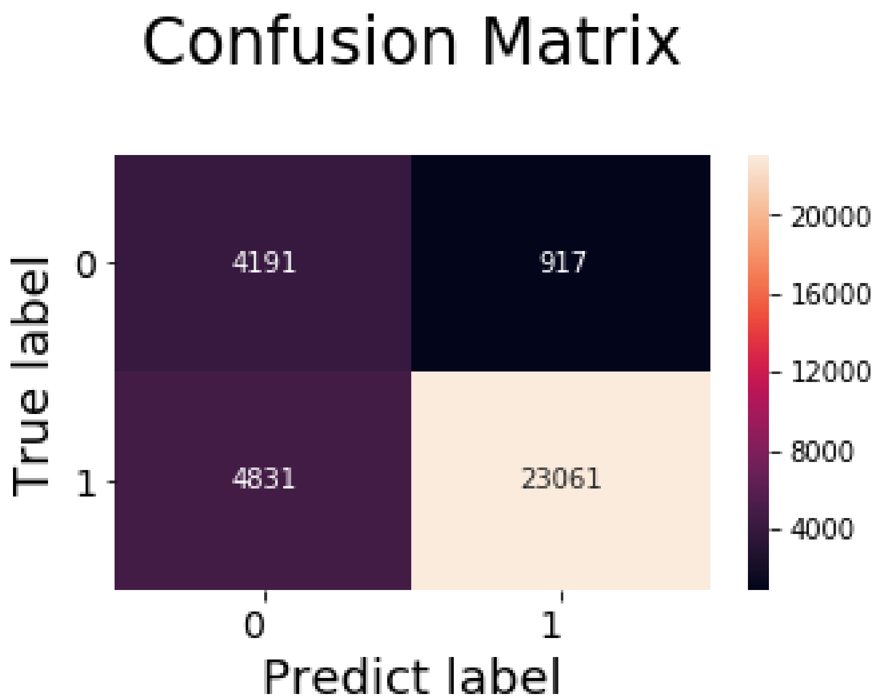
```
100%|| 7/7 [00:02<00:00,  3.18it/s]
```



```
--------------------------
Cv auc scores with penalty L1
[0.7149699199648194, 0.8623288923876233, 0.8972410900489787, 0.896310926469845, 0.8960070373230
Maximun Auc value : 0.8972410900489787
Index 2
The optimal value of Lambda =  0.1
```



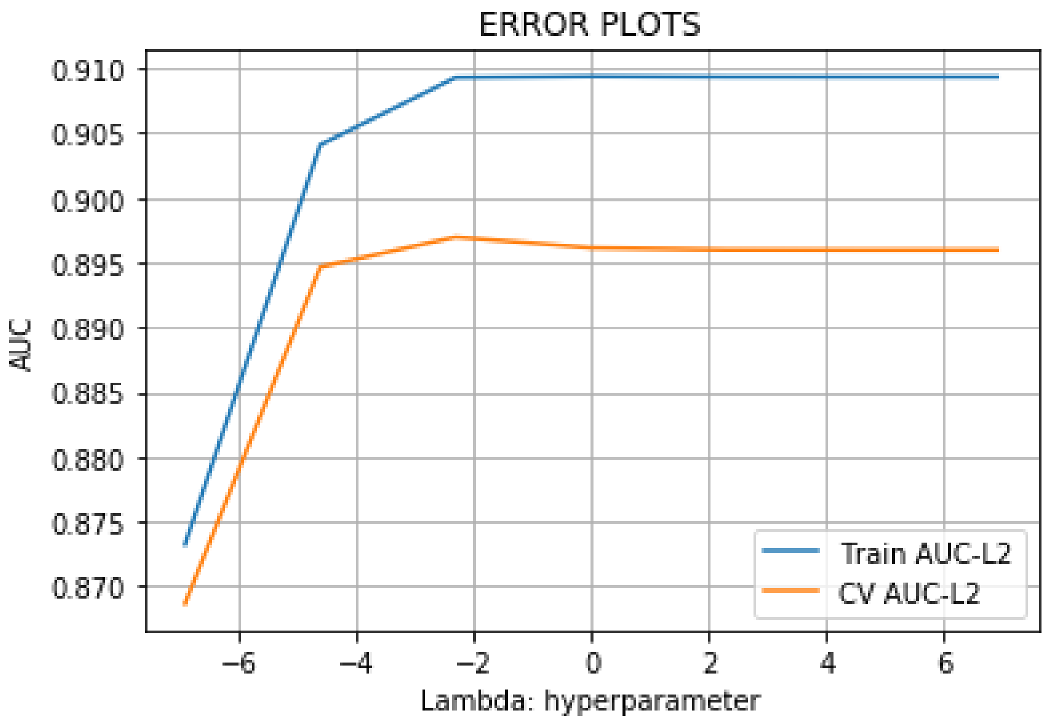

```
Train confusion matrix
[[ 6174  1081]
 [ 6539 31096]]
Test confusion matrix
[[ 4191   917]
 [ 4831 23061]]
```



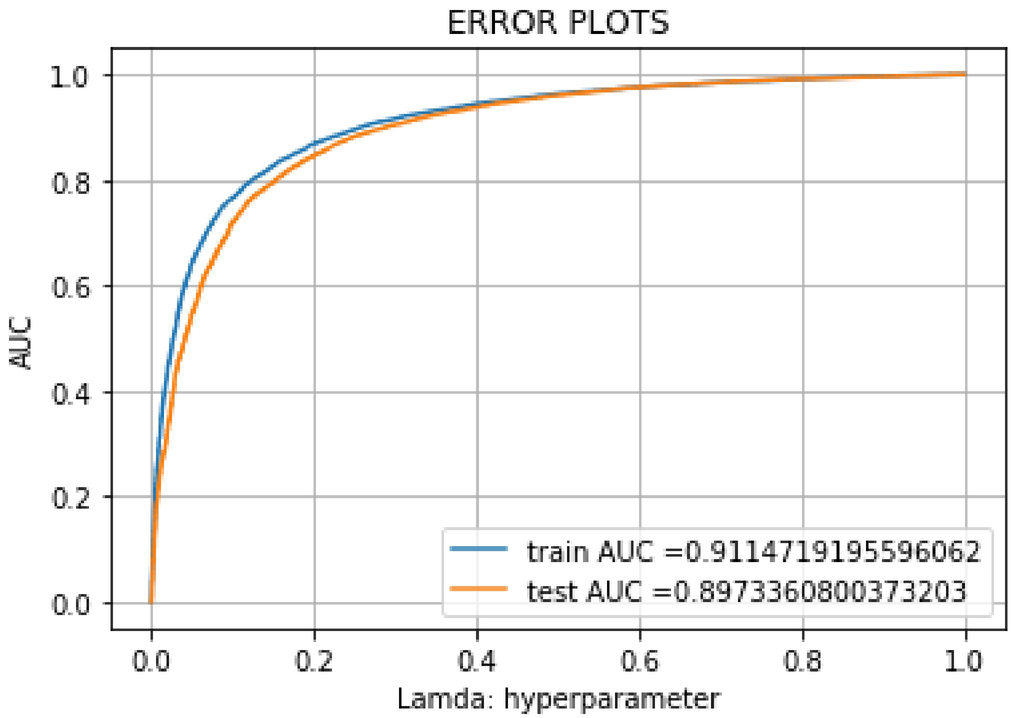
7.2.2 [5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

```
In [249]: all_lr(X_train_tfidf,y_train,X_cv_tfidf,'l2')
```

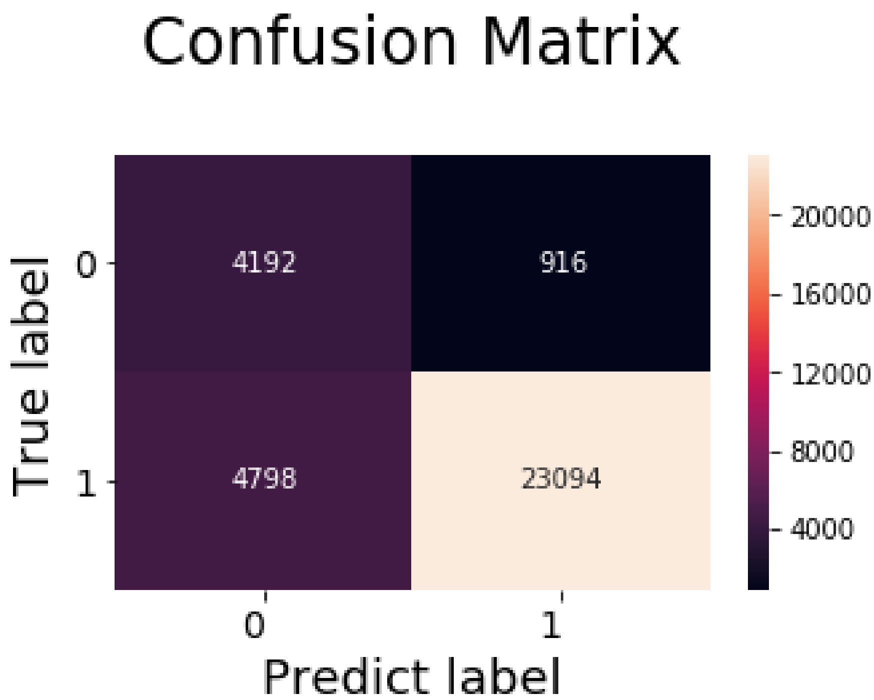
```
100%|| 7/7 [00:04<00:00,  1.46it/s]
```




```
--------------------------
Cv auc scores with penalty L2
[0.8686668268851596, 0.8946634880571093, 0.8969706221466804, 0.8961376090875506, 0.895989884137
Maximun Auc value : 0.8969706221466804
Index 2
The optimal value of Lambda =  0.1
```




```
Train confusion matrix
[[ 6162  1093]
 [ 6475 31160]]
Test confusion matrix
[[ 4192   916]
 [ 4798 23094]]
```



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 [250]: # Please write all the code with proper documentation


          # Please write all the code with proper documentation
          all_features = tf_idf_vect.get_feature_names()

          def most_informative_features(tf_idf_vect, lr, n= 25):
              feature_names = all_features
              coefs_with_fns = sorted(zip(lr.coef_[0], feature_names))
              top = zip(coefs_with_fns[:(n + 1): -1], coefs_with_fns[:n])
              print("\t\tPositive\t\t\t\t\tNegative")
              print("__________________________________________________________________________
              for (coef_1, fn_2), (coef_2, fn_1) in top:
                  print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_2, coef_2, fn_1))

In [251]: most_informative_features(X_train_tfidf,lr)
```

```
                Positive                                                Negative
-----------------------------------------------------------------------------------

        1.8518        amount                                          -1.5299        drinking
```

```
        1.6625        pieces                                                     -1.2900        never
        1.6435        fan                                                        -1.0010        stores
        1.5841        dog                                                        -0.7998        baby
        1.5318        plus                                                       -0.7797        three
        1.4619        house                                                      -0.7468        nuts
        1.4241        smooth                                                     -0.7252        happy
        1.3956        work                                                       -0.6910        bags
        1.2573        yummy                                                      -0.6908        read
        1.2346        back                                                       -0.6460        orange
        1.2338        maybe                                                      -0.6136        review
        1.2224        got                                                        -0.6096        tastes like
        1.2101        gum                                                        -0.5683        reason
        1.1767        take                                                       -0.5632        likes
        1.1650        big                                                        -0.5628        service
        1.1544        thanks                                                     -0.5375        makes
        1.0184        tea                                                        -0.5335        cats
        1.0117        family                                                     -0.5204        months
        1.0067        not good                                                   -0.5130        kind
        0.9683        subscribe                                                  -0.5098        boxes
        0.9572        thing                                                      -0.5019        bold
        0.9096        disappointed                                               -0.4868        giving
        0.9057        help                                                       -0.4864        excellent
        0.8527        end                                                        -0.4828        ago
        0.8428        worth                                                      -0.4777        keurig
```

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

In [252]:
```
# Please write all the code with proper documentation
most_informative_features(X_train_tfidf,lr)
```

```
                Positive                                                Negative
--------------------------------------------------------------------------------

        1.8518        amount                                                     -1.5299        drinking
        1.6625        pieces                                                     -1.2900        never
        1.6435        fan                                                        -1.0010        stores
        1.5841        dog                                                        -0.7998        baby
        1.5318        plus                                                       -0.7797        three
        1.4619        house                                                      -0.7468        nuts
        1.4241        smooth                                                     -0.7252        happy
        1.3956        work                                                       -0.6910        bags
        1.2573        yummy                                                      -0.6908        read
        1.2346        back                                                       -0.6460        orange
        1.2338        maybe                                                      -0.6136        review
        1.2224        got                                                        -0.6096        tastes like
        1.2101        gum                                                        -0.5683        reason
        1.1767        take                                                       -0.5632        likes
```

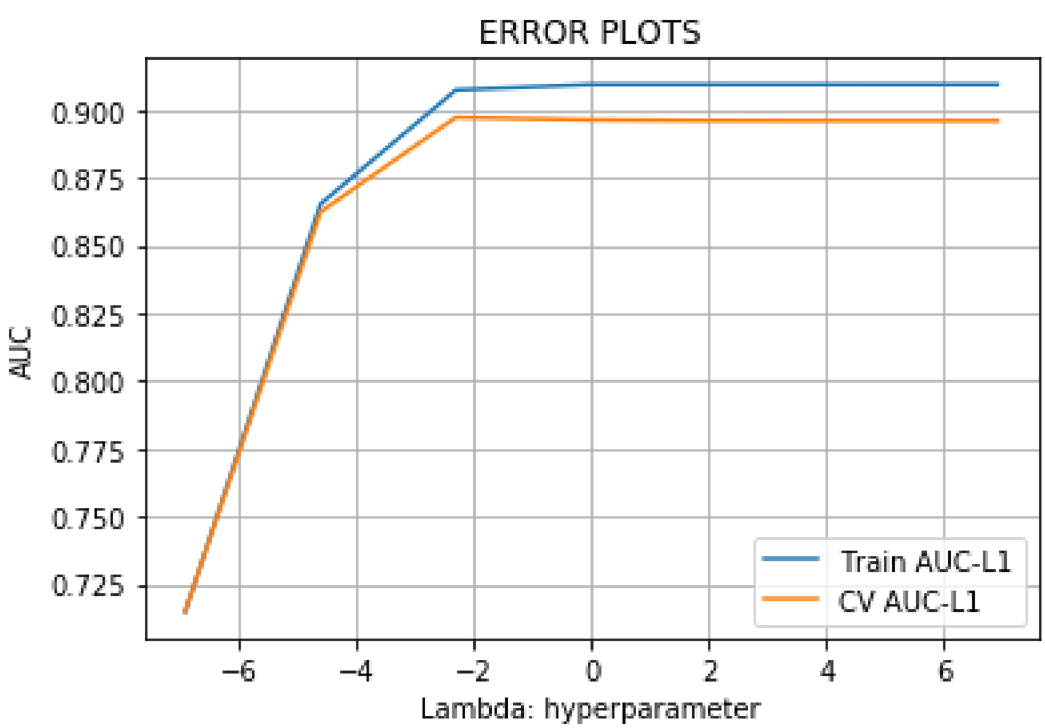
1.1650	big	-0.5628	service
1.1544	thanks	-0.5375	makes
1.0184	tea	-0.5335	cats
1.0117	family	-0.5204	months
1.0067	not good	-0.5130	kind
0.9683	subscribe	-0.5098	boxes
0.9572	thing	-0.5019	bold
0.9096	disappointed	-0.4868	giving
0.9057	help	-0.4864	excellent
0.8527	end	-0.4828	ago
0.8428	worth	-0.4777	keurig

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

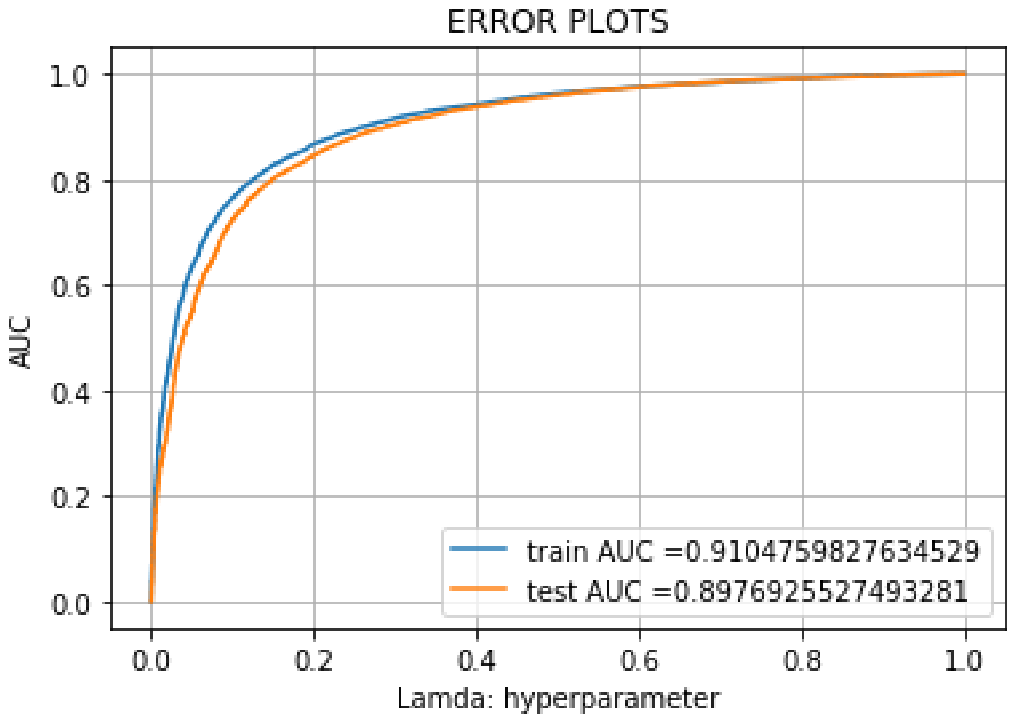
7.3.1 [5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

```
In [253]: # Please write all the code with proper documentation

          lr_all(train_vectors,y_train,X_cv,'l1')
```

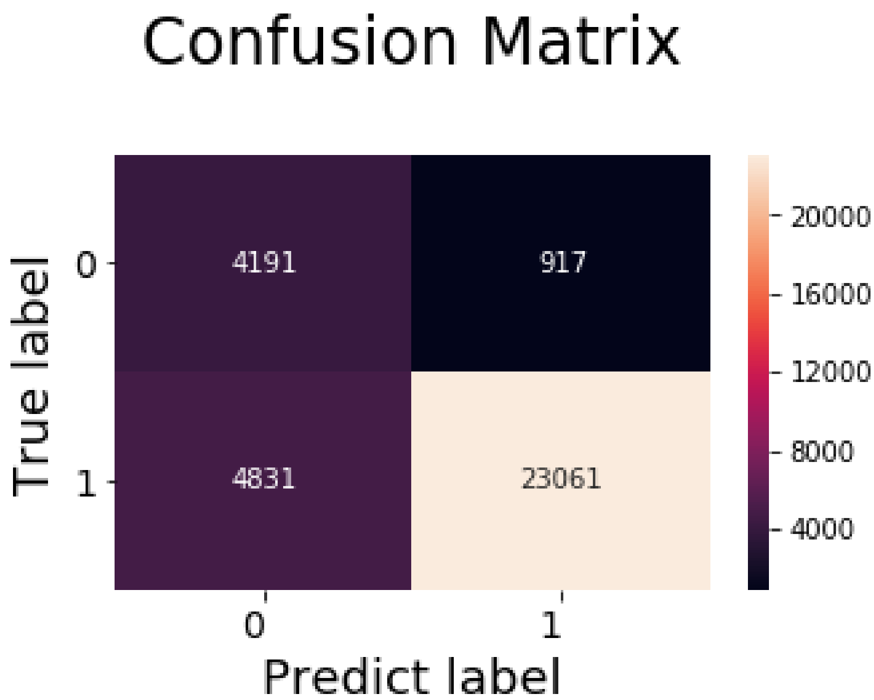
```
100%|| 7/7 [00:02<00:00,  3.00it/s]
```



```
-------------------------
Cv auc scores with penalty L1
[0.7149699199648194, 0.8623289381701493, 0.8972420820037071, 0.8963110790782647, 0.896006442150
Maximun Auc value : 0.8972420820037071
Index 2
The optimal value of Lambda =  0.1
```



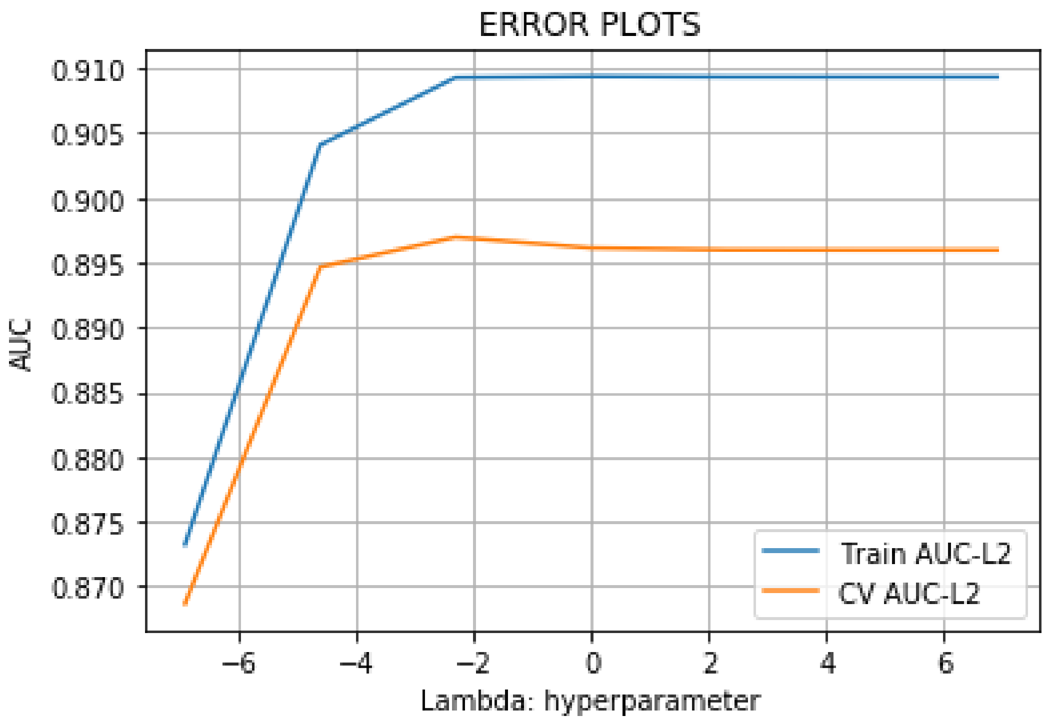

```
Train confusion matrix
[[ 6174  1081]
 [ 6539 31096]]
Test confusion matrix
[[ 4191   917]
 [ 4831 23061]]
```



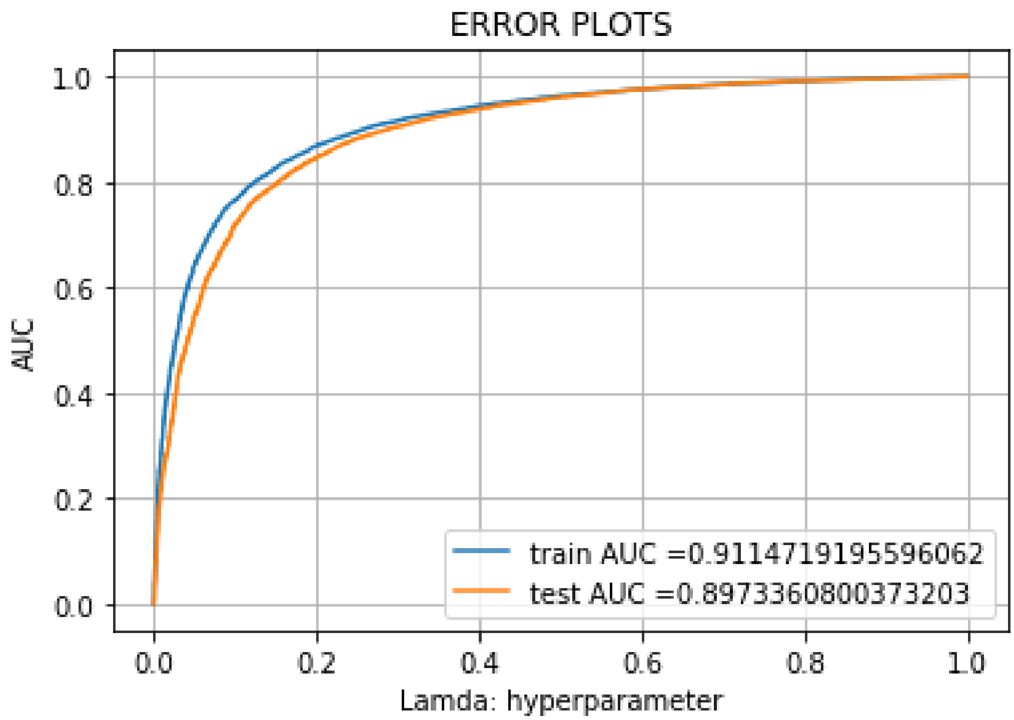
7.3.2 [5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

```
In [254]: # Please write all the code with proper documentation
          all_lr(train_vectors,y_train,X_cv,'l2')
```

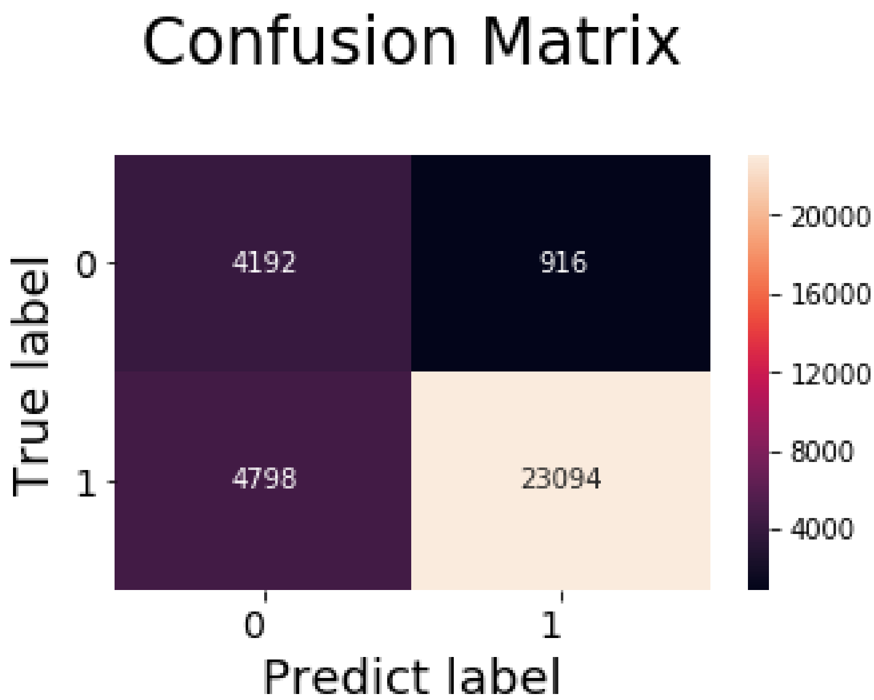
```
100%|| 7/7 [00:04<00:00,  1.43it/s]
```




```
--------------------------
Cv auc scores with penalty L2
[0.8686668268851596, 0.8946634880571093, 0.8969706221466804, 0.8961376090875506, 0.89598988413
Maximun Auc value : 0.8969706221466804
Index 2
The optimal value of Lambda =  0.1
```




```
Train confusion matrix
[[ 6162  1093]
 [ 6475 31160]]
Test confusion matrix
[[ 4192   916]
 [ 4798 23094]]
```

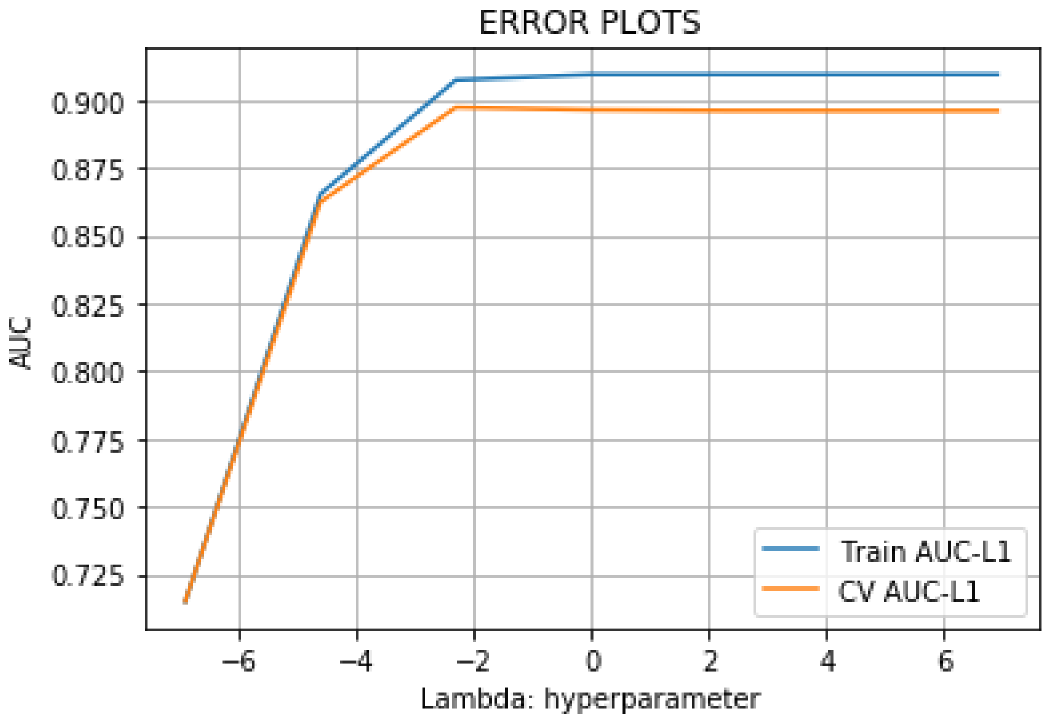


7.4 [5.4] Logistic Regression on TFIDF W2V, SET 4

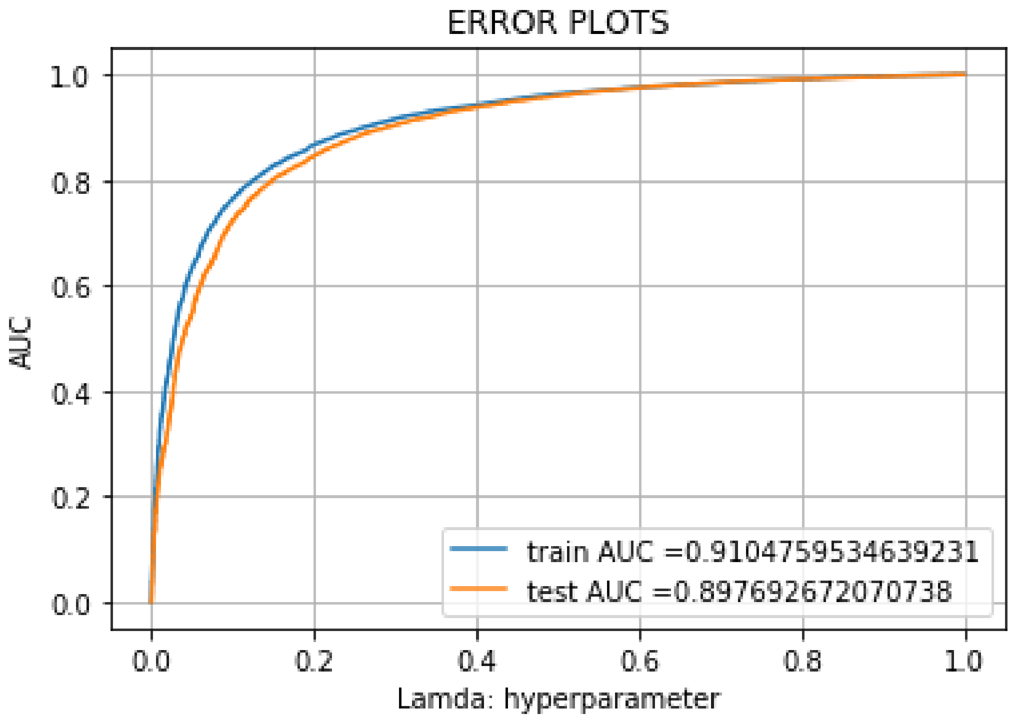
7.4.1 [5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

In [255]:
```
# Please write all the code with proper documentation
lr_all(tfidf_train_vectors,y_train,X_cv,'l1')
```

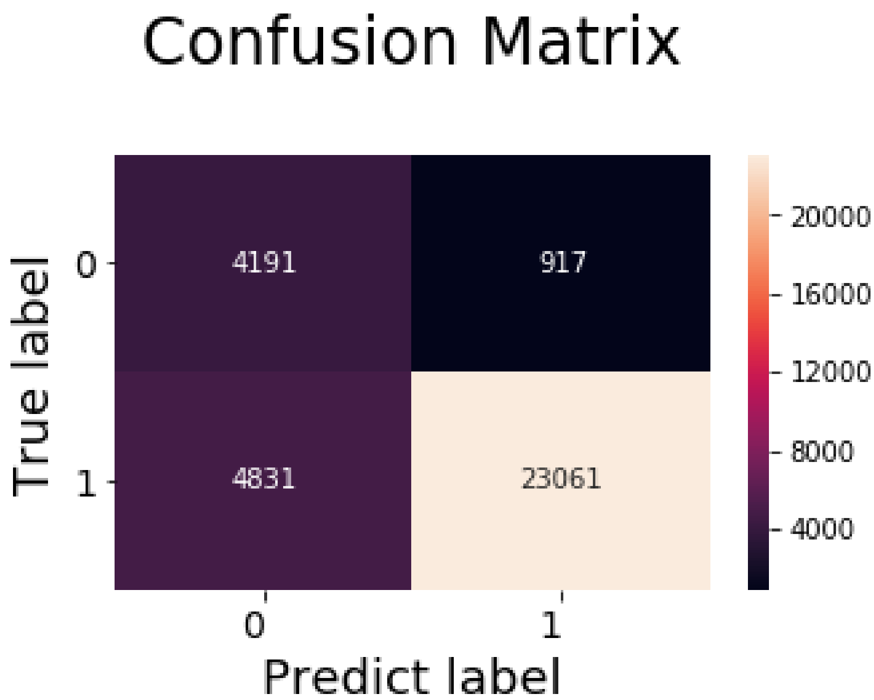
```
100%|| 7/7 [00:02<00:00,  2.70it/s]
```




```
--------------------------
Cv auc scores with penalty L1
[0.7149699199648194, 0.8623300979941393, 0.897239838659937, 0.8963122846847806, 0.896006747367
Maximun Auc value : 0.897239838659937
Index 2
The optimal value of Lambda =  0.1
```



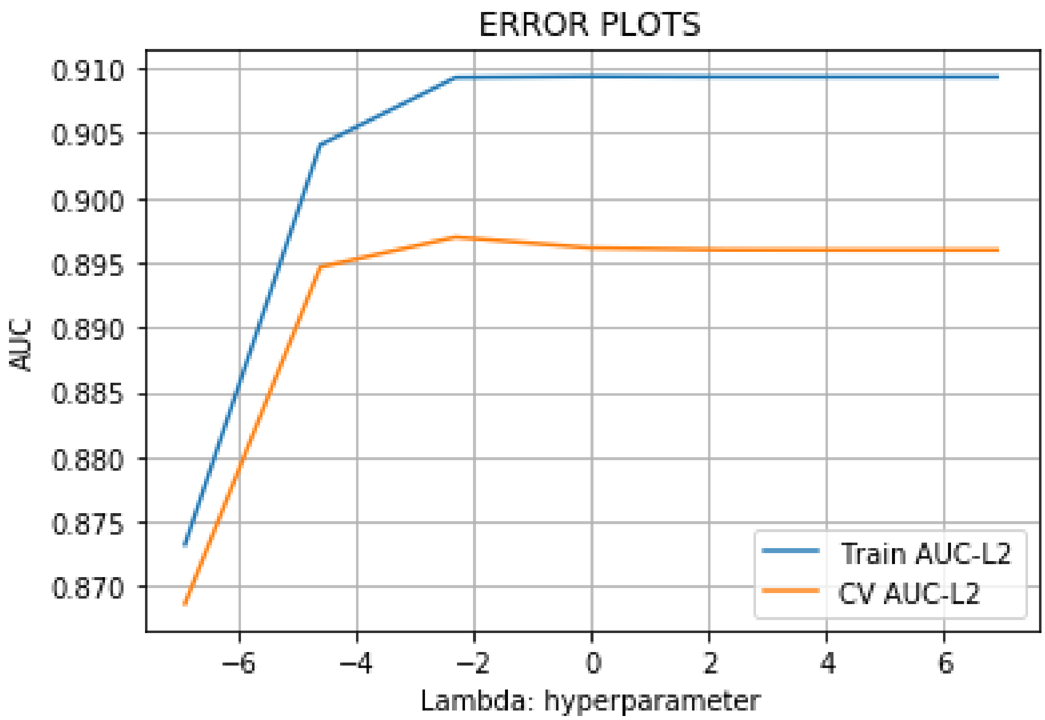

```
Train confusion matrix
[[ 6174  1081]
 [ 6539 31096]]
Test confusion matrix
[[ 4191   917]
 [ 4831 23061]]
```



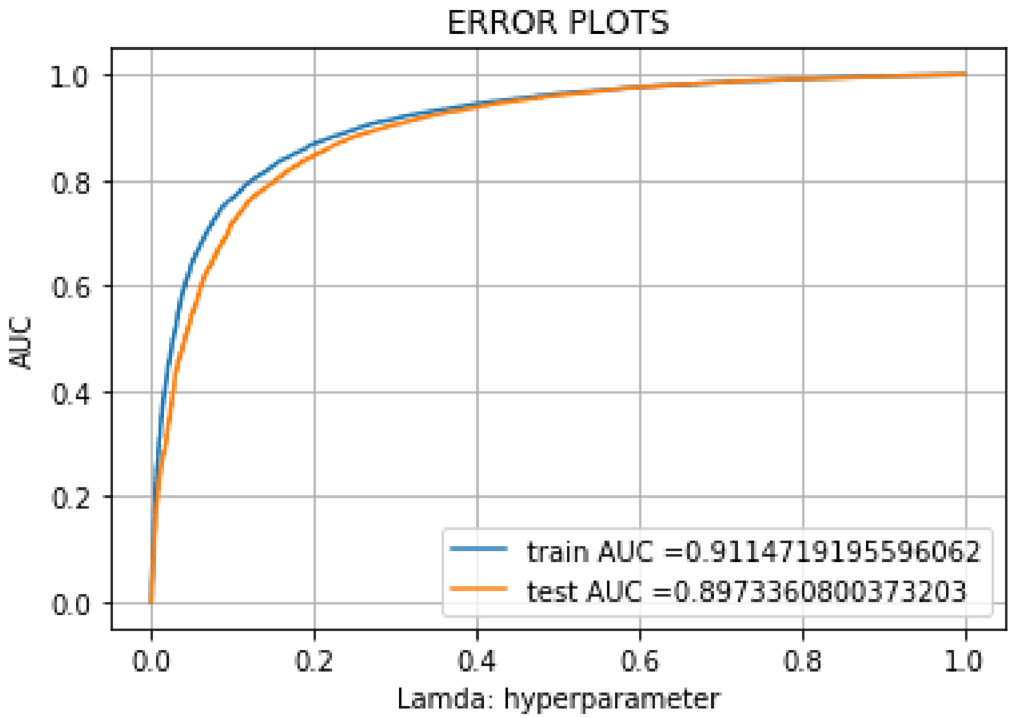
7.4.2 [5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

```
In [256]: # Please write all the code with proper documentation

          all_lr(tfidf_train_vectors,y_train,X_cv,'l2')
```

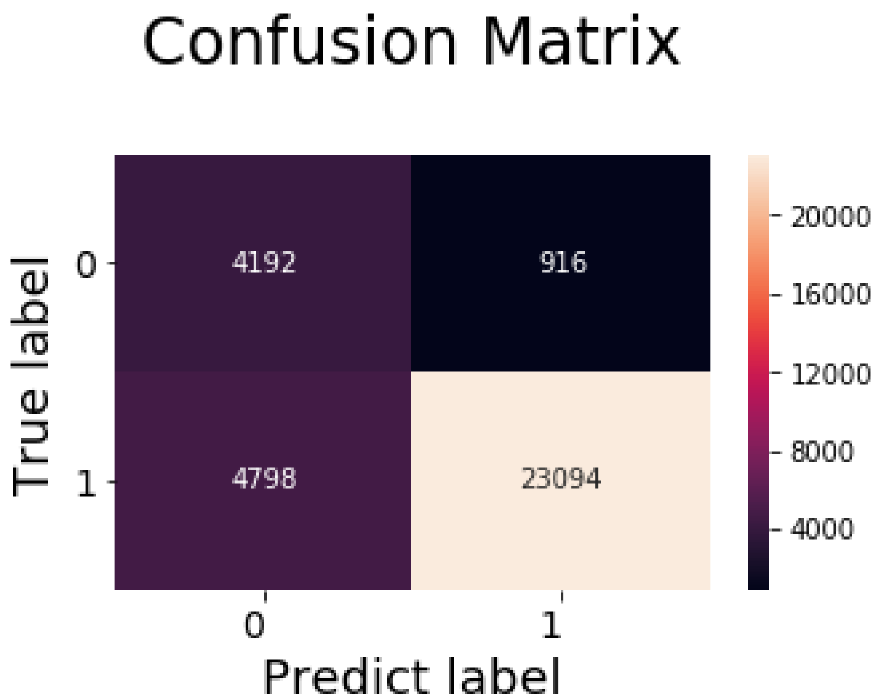
```
100%|| 7/7 [00:04<00:00,  1.54it/s]
```




```
--------------------------
Cv auc scores with penalty L2
[0.8686668268851596, 0.8946634880571093, 0.8969706221466804, 0.8961376090875506, 0.89598988413
Maximun Auc value : 0.8969706221466804
Index 2
The optimal value of Lambda =  0.1
```




```
Train confusion matrix
[[ 6162  1093]
 [ 6475 31160]]
Test confusion matrix
[[ 4192   916]
 [ 4798 23094]]
```



8 [6] Conclusions

```
In [257]: # Please compare all your models using Prettytable library
          from prettytable import PrettyTable

          # Names of models
          Vectorizer = ['Bag of Words','Bag of Words','TFIDF ','TFIDF ','AVG W2V','AVG W2V','TI


          Param=[0.1, 0.1,0.1,0.1,0.1, 0.1,0.1, 0.1]

          auc =[0.89,0.89,0.89,0.89,0.89,0.89,0.89,0.89]

          numbering = [1,2,3,4,5,6,7,8]

          # Initializing prettytable
          ptable = PrettyTable()

          # Adding columns
          ptable.add_column("S.NO.",numbering)
          ptable.add_column("MODEL",Vectorizer)

          ptable.add_column("Hyper Parameter",Param)
```

```python
ptable.add_column("AUC",auc)


print(ptable)
```

```
+--------+--------------+-----------------+------+
| S.NO. |     MODEL     | Hyper Parameter | AUC  |
+--------+--------------+-----------------+------+
|   1    | Bag of Words |       0.1       | 0.89 |
|   2    | Bag of Words |       0.1       | 0.89 |
|   3    |    TFIDF     |       0.1       | 0.89 |
|   4    |    TFIDF     |       0.1       | 0.89 |
|   5    |   AVG W2V    |       0.1       | 0.89 |
|   6    |   AVG W2V    |       0.1       | 0.89 |
|   7    |  TFIDF W2V   |       0.1       | 0.89 |
|   8    |  TFIDF W2V   |       0.1       | 0.89 |
+--------+--------------+-----------------+------+
```

8.0.1 Conclution

This LR classifier is faster than some of the previous models. TFIDF and BOW both L1 and L2 gave 89% AUC value. The model can be improved by taking more data points, and by taking some other features that may provide us with better insight about the data.