Amazon Fine Food Reviews Analysis

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

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

[1]. Reading Data

[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 [240]:

```
%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 [241]:
```
# 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 p
# 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 LIM
# for tsne assignment you can take 5k data points

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

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a neg
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[241]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominat
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [242]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [243]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[243]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [244]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[244]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	5

In [245]:
```
display['COUNT(*)'].sum()
```

Out[245]: 393063

[2] Exploratory Data Analysis

[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 [246]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[246]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
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	

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 [247]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplac
```

In [248]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, 
final.shape
```

Out[248]:
```
(87775, 10)
```

In [249]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[249]:
```
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 [250]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[250]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [251]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [252]:
```
#Before starting the next phase of preprocessing lets see the number of entries le
print(final.shape)

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

```
(87773, 10)
```

Out[252]:
```
1    73592
0    14181
Name: Score, dtype: int64
```

[3] Preprocessing

[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 [253]:
```
# 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 very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
==================================================
```

In [254]:
```
# 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 very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
```

In [255]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-
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 very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
==================================================
```

In [256]:
```
# 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 [257]:
```
# sent_1500 = decontracted(sent_1500)
# print(sent_1500)
# print("="*50)
```

In [258]:
```
#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 very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
```

In [259]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
# sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
# print(sent_1500)
```

In [260]:
```
# 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 ste

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ours
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'h
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itsel
            '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'
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'th
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all'
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than',
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "di
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn'
            'won', "won't", 'wouldn', "wouldn't"])
```

In [261]:
```
# 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 st
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████
█| 87773/87773 [00:41<00:00, 2126.88it/s]
```

In [262]:
```
# preprocessed_reviews[1500]
```

[3.2] Preprocessing Review Summary

In [263]:
```
## Similartly you can do preprocessing for review summary also.
```

In [264]:
```
from sklearn.model_selection import train_test_split

print(type(final['Text']))
final['Text'] = preprocessed_reviews

X = final['Text'].values
Y = final['Score'].values

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

print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
<class 'pandas.core.series.Series'>
(61441,) (61441,)
(26332,) (26332,)
```

[4] Featurization

[4.1] BAG OF WORDS

In [265]:
```
#BoW
from scipy.sparse import hstack

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

X_train_bow = count_vect.transform(X_train)
X_test_bow = count_vect.transform(X_test)

print("the type of count vectorizer ",type(X_train_bow))
print("the shape of out text BOW vectorizer ",X_train_bow.get_shape())
print("the number of unique words ", X_train_bow.get_shape()[1])
```

```
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (61441, 46442)
the number of unique words  46442
```

[4.3] TF-IDF

In [266]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_train)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_n
print('='*50)

X_train_tfidf = tf_idf_vect.transform(X_train)
X_test_tfidf = tf_idf_vect.transform(X_test)

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

```
some sample features(unique words in the corpus) ['aa', 'abandoned', 'abdomina
l', 'ability', 'able', 'able add', 'able buy', 'able chew', 'able drink', 'abl
e eat']
==================================================
the type of TFIDF vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (61441, 36359)
the number of unique words including both unigrams and bigrams  36359
```

[4.4] Word2Vec

In [267]:
```
# 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())

w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=2)
```

In [268]:
```
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  14813
sample words  ['really', 'like', 'wild', 'ride', 'jerky', 'good', 'bang', 'buc
k', 'bbq', 'not', 'would', 'recommend', 'even', 'trying', 'tastes', 'dried',
'sauce', 'always', 'liked', 'chocolate', 'covered', 'almonds', 'something', 'c
ombination', 'enjoyable', 'got', 'chance', 'try', 'jumped', 'right', 'away',
'first', 'container', 'much', 'bigger', 'thought', 'lot', 'nuts', 'one', 'pack
age', 'secondly', 'unlike', 'baked', 'dipped', 'dramatically', 'cuts', 'mess',
'flavor', 'normally', 'big']
```

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

[4.4.1.1] Avg W2v

In [269]:
```
# average Word2Vec
# compute average word2vec for each review.
def avgw2v(list_of_sentance):
    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this l
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length 50, you migh
        cnt_words =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words:
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        sent_vectors.append(sent_vec)
    return sent_vectors
```

In [270]:
```
sent_vectors_train = avgw2v(list_of_sentance_train)
print(len(sent_vectors_train[0]))
print(len(list_of_sentance_train))
```

```
100%|██████████████████████████████████████████
█| 61441/61441 [02:11<00:00, 466.95it/s]

50
61441
```

In [271]:
```
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())

sent_vectors_test = avgw2v(list_of_sentance_test)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
100%|██████████████████████████████████████████
█| 26332/26332 [00:56<00:00, 468.48it/s]

26332
50
```

[4.4.1.2] TFIDF weighted W2v

In [272]:
```
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))
```

In [273]:
```
# TF-IDF weighted Word2Vec
def tfidfw2v(list_of_sentance):
    tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
    # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val

    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored i
    row=0;
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words and word in tfidf_feat:
                vec = w2v_model.wv[word]
    #             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
    return tfidf_sent_vectors
```

In [274]:
```
tfidf_sent_vectors_train = tfidfw2v(list_of_sentance_train)
```

```
100%|██████████████████████████████████████████████████
███| 61441/61441 [33:34<00:00, 30.50it/s]
```

In [275]:
```
tfidf_sent_vectors_test = tfidfw2v(list_of_sentance_test)
```

```
100%|██████████████████████████████████████████████████
███| 26332/26332 [13:29<00:00, 32.52it/s]
```

Applying Logistic Regression

[5.1] Logistic Regression on BOW, SET 1

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

In [276]:
```
%config IPCompleter.greedy=True
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, roc_auc_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import StandardScaler
```

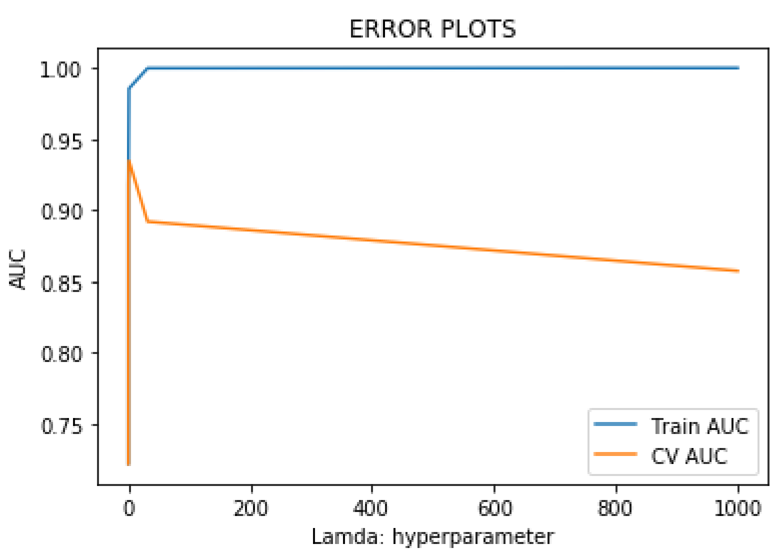
In [277]:

```
# Function to find the best optimal Lamda using LogisticRegression and GridSearch(
def getOptimizedLamda(X_train_vector, Y_train, regularization):
    lamda_vals = np.logspace(-3, 3, 5) # 10^-3 to 10^3 and no. of samples =5

    param_grid = dict(C=lamda_vals)
    clf = LogisticRegression(penalty = regularization)

    grid = GridSearchCV(clf, param_grid, cv=10, scoring='roc_auc')  # 10 fold cro
    grid.fit(X_train_vector, Y_train)

    print("Best Estimator: ",grid.best_estimator_)
#     print("Best Estimator Coef/Weight: ",grid.best_estimator_.coef_)
    print("Best cross-validation score: {:.2f}".format(grid.best_score_))  # best
    best_lamda = round(grid.best_params_['C'],3)  # best lamda value after 10 fold
    print("Best parameters: ", best_lamda)

    train_auc= grid.cv_results_['mean_train_score']
    cv_auc = grid.cv_results_['mean_test_score']

    plt.plot(lamda_vals, train_auc, label='Train AUC')
    plt.plot(lamda_vals, cv_auc, label='CV AUC')

    plt.legend()
    plt.xlabel("Lamda: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()
    return best_lamda, grid.best_estimator_.coef_
```

In [278]:

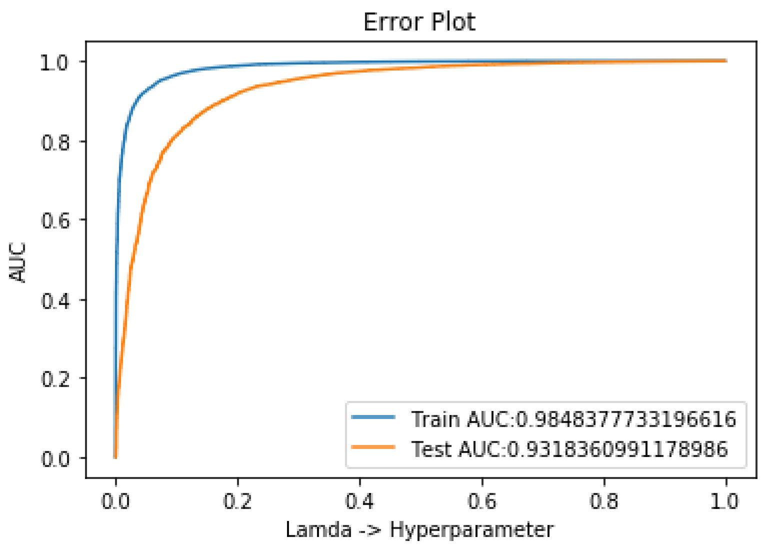
```
bestLamda_bow_l1, weight_bow_l1 = getOptimizedLamda(X_train_bow, Y_train, regular
```

```
Best Estimator:  LogisticRegression(C=1.0, 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)
Best cross-validation score: 0.93
Best parameters:  1.0
```

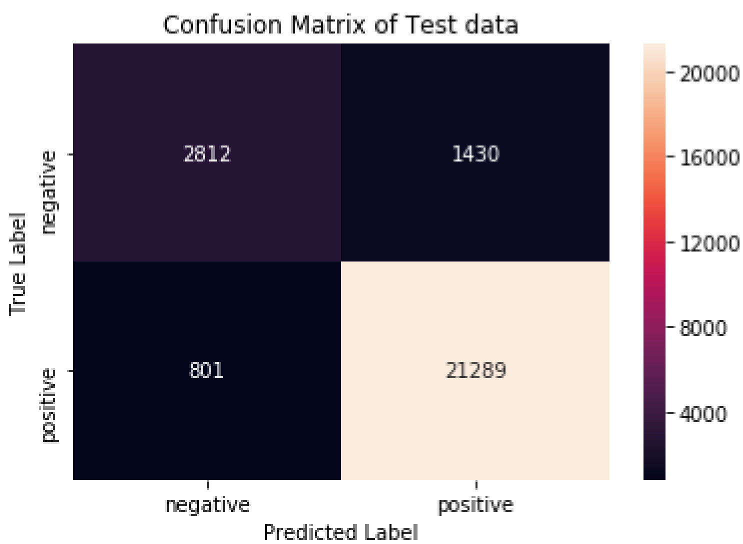


In [279]:
```
# Applying the model on test data with optimal value of C and find the AUC for Log
def LR_test(X_train_vector, Y_train, X_test_vector, Y_test, best_lamda, regulariz
    clf = LogisticRegression(penalty = regularization, C=best_lamda)
    clf.fit(X_train_vector, Y_train)

    train_fpr, train_tpr, threshold = roc_curve(Y_train, clf.predict_log_proba(X_
    test_fpr, test_tpr, threshold = roc_curve(Y_test, clf.predict_log_proba(X_tes

    test_auc = auc(test_fpr, test_tpr)
    plt.plot(train_fpr, train_tpr, label = "Train AUC:"+str(auc(train_fpr,train_t
    plt.plot(test_fpr, test_tpr, label = "Test AUC:"+str(test_auc))

    plt.legend()
    plt.xlabel("Lamda -> Hyperparameter")
    plt.ylabel("AUC")
    plt.title("Error Plot")
    plt.show()

    print("training confusion matrix")
    print(confusion_matrix(Y_train, clf.predict(X_train_vector)))
    test_cm = confusion_matrix(Y_test, clf.predict(X_test_vector))

    # plot confusion matrix to describe the performance of classifier.
    class_label = ["negative", "positive"]
    df_cm = pd.DataFrame(test_cm, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Confusion Matrix of Test data")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

    return test_auc, clf
```

In [280]:
```
auc_bow_l1, classifier_bow_l1 = LR_test(X_train_bow, Y_train, X_test_bow, Y_test,
```




```
training confusion matrix
[[ 8022  1917]
 [  663 50839]]
```



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

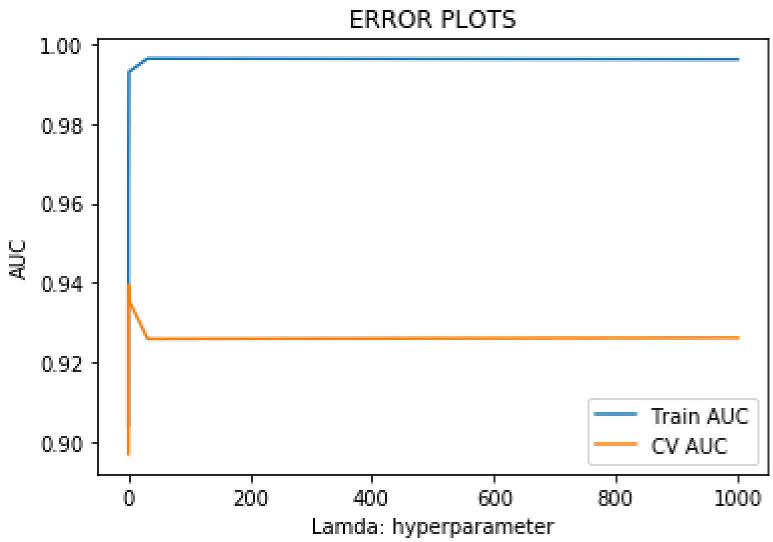
In [281]:
```
for i in [0.001,0.1,1,10,100,1000]:
    clf = LogisticRegression(C= i, penalty= 'l1')
    clf.fit(X_train_bow,Y_train)
    print("For C =",i)
    print("Non Zero weights:",np.count_nonzero(clf.coef_))
    print("---------------")
```

```
For C = 0.001
Non Zero weights: 5
---------------
For C = 0.1
Non Zero weights: 912
---------------
For C = 1
Non Zero weights: 4669
---------------
For C = 10
Non Zero weights: 9580
---------------
For C = 100
Non Zero weights: 11244
---------------
For C = 1000
Non Zero weights: 17160
---------------
```

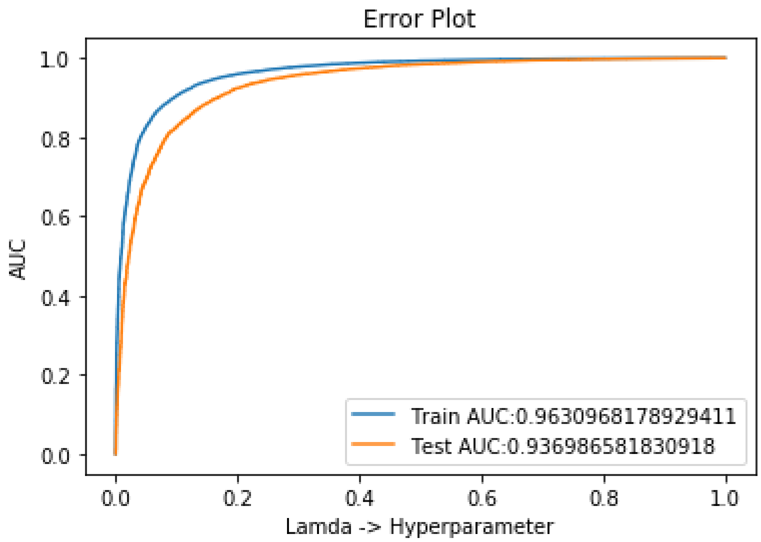
[5.1.2] Applying Logistic Regression with L2 regularization on BOW, SET 1

In [282]:
```
bestLamda_bow_l2, weight_bow_l2 = getOptimizedLamda(X_train_bow, Y_train, regular
```

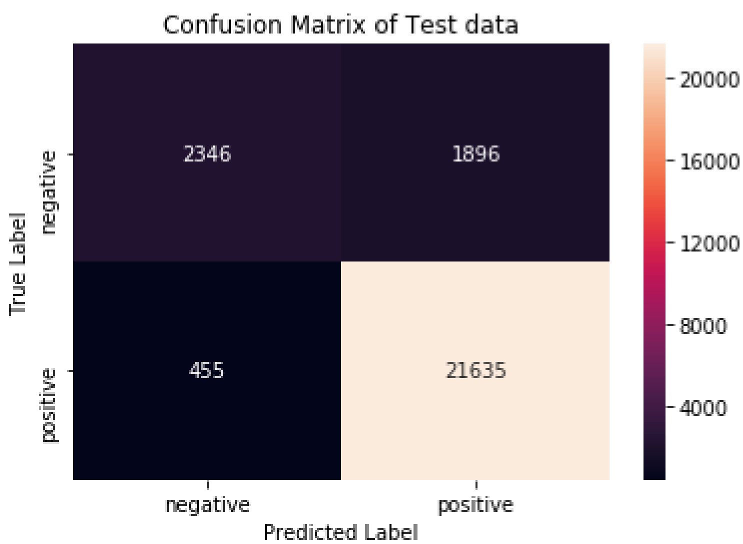
```
Best Estimator:  LogisticRegression(C=0.03162277660168379, class_weight=None,
dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
Best cross-validation score: 0.94
Best parameters:  0.032
```



In [283]:
```
auc_bow_l2, classifier_bow_l2 = LR_test(X_train_bow, Y_train, X_test_bow, Y_test,
```




```
training confusion matrix
[[ 6225  3714]
 [  741 50761]]
```



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

In [284]:
```
import copy
from scipy.sparse import csr_matrix

# Get the weights W after fit your model with the data X i.e Train data.
weights_org = weight_bow_l1  #weight vector of best estimator of original classif

X_train_bow_pert = copy.deepcopy(X_train_bow)   # copy X_train_bow to X_train_bow_

e = 0.02
X_train_bow_pert = csr_matrix(X_train_bow_pert,dtype=np.float64) # Convert dbtype

# Add a noise to the X (X' = X + e) and get the new data set X' (if X is a sparse
#adding a nonzero scalar to a sparse matrix is not supported so we add only to non
X_train_bow_pert[np.nonzero(X_train_bow_pert)] += e   # adding small error in tra

# Fit the model again on data X' and get the weights W'
clf_pert = LogisticRegression(penalty = 'l1', C=bestLamda_bow_l1)
clf_pert.fit(X_train_bow_pert, Y_train)
weight_pert = clf_pert.coef_

# Now find the % change between W and W' (| (W-W') / (W) |)*100)
weights_diff_percentage=abs((weights_org-weight_pert)/weights_org)*100
```

In [309]:
```
# Calculate the 0th, 10th, 20th, 30th, ...100th percentiles, and observe any sudde
# percentage_change_vector
print(np.nanpercentile(weights_diff_percentage, 10))
print(np.nanpercentile(weights_diff_percentage, 20))
print(np.nanpercentile(weights_diff_percentage, 30))
print(np.nanpercentile(weights_diff_percentage, 40))
print(np.nanpercentile(weights_diff_percentage, 50))
print(np.nanpercentile(weights_diff_percentage, 60))
print(np.nanpercentile(weights_diff_percentage, 70))
print(np.nanpercentile(weights_diff_percentage, 80))
print(np.nanpercentile(weights_diff_percentage, 90))
print(np.nanpercentile(weights_diff_percentage, 99))
print('='*20)
print(np.nanpercentile(weights_diff_percentage, 98.1))
print(np.nanpercentile(weights_diff_percentage, 98.2))
print(np.nanpercentile(weights_diff_percentage, 98.3))
print(np.nanpercentile(weights_diff_percentage, 98.4))
print(np.nanpercentile(weights_diff_percentage, 98.5))
print(np.nanpercentile(weights_diff_percentage, 98.6))
print(np.nanpercentile(weights_diff_percentage, 98.7))
print(np.nanpercentile(weights_diff_percentage, 98.8))
print(np.nanpercentile(weights_diff_percentage, 98.9))
print(np.nanpercentile(weights_diff_percentage, 99))
```

```
0.3317105004167928
0.6414854778682685
0.9522476030388332
1.2648297332738812
1.5491929323216613
1.9654091820151085
2.795449300490577
5.064035572969312
13.951757079274428
inf
====================
217.24733794619414
336.5712756741769
524.9039724576016
700.0535329519273
inf
inf
inf
inf
inf
inf
```

As per above analysis we can set 98.6 as threshold above which the weights are increased drastically.

In [310]:
```
# Print the features whose % change is more than a threshold x
features = count_vect.get_feature_names()
print("No of features having weight changes greater than 98.1%: ", weights_diff_pe
collinear_features=[]
print("\nBelow features are collinear:")
for i in np.where(weights_diff_percentage > 98.1)[1]:
    collinear_features.append(features[i])
print(collinear_features[:10])
```

```
No of features having weight changes greater than 98.1%:  131

Below features are collinear:
['addictively', 'afghanistan', 'appeal', 'arnt', 'average', 'avoids', 'badoi
t', 'bellies', 'bike', 'blenders']
```

[5.1.3] Feature Importance on BOW, SET 1

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

In [287]:
```
# Positive important features
def positive_imp_features(model,classifier):
    vocabulary = model.get_feature_names()
    words = list(classifier.coef_[0])
    pos_coef = []
    pos_words = []
    for index,coef in enumerate(words):
        if coef > 0:
            pos_coef.append(coef)
            pos_words.append(vocabulary[index])
    pos_df = pd.DataFrame(columns = ['Words','Coef'])
    pos_df['Words'] = pos_words
    pos_df['Coef'] = pos_coef
    pos_df = pos_df.sort_values("Coef",axis = 0,ascending = False).reset_index(dro
    print("Top ten positive features:\n",pos_df.head(10))
```

In [288]:
```
positive_imp_features(count_vect,classifier_bow_l1)
```

```
Top ten positive features:
             Words      Coef
0  emeraldforest  6.470649
1        spooned  4.040515
2          picks  3.251943
3     pleasantly  3.082287
4           haha  3.081073
5         hooked  2.860193
6       feridies  2.850962
7     eliminated  2.788684
8         amazed  2.680289
9         earthy  2.611118
```

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

In [289]:
```
# Negative important features
def negative_imp_features(model,classifier):
    vocabulary = model.get_feature_names()
    words = list(classifier.coef_[0])
    neg_coef = []
    neg_words = []
    for index,coef in enumerate(words):
        if coef < 0:
            neg_coef.append(abs(coef))
            neg_words.append(vocabulary[index])
    neg_df = pd.DataFrame(columns = ['Words','Coef'])
    neg_df['Words'] = neg_words
    neg_df['Coef'] = neg_coef
    neg_df = neg_df.sort_values("Coef",axis = 0,ascending = False).reset_index(dro
    print("Top ten negative predictors:\n",neg_df.head(10))
```

In [290]:
```
negative_imp_features(count_vect, classifier_bow_l1)
```

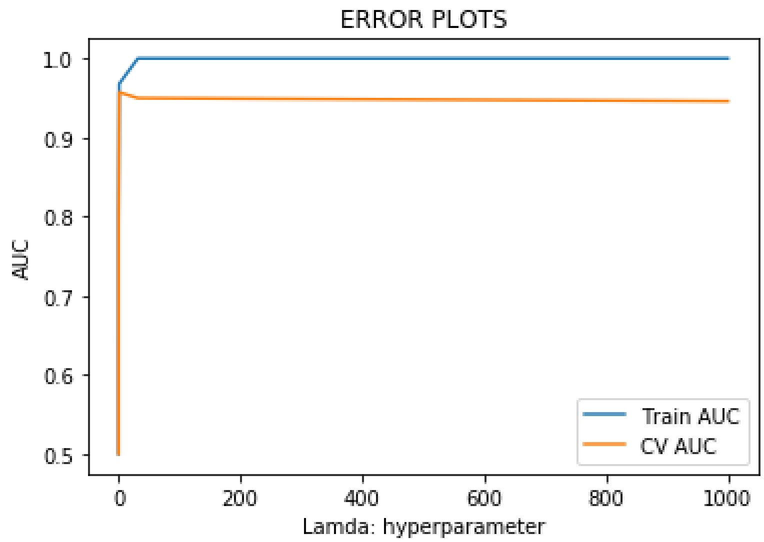
```
Top ten negative predictors:
            Words      Coef
0        stassen  6.278858
1          ifyou  5.922778
2         charts  5.515742
3       avocados  4.376358
4      cancelled  4.074063
5   intermediate  3.873483
6          shaft  3.683294
7     undrinkable  3.430069
8    unappealing  3.349508
9      glorified  3.344416
```

[5.2] Logistic Regression on TFIDF, SET 2

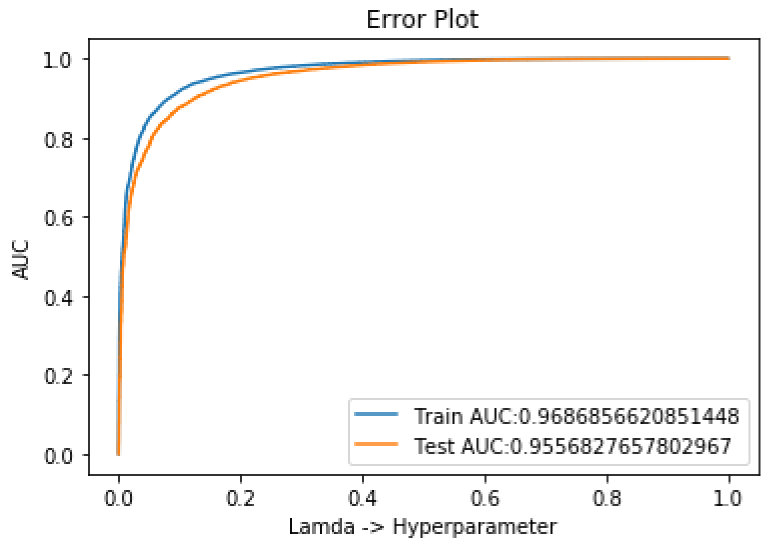
[5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

In [291]:
```
bestLamda_tfidf_l1, weight_tfidf_l1 = getOptimizedLamda(X_train_tfidf, Y_train, r
```

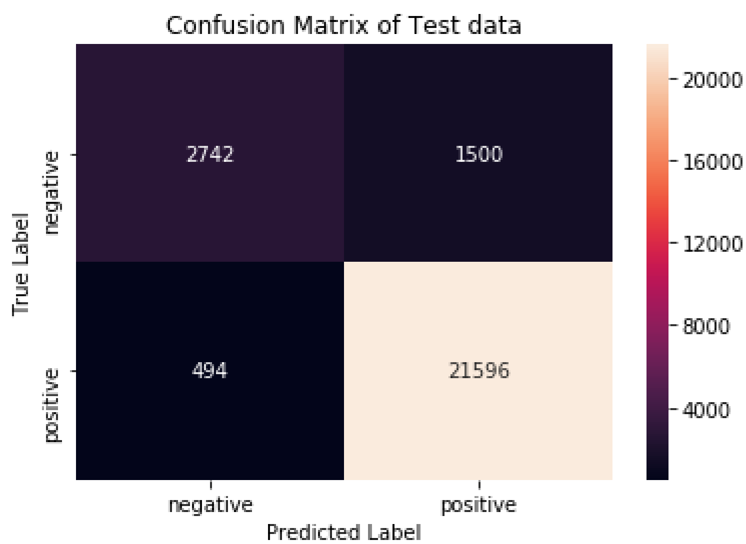
```
Best Estimator:  LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Best cross-validation score: 0.96
Best parameters:  1.0
```



In [292]:
```
auc_tfidf_l1, classifier_tfidf_l1 = LR_test(X_train_tfidf, Y_train, X_test_tfidf,
                                            regularization = 'l1')
```



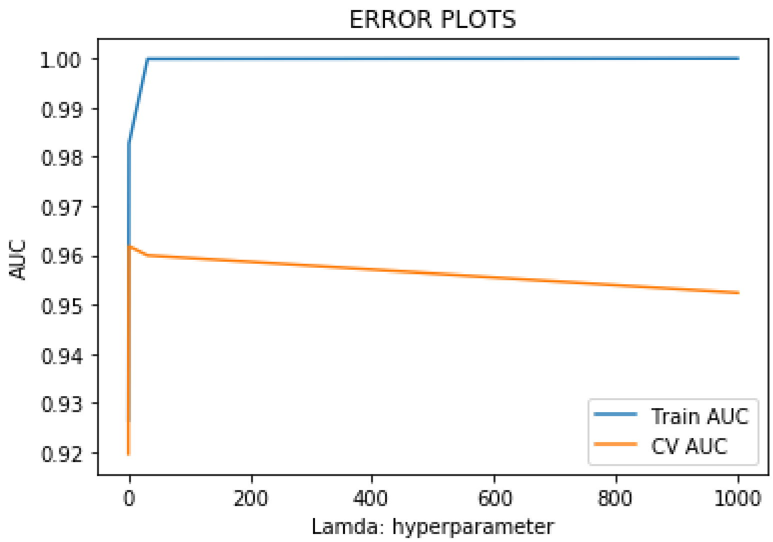

```
training confusion matrix
[[ 6936  3003]
 [  911 50591]]
```



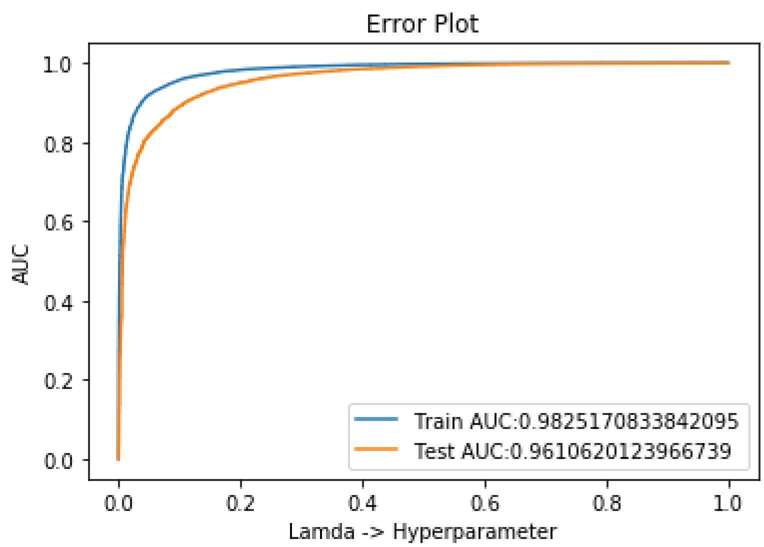
[5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [293]:
```
bestLamda_tfidf_l2, weight_tfidf_l2 = getOptimizedLamda(X_train_tfidf, Y_train, r
```

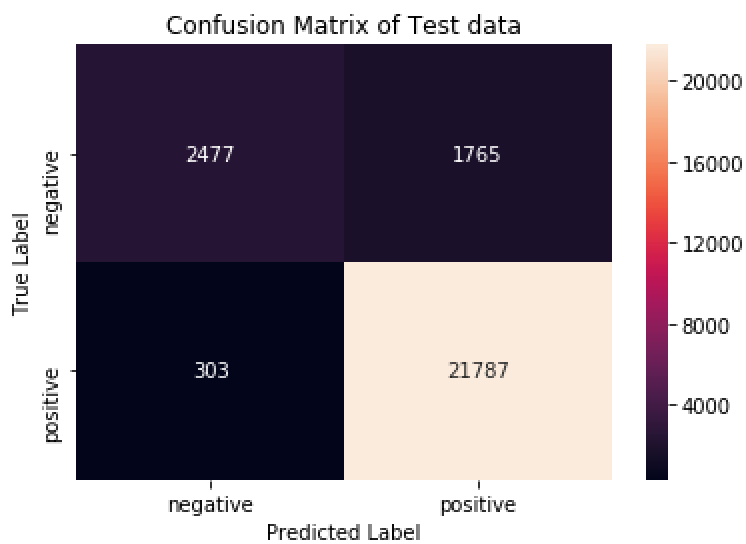
```
Best Estimator:  LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Best cross-validation score: 0.96
Best parameters:  1.0
```



In [294]:
```
auc_tfidf_l2, classifier_tfidf_l2 = LR_test(X_train_tfidf, Y_train, X_test_tfidf,
                                            regularization = 'l2')
```




```
training confusion matrix
[[ 6854  3085]
 [  442 51060]]
```



[5.2.3] Feature Importance on TFIDF, SET 2

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

In [295]:
```
positive_imp_features(tf_idf_vect,classifier_tfidf_l1)
```

```
Top ten positive features:
                Words       Coef
0  not disappointed  22.825052
1             great  19.626507
2         delicious  18.857224
3           perfect  15.811481
4              best  15.667930
5           amazing  13.506844
6             loves  13.127457
7         excellent  13.110314
8              good  12.962244
9         wonderful  11.628322
```

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

In [296]:
```
negative_imp_features(tf_idf_vect,classifier_tfidf_l1)
```

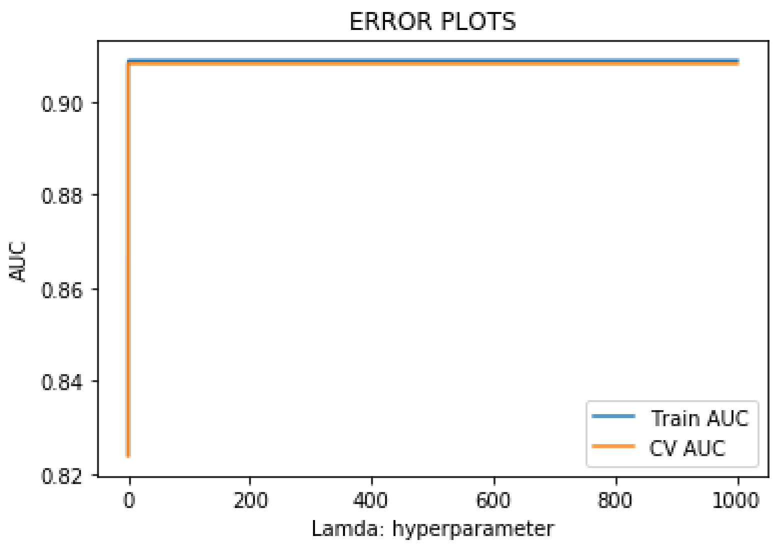
```
Top ten negative predictors:
             Words       Coef
0        two stars  24.526229
1     disappointed  17.333876
2            worst  17.055447
3        not worth  15.598416
4    not recommend  13.147358
5            awful  12.820031
6         not good  11.921305
7         terrible  11.698929
8         horrible  11.669424
9    disappointing  11.433242
```

[5.3] Logistic Regression on AVG W2V, SET 3

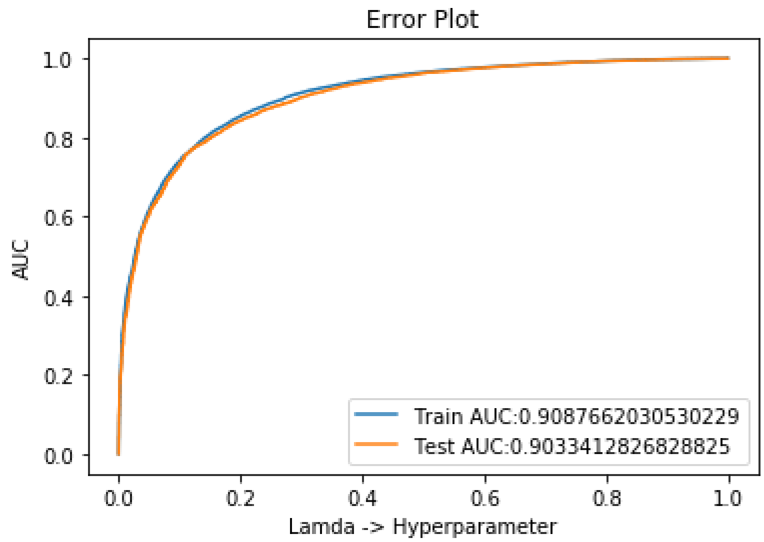
[5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

In [297]:
```
bestLamda_avgw2v_l1, weight_avgw2_l1 = getOptimizedLamda(sent_vectors_train, Y_tra
```

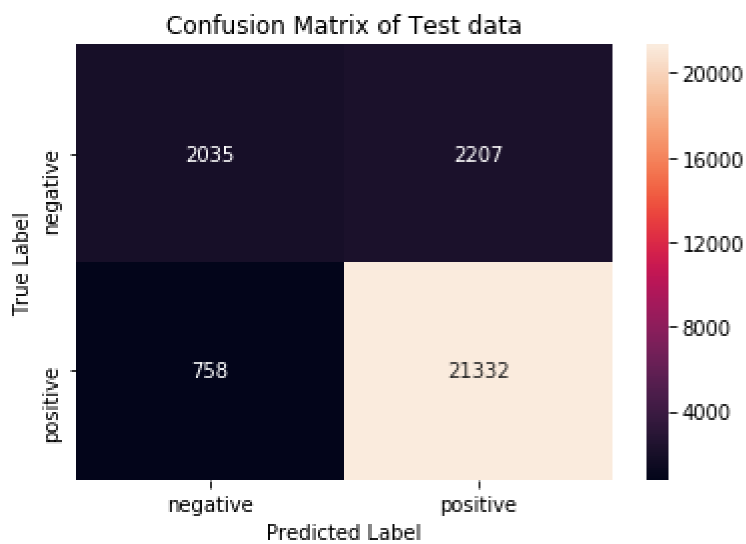
```
Best Estimator:  LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Best cross-validation score: 0.91
Best parameters:  1.0
```



In [298]:
```
auc_avgw2v_l1, classifier_avgw2_l1 = LR_test(sent_vectors_train, Y_train, sent_ve
                                             regularization = 'l1')
```



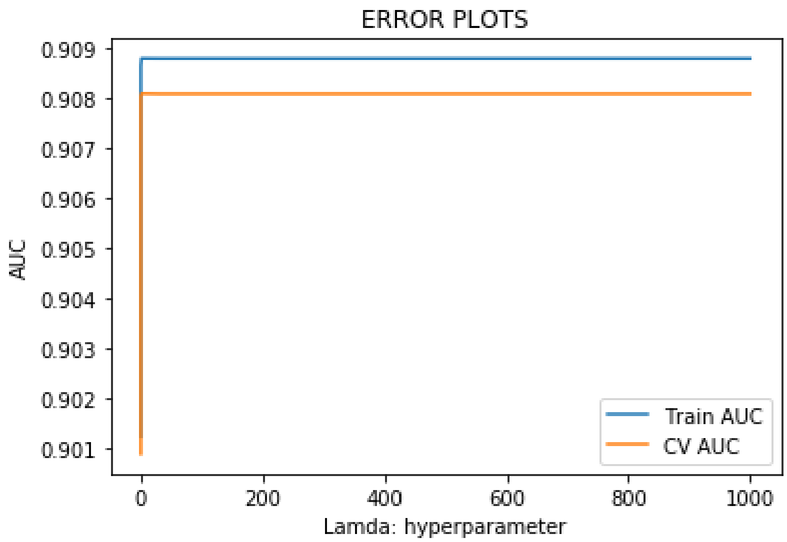

```
training confusion matrix
[[ 4908  5031]
 [ 1752 49750]]
```



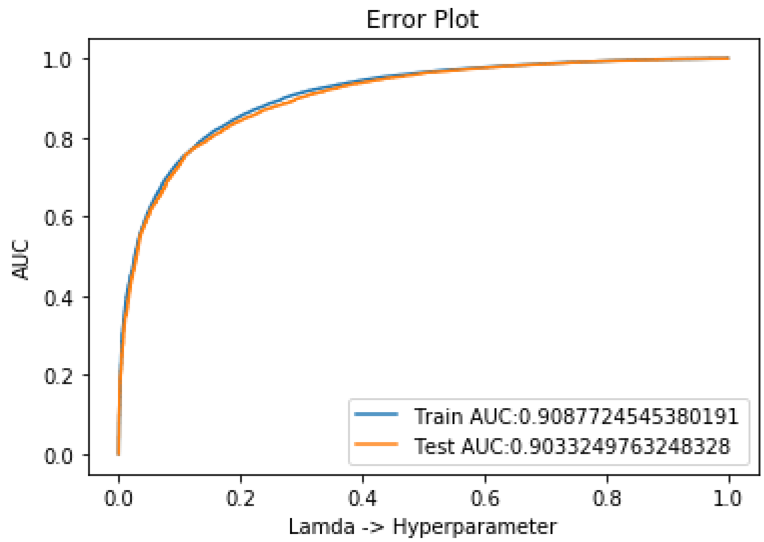
[5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

In [299]:
```
bestLamda_avgw2v_l2, weight_avgw2_l2 = getOptimizedLamda(sent_vectors_train, Y_tra
```

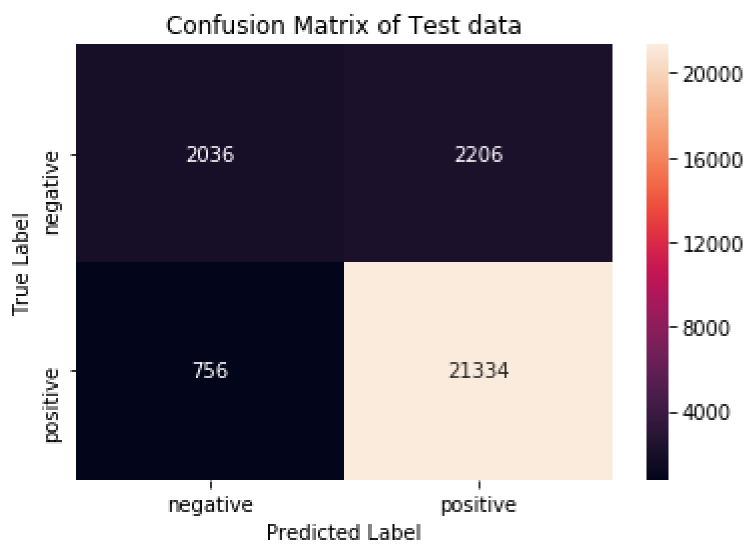
```
Best Estimator:  LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Best cross-validation score: 0.91
Best parameters:  1.0
```



In [300]:
```
auc_avgw2_l2, classifier_avgw2_l2 = LR_test(sent_vectors_train, Y_train, sent_vec
                                            regularization = 'l2')
```




```
training confusion matrix
[[ 4909  5030]
 [ 1752 49750]]
```

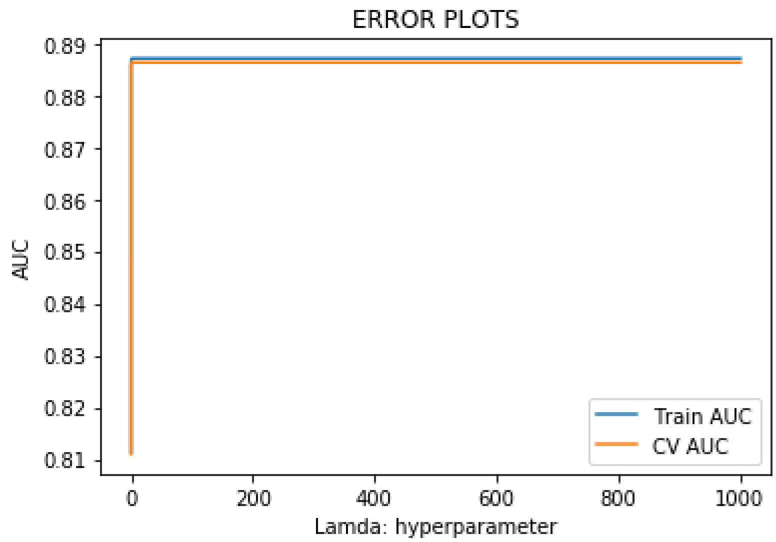


[5.4] Logistic Regression on TFIDF W2V, SET 4

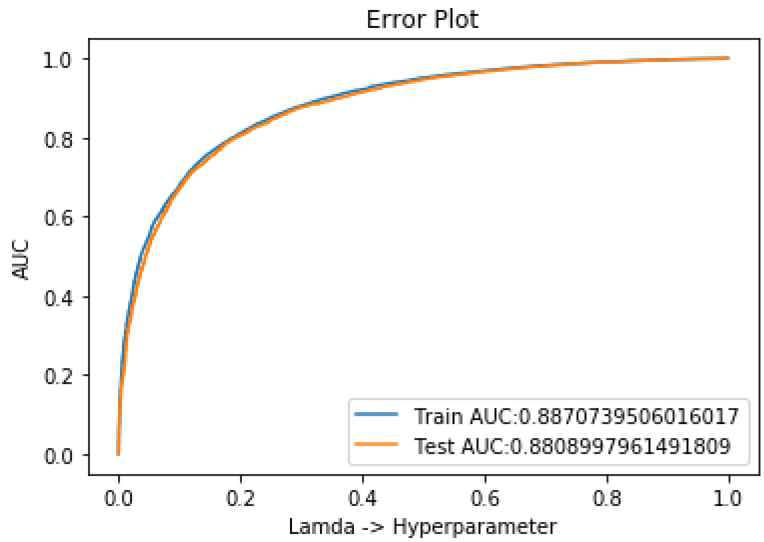
[5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

In [301]:
```
bestLamda_tfidfw2v_l1, weight_tfidfw2v_l1 = getOptimizedLamda(tfidf_sent_vectors_
```

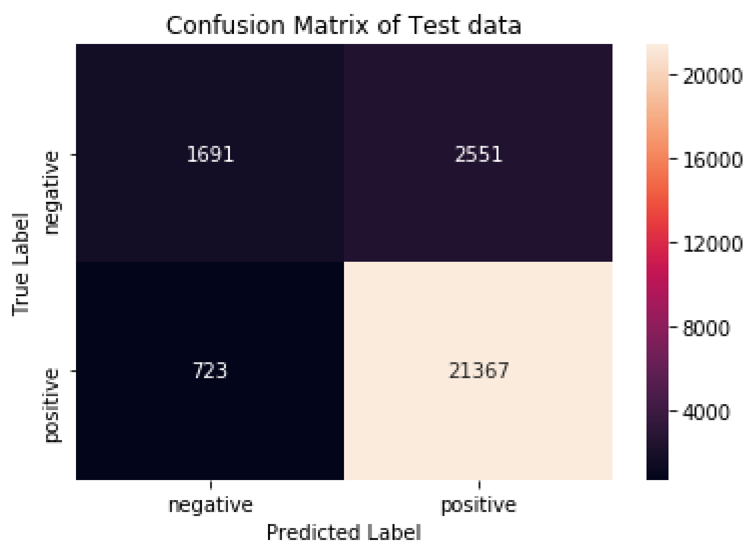
```
Best Estimator:  LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Best cross-validation score: 0.89
Best parameters:  1.0
```



In [302]:
```
auc_tfidfw2v_l1, classifier_tfidfw2v_l1 = LR_test(tfidf_sent_vectors_train, Y_tra
                                          bestLamda_tfidfw2v_l1, regularization
```



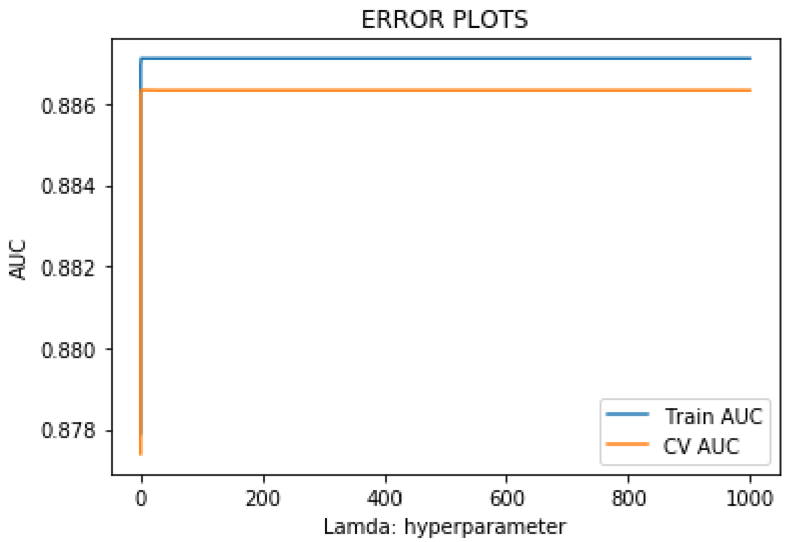

```
training confusion matrix
[[ 4134  5805]
 [ 1740 49762]]
```



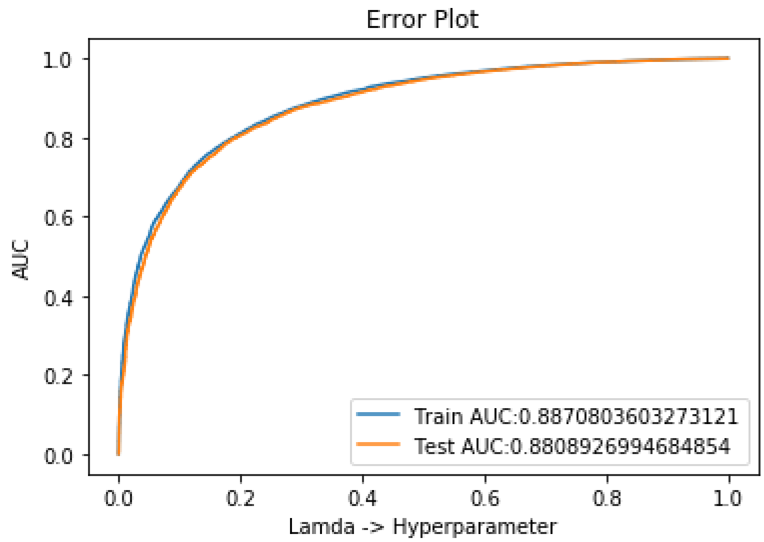
[5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

In [303]:
```
bestLamda_tfidfw2v_l2, weight_tfidfw2v_l2 = getOptimizedLamda(tfidf_sent_vectors_t
```

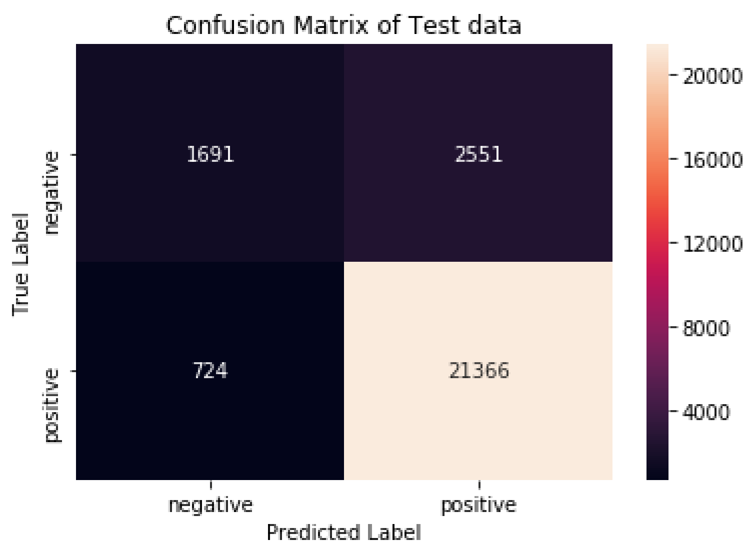
```
Best Estimator:  LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Best cross-validation score: 0.89
Best parameters:  1.0
```



In [304]:
```
auc_tfidfw2v_l2, classifier_tfidfw2v_l2 = LR_test(tfidf_sent_vectors_train, Y_tra
                                            bestLamda_tfidfw2v_l2, regularization
```




```
training confusion matrix
[[ 4139  5800]
 [ 1744 49758]]
```



[6] Conclusions

In [305]:
```
models = pd.DataFrame({
'Vectorizer': ["BOW", "BOW", "TFIDF", "TFIDF",
                "AVGW2V", "AVGW2V", "TFIDFW2V", "TFIDFW2V"],
'Model' : ['LogisticRegression', 'LogisticRegression', 'LogisticRegression', 'Log
           'LogisticRegression', 'LogisticRegression', 'LogisticRegression', 'Log
'Regulizer' : ['L1', 'L2','L1', 'L2',
                'L1', 'L2','L1', 'L2'],
'Hyper Parameter(Lamda)': [bestLamda_bow_l1, bestLamda_bow_l2, bestLamda_tfidf_l1
                            bestLamda_avgw2v_l1,bestLamda_avgw2v_l2, bestLamda_tfi
'AUC': [auc_bow_l1, auc_bow_l2, auc_tfidf_l1, auc_tfidf_l2,
        auc_avgw2v_l1, auc_avgw2_l2, auc_tfidfw2v_l1, auc_tfidfw2v_l2]},
columns = ["Vectorizer", "Model", "Regulizer", "Hyper Parameter(Lamda)", "AUC"])
print(models)
```

```
  Vectorizer               Model Regulizer  Hyper Parameter(Lamda)       AUC
0        BOW  LogisticRegression        L1                   1.000  0.931836
1        BOW  LogisticRegression        L2                   0.032  0.936987
2      TFIDF  LogisticRegression        L1                   1.000  0.955683
3      TFIDF  LogisticRegression        L2                   1.000  0.961062
4     AVGW2V  LogisticRegression        L1                   1.000  0.903341
5     AVGW2V  LogisticRegression        L2                   1.000  0.903325
6   TFIDFW2V  LogisticRegression        L1                   1.000  0.880900
7   TFIDFW2V  LogisticRegression        L2                   1.000  0.880893
```

- BOW and TFIDF performs better than AVGW2V and TFIDFW2V