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 [2]:
```
%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
```

```
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\gens
im\utils.py:1197: UserWarning: detected Windows; aliasing chunkize to chunkize
_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [3]:
```
# 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[3]:

	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 [4]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [5]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[5]:

	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 [6]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[6]:

	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 [7]:
```
display['COUNT(*)'].sum()
```

Out[7]:
```
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 [8]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[8]:

	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 [9]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace
```

In [10]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, k
final.shape
```

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

In [11]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[11]:
```
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 [12]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[12]:

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

In [13]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [14]:
```
#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[14]:
```
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 [15]:
```
# 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 [16]:
```
# 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 [17]:
```
# 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 [18]:
```
# 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 [19]:
```
# sent_1500 = decontracted(sent_1500)
# print(sent_1500)
# print("="*50)
```

In [20]:
```
#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 [21]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
# sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
# print(sent_1500)
```

In [22]:
```
# 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', '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',
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'thr
            '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', "did
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't
            'won', "won't", 'wouldn', "wouldn't"])
```

In [23]:
```
# 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 [00:39<00:00, 2241.77it/s]
```

[3.2] Preprocessing Review Summary

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

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)
X_train, X_cv, Y_train, Y_cv = train_test_split(X_train, Y_train, test_size=0.3)

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

```
(43008,) (43008,)
(18433,) (18433,)
(26332,) (26332,)
```

[4] Featurization

[4.1] BAG OF WORDS

In [25]:
```
from scipy.sparse import hstack, coo_matrix
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(X_train)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

print(X_train.shape)
X_train_bow = count_vect.transform(X_train)
X_cv_bow = count_vect.transform(X_cv)
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])
```

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaaaaaaaaa', 'aaah', 'aaahs', 'aa
chen', 'aaf', 'aafco', 'aahs']
==================================================
(43008,)
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (43008, 39235)
the number of unique words  39235
```

In [26]:
```
# Data-preprocessing: Standardizing the data
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_bow)

X_train_bow = scaler.transform(X_train_bow)
X_cv_bow = scaler.transform(X_cv_bow)
X_test_bow = scaler.transform(X_test_bow)

print(X_train_bow.shape)
```

```
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)

(43008, 39235)
```

[4.3] TF-IDF

In [27]:
```
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_cv_tfidf = tf_idf_vect.transform(X_cv)
X_test_tfidf = tf_idf_vect.transform(X_test)

print("the type of count 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) ['ability', 'able', 'able bu
y', 'able chew', 'able drink', 'able eat', 'able enjoy', 'able find', 'able fi
nish', 'able get']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (43008, 25466)
the number of unique words including both unigrams and bigrams  25466
```

In [28]:
```
scaler.fit(X_train_tfidf)

X_train_tfidf = scaler.transform(X_train_tfidf)
X_cv_tfidf = scaler.transform(X_cv_tfidf)
X_test_tfidf = scaler.transform(X_test_tfidf)

print(X_test_tfidf.shape)
```

```
(26332, 25466)
```

[4.4] Word2Vec

In [29]:
```
# 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 [30]:
```
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  12531
sample words  ['whole', 'wheat', 'orzo', 'quite', 'difficult', 'find', 'home',
'town', 'pleased', 'amazon', 'product', 'shipped', 'quickly', 'excellent', 'va
lue', 'kind', 'bars', 'one', 'okay', 'not', 'particularly', 'care', 'taste',
'opinion', 'sweet', 'occasionally', 'indulge', 'things', 'expected', 'every',
'bar', 'sugar', 'yikes', 'wish', 'looked', 'purchased', 'nine', 'worse', 'inst
ead', 'getting', 'twelve', 'box', 'came', 'ten', 'ordering', 'best', 'browni
e', 'mix', 'found', 'bad']
```

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

[4.4.1.1] Avg W2v

In [31]:
```
# 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 li
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
        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 [32]:
```
sent_vectors_train = avgw2v(list_of_sentance_train)
print(len(sent_vectors_train[0]))
print(len(list_of_sentance_train))
```

```
100%|████████████████████████████████████████
█| 43008/43008 [01:21<00:00, 525.99it/s]

50
43008
```

In [33]:
```
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())

sent_vectors_cv = avgw2v(list_of_sentance_cv)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))
```

```
100%|████████████████████████████████████████
█| 18433/18433 [00:35<00:00, 517.56it/s]

18433
50
```

In [34]:
```
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 [00:51<00:00, 510.03it/s]

26332
50
```

[4.4.1.2] TFIDF weighted W2v

In [35]:
```
# 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 [36]:
```
# 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 in
    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 [37]:
```
tfidf_sent_vectors_train = tfidfw2v(list_of_sentance_train)
```

```
100%|██████████████████████████████████████████████████| 43008/43008 [12:13<00:00, 58.65it/s]
```

In [38]:
```
tfidf_sent_vectors_cv = tfidfw2v(list_of_sentance_cv)
```

```
100%|██████████████████████████████████████████████████| 18433/18433 [05:13<00:00, 58.85it/s]
```

In [39]:
```
tfidf_sent_vectors_test = tfidfw2v(list_of_sentance_test)
```

```
100%|██████████████████████████████████████████████████| 26332/26332 [07:24<00:00, 59.24it/s]
```

Applying SVM

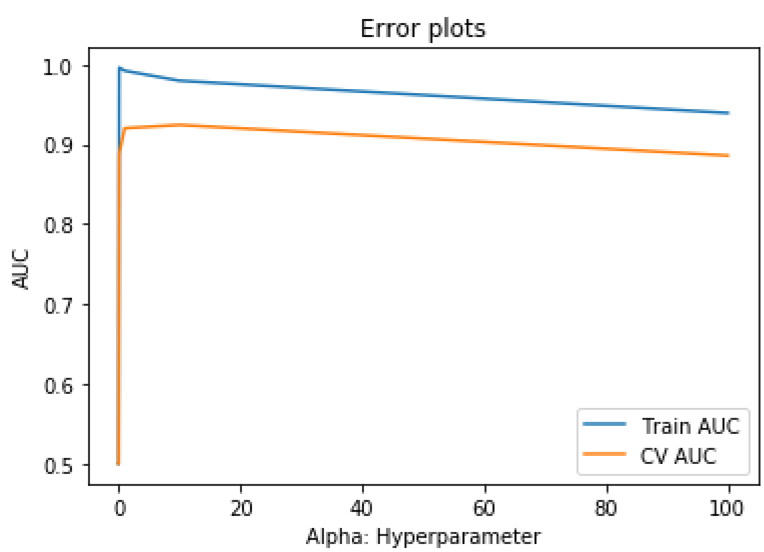
[5.1] Linear SVM

[5.1.1] Applying Linear SVM on BOW, SET 1

In [40]:
```
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
```

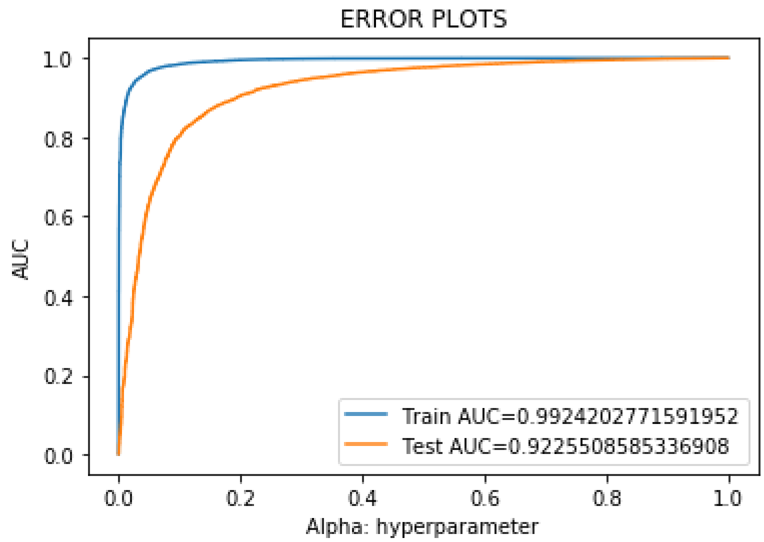
In [41]:
```
def Get_Alpha_LinearSVM(X_train_vector, X_cv_vector):
    alpha = [100,10,1,0.1,0.01,0.001]
    train_auc = []
    cv_auc = []
    for i in alpha:
        model = SGDClassifier(alpha=i, loss='hinge', class_weight='balanced')#crea
        model.fit(X_train_vector, Y_train) #fit the base model
        Cal_CV_model = CalibratedClassifierCV(model, method="sigmoid",cv='prefit')
        Cal_CV_model.fit(X_train_vector, Y_train) #fit the classifier
        train_predict_y = Cal_CV_model.predict_proba(X_train_vector)[:,1] #predict
        cv_predict_y = Cal_CV_model.predict_proba(X_cv_vector)[:,1] #predict cv

        train_auc.append(roc_auc_score(Y_train, train_predict_y))
        cv_auc.append(roc_auc_score(Y_cv, cv_predict_y))

    plt.plot(alpha, train_auc, label='Train AUC')
    plt.plot(alpha, cv_auc, label="CV AUC")
    plt.legend()
    plt.xlabel("Alpha: Hyperparameter")
    plt.ylabel("AUC")
    plt.title("Error plots")
    plt.show()
```

In [42]:
```
Get_Alpha_LinearSVM(X_train_bow, X_cv_bow)
```

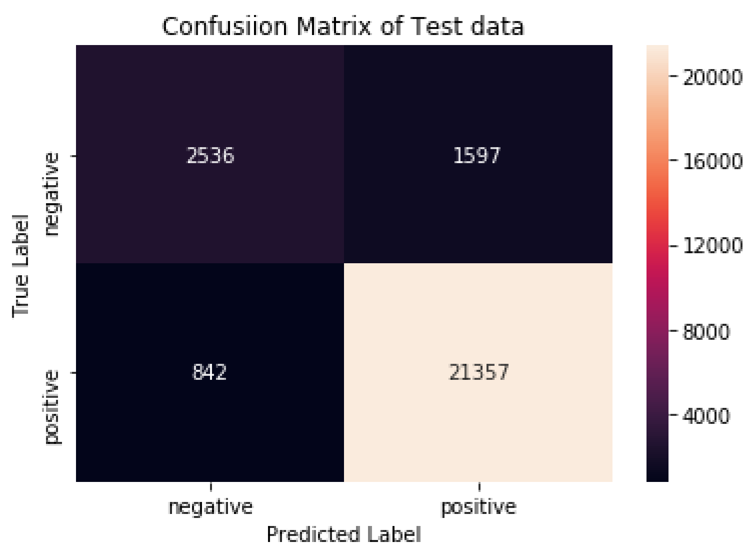


In [43]:
```
def SVM_Test(X_train_vector, X_test_vector, bestAlpha):
    model = SGDClassifier(alpha=bestAlpha, loss='hinge', class_weight='balanced')
    model.fit(X_train_vector, Y_train) #fit the classifier

    calibrated_model = CalibratedClassifierCV(model, method="sigmoid",cv='prefit')
    calibrated_model.fit(X_train_vector, Y_train) #fit the classifier

    train_FPR, train_TPR, thresholds = roc_curve(Y_train, calibrated_model.predict
    test_FPR, test_TPR, thresholds = roc_curve(Y_test, calibrated_model.predict_pr

    test_auc = auc(test_FPR, test_TPR)
    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(test_auc))

    plt.legend()
    plt.xlabel("Alpha: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()

    from sklearn.metrics import confusion_matrix
    print("Train confusion metric")
    print(confusion_matrix(Y_train, calibrated_model.predict(X_train_vector)))

    print("Testing confusion metric")
    cm = confusion_matrix(Y_test, calibrated_model.predict(X_test_vector))
    print(cm)

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

    return test_auc
```

In [44]:
```
linearSVM_auc_bow = SVM_Test(X_train_bow, X_test_bow, bestAlpha=1)
```

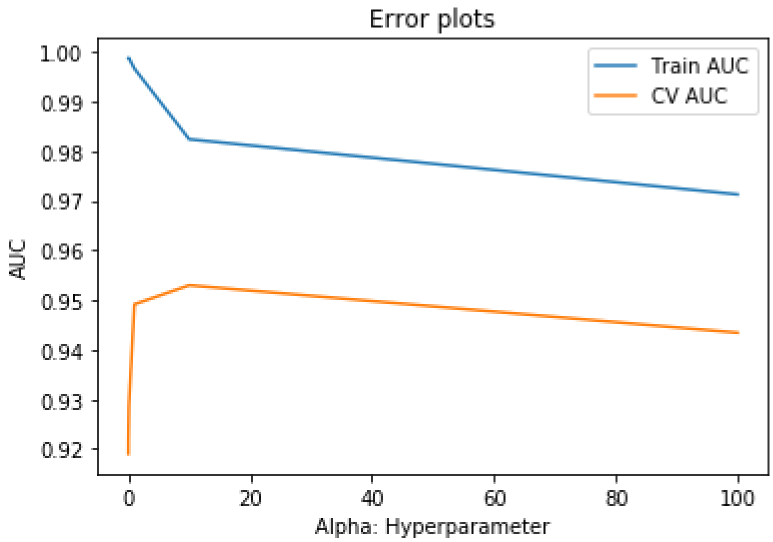



```
Train confusion metric
[[ 6216   836]
 [  436 35520]]
Testing confusion metric
[[ 2536  1597]
 [  842 21357]]
```

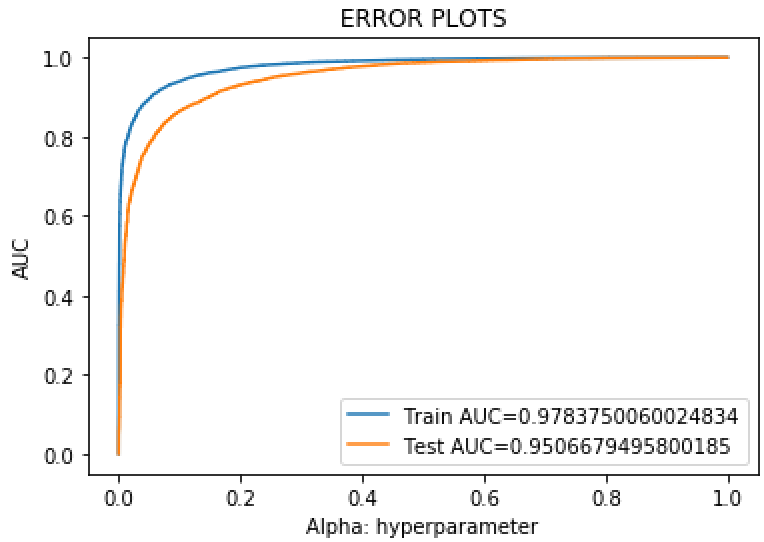


[5.1.2] Applying Linear SVM on TFIDF, SET 2

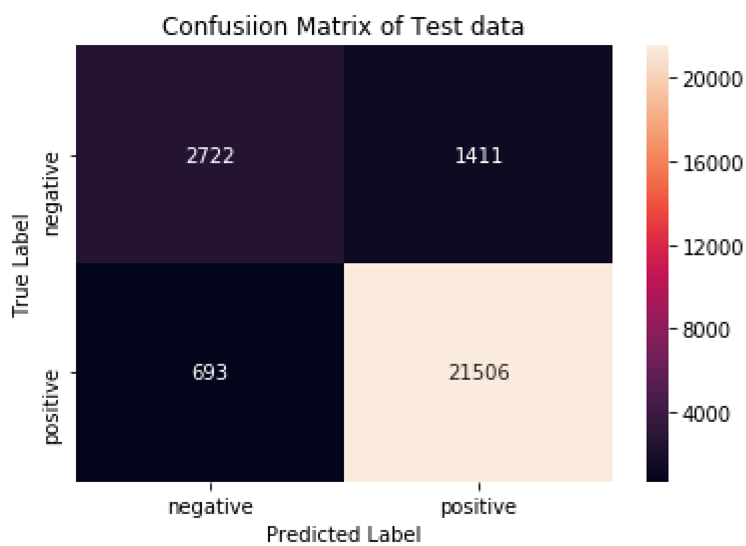
In [45]:
```
Get_Alpha_LinearSVM(X_train_tfidf, X_cv_tfidf)
```



In [46]:
```
linearSVM_auc_tfidf = SVM_Test(X_train_tfidf, X_test_tfidf, bestAlpha=15)
```

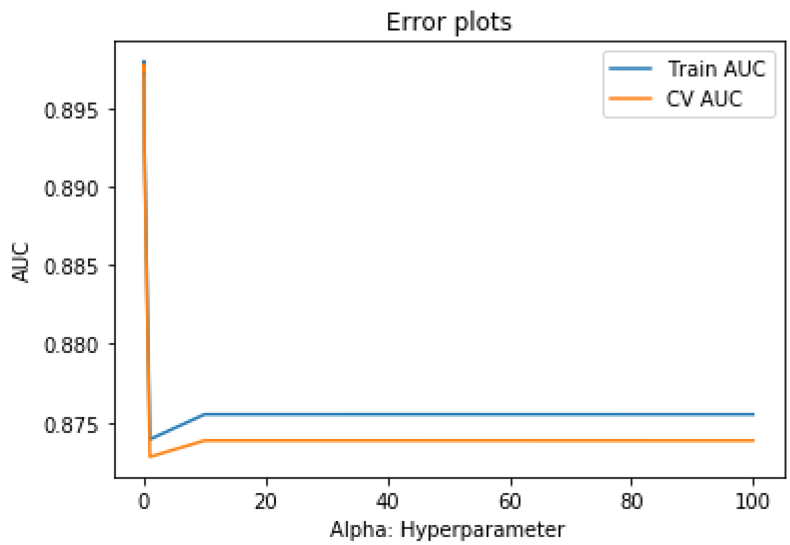



```
Train confusion metric
[[ 5560  1492]
 [  851 35105]]
Testing confusion metric
[[ 2722  1411]
 [  693 21506]]
```

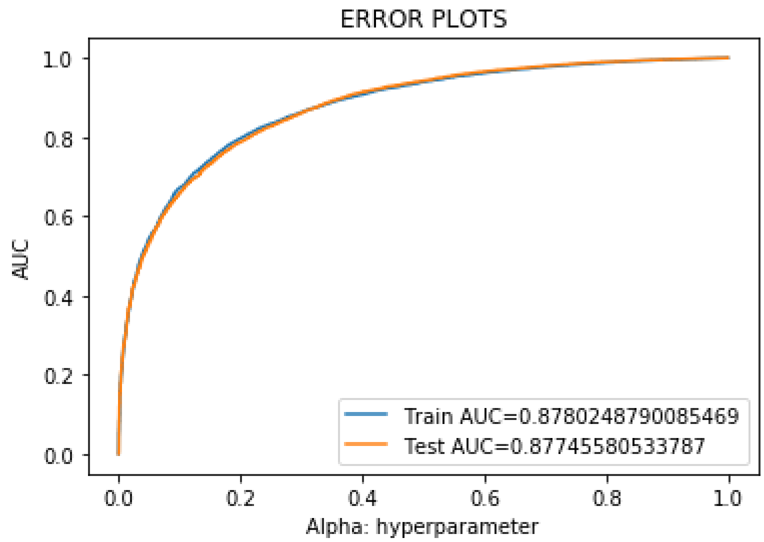


[5.1.3] Applying Linear SVM on AVG W2V, SET 3

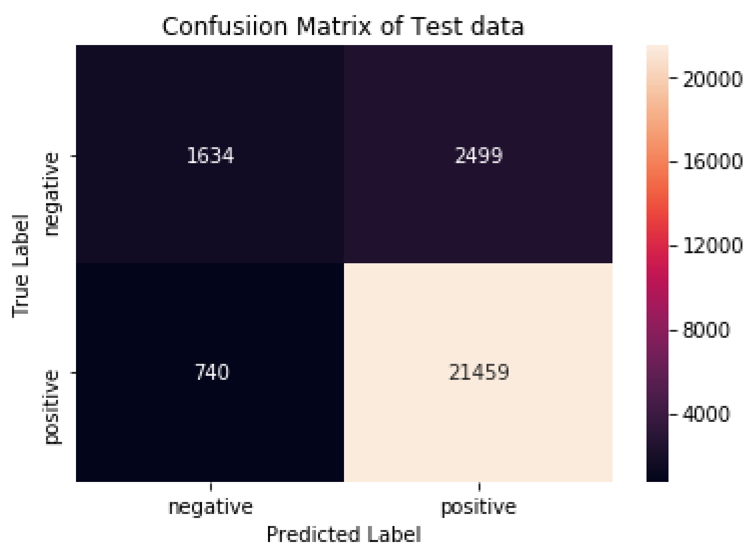
In [47]:
```
Get_Alpha_LinearSVM(sent_vectors_train, sent_vectors_cv)
```



In [48]:
```
linearSVM_auc_avgw2v = SVM_Test(sent_vectors_train, sent_vectors_test, bestAlpha=1
```

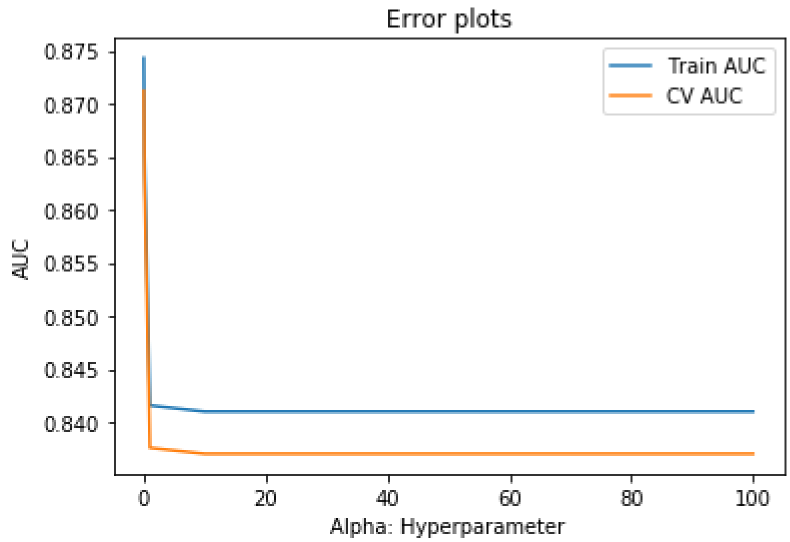



```
Train confusion metric
[[ 2729  4323]
 [ 1280 34676]]
Testing confusion metric
[[ 1634  2499]
 [  740 21459]]
```

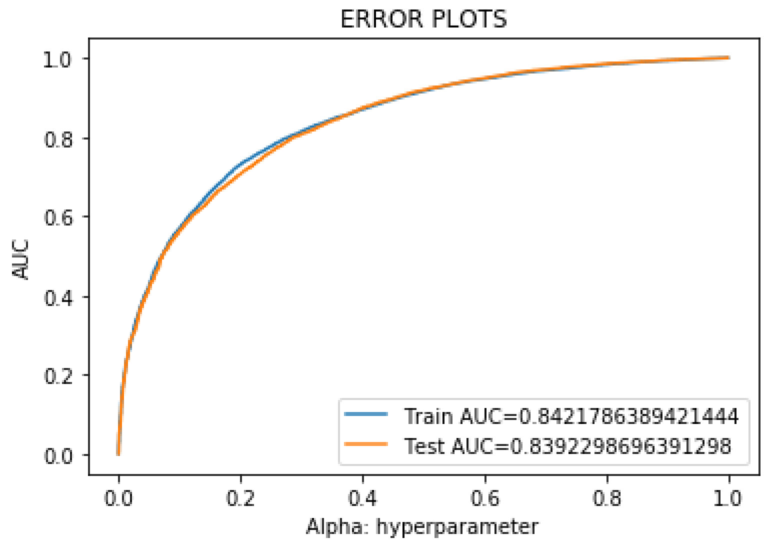


[5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

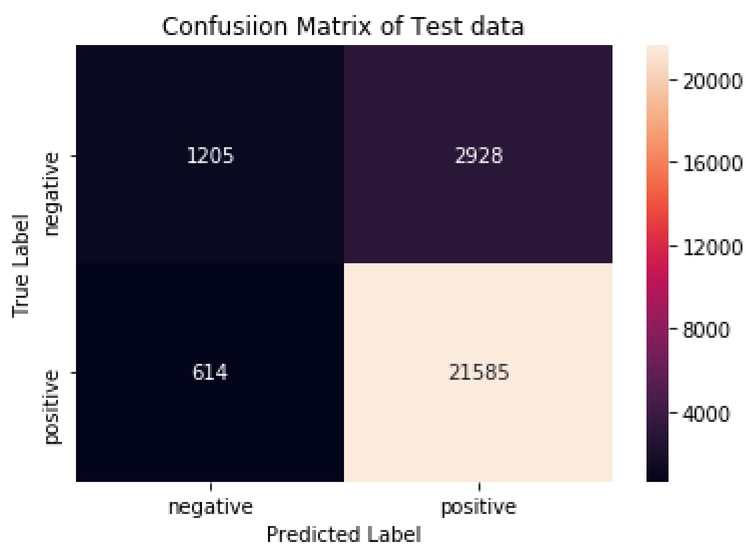
In [49]:
```
Get_Alpha_LinearSVM(tfidf_sent_vectors_train, tfidf_sent_vectors_cv)
```



In [50]:
```
linearSVM_auc_tfidfw2v = SVM_Test(tfidf_sent_vectors_train, tfidf_sent_vectors_tes
```




```
Train confusion metric
[[ 2068  4984]
 [ 1086 34870]]
Testing confusion metric
[[ 1205  2928]
 [  614 21585]]
```



[5.2] RBF SVM

Selecting only 20K records for RBF Kernel

In [51]:
```
rbf_data = final.sample(n=20000, random_state=1)
```

In [52]:
```
# Spliting the data for RBF SVM
X_rbf = rbf_data['Text'].values
Y_rbf = rbf_data['Score'].values

X_train_rbf, X_test_rbf, Y_train_rbf, Y_test_rbf = train_test_split(X_rbf, Y_rbf,

print(X_train_rbf.shape, Y_train_rbf.shape)
print(X_test_rbf.shape, Y_test_rbf.shape)
```

```
(14000,) (14000,)
(6000,) (6000,)
```

BoW with 500 features

In [53]:
```
count_vect_rbf = CountVectorizer(min_df=10, max_features=500)
count_vect_rbf.fit(X_train_rbf)

X_train_bow_rbf = count_vect_rbf.transform(X_train_rbf)
X_test_bow_rbf = count_vect_rbf.transform(X_test_rbf)
```

In [54]:
```
scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_bow_rbf)

X_train_bow_rbf = scaler.transform(X_train_bow_rbf)
X_test_bow_rbf = scaler.transform(X_test_bow_rbf)

print(X_train_bow_rbf.shape)
```

```
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\vidhan.patel\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\utils\validation.py:475: DataConversionWarning: Data with input dtype int6
4 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)

(14000, 500)
```

TFIDF with 500 features

In [55]:
```
tf_idf_vect_rbf = TfidfVectorizer(min_df=10, max_features=500)
tf_idf_vect_rbf.fit(X_train_rbf)

X_train_tfidf_rbf = tf_idf_vect_rbf.transform(X_train_rbf)
X_test_tfidf_rbf = tf_idf_vect_rbf.transform(X_test_rbf)
```

In [56]:
```
scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_tfidf_rbf)

X_train_bow_rbf = scaler.transform(X_train_tfidf_rbf)
X_test_tfidf_rbf = scaler.transform(X_test_tfidf_rbf)

print(X_train_tfidf_rbf.shape)
```

```
(14000, 500)
```

In [57]:
```
#W2V
def avgw2v_rbf(list_of_sentance):
    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
        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_rbf:
                vec = w2v_model_rbf.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 [58]:
```
list_of_sentance_train_rbf=[]
for sentance in X_train_rbf:
    list_of_sentance_train_rbf.append(sentance.split())

w2v_model_rbf=Word2Vec(list_of_sentance_train_rbf,min_count=5,size=50, workers=2)

w2v_words_rbf = list(w2v_model_rbf.wv.vocab)

sent_vectors_train_rbf = avgw2v_rbf(list_of_sentance_train_rbf)
```

```
100%|██████████████████████████████████████████████
██| 14000/14000 [00:18<00:00, 746.80it/s]
```

In [59]:
```
list_of_sentance_test_rbf=[]
for sentance in X_test_rbf:
    list_of_sentance_test_rbf.append(sentance.split())

sent_vectors_test_rbf = avgw2v_rbf(list_of_sentance_test_rbf)
```

```
100%|██████████████████████████████████████████████
████| 6000/6000 [00:08<00:00, 733.69it/s]
```

In [60]:
```
#TFIDF W2V
# we are converting a dictionary with word as a key, and the idf as a value
dictionary_rbf = dict(zip(tf_idf_vect_rbf.get_feature_names(), list(tf_idf_vect_rb
```

In [61]:
```python
# TF-IDF weighted Word2Vec
def tfidfw2v_rbf(list_of_sentance):
    tfidf_feat = tf_idf_vect_rbf.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 in
    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_rbf and word in tfidf_feat:
                vec = w2v_model_rbf.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_rbf[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 [62]:
```python
tfidf_sent_vectors_train_rbf = tfidfw2v_rbf(list_of_sentance_train_rbf)
```

```
100%|████████████████████████████████████████
█| 14000/14000 [00:23<00:00, 595.96it/s]
```

In [63]:
```python
tfidf_sent_vectors_test_rbf = tfidfw2v_rbf(list_of_sentance_test_rbf)
```

```
100%|████████████████████████████████████████
██| 6000/6000 [00:10<00:00, 574.71it/s]
```

[5.2.1] Applying RBF SVM on BOW, SET 1

In [64]:
```python
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
```

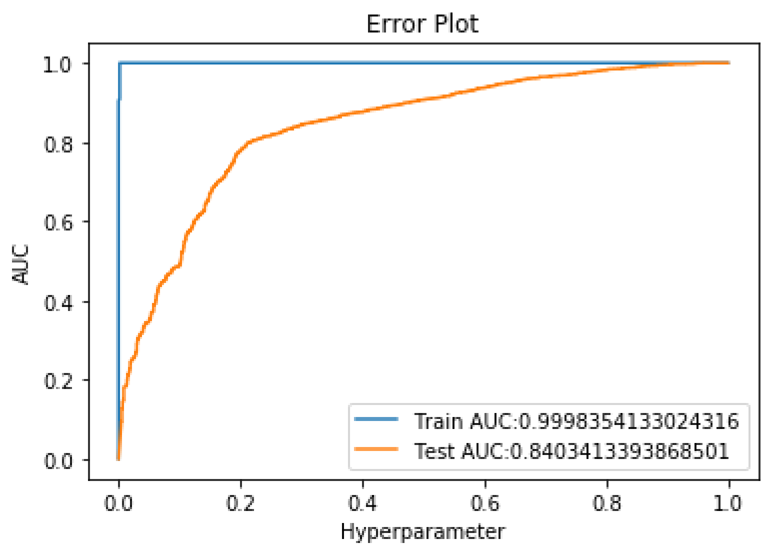
In [65]:
```
def find_best_Hyperparameters(X_train_vector_rbf):
    parameters = {'gamma':[10,1,0.1,0.01], 'C':[10,1,0.1,0.01]}

    svc = SVC(kernel='rbf',class_weight='balanced')

    grid = GridSearchCV(svc, parameters, cv=10, scoring='roc_auc',return_train_sco
    grid.fit(X_train_vector_rbf, Y_train_rbf)

    print("Best Estimator: ",grid.best_estimator_)

    print("Best cross-validation score: {:.2f}".format(grid.best_score_))  # best
    best_C = grid.best_params_['C']  # best C value after 10 fold cross validation
    print("Best C: ", best_C)

    best_gamma = grid.best_params_['gamma']  # best gamma value after 10 fold cros
    print("Best Gamma: ", best_gamma)

    return best_C, best_gamma
```

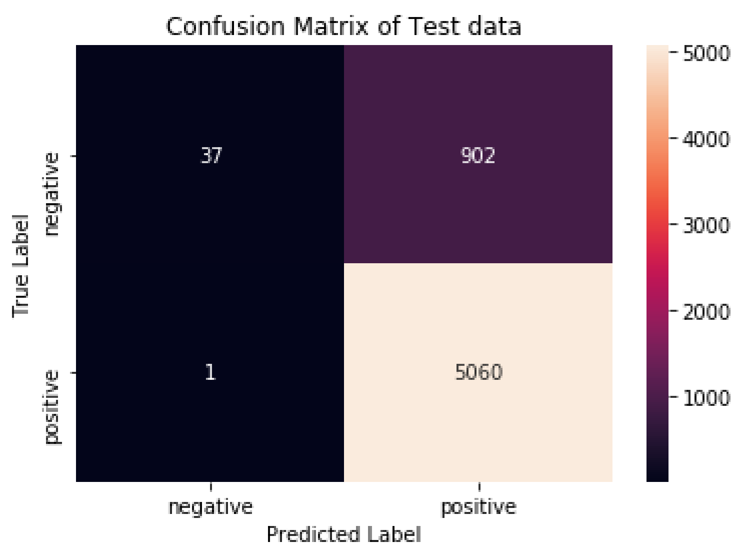
In [66]:
```
best_C_bow, best_gamma_bow = find_best_Hyperparameters(X_train_bow_rbf)
```

```
Best Estimator:  SVC(C=10, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.01, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
Best cross-validation score: 0.84
Best C:  10
Best Gamma:  0.01
```

In [67]:
```
def test_rbf_kernel(X_train_vector_rbf, X_test_vector_rbf, best_C_vector, best_gam
    clf = SVC(C=best_C_vector, gamma=best_gamma_vector, kernel='rbf',class_weight=
    clf.fit(X_train_vector_rbf, Y_train_rbf)

    train_fpr, train_tpr, threshold = roc_curve(Y_train_rbf, clf.predict_log_proba
    test_fpr, test_tpr, threshold = roc_curve(Y_test_rbf, clf.predict_log_proba(X_

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

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

    test_cm = confusion_matrix(Y_test_rbf, clf.predict(X_test_vector_rbf))

    # 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
```

In [68]:
```
auc_bow_rdf = test_rbf_kernel(X_train_bow_rbf, X_test_bow_rbf, best_C_bow, best_ga
```



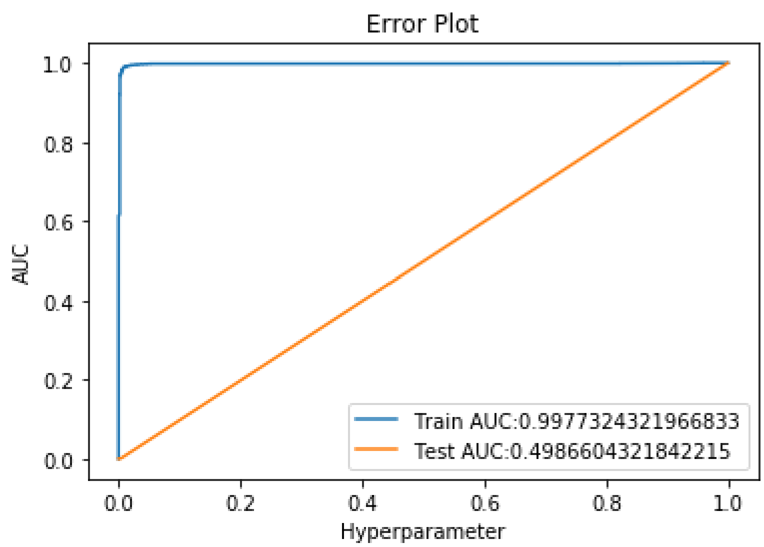


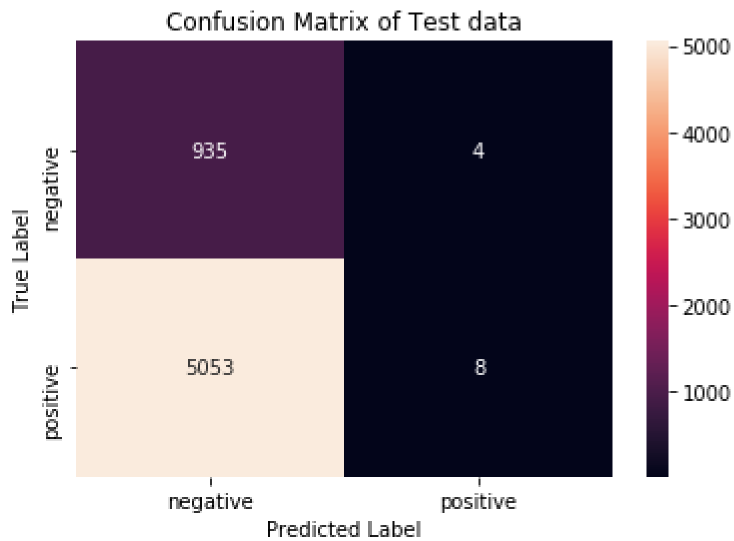
[5.2.2] Applying RBF SVM on TFIDF, SET 2

In [69]:
```
best_C_tfidf, best_gamma_tfidf = find_best_Hyperparameters(X_train_tfidf_rbf)
```

```
Best Estimator:  SVC(C=1, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
Best cross-validation score: 0.91
Best C:  1
Best Gamma:  1
```

In [70]:
```
auc_tfidf_rdf =test_rbf_kernel(X_train_tfidf_rbf, X_test_tfidf_rbf, best_C_tfidf,
```



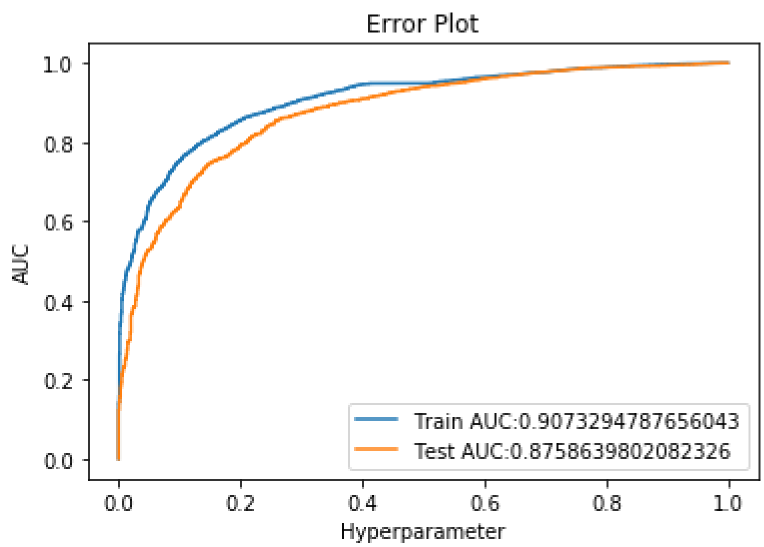


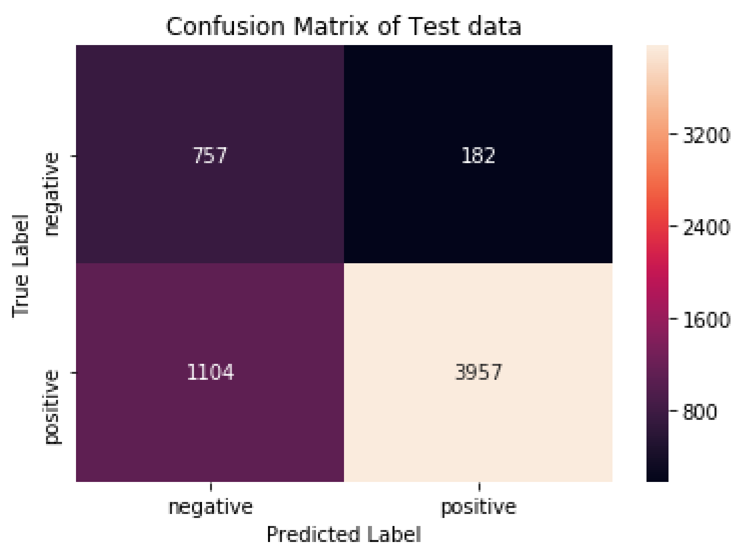
[5.2.3] Applying RBF SVM on AVG W2V, SET 3

In [71]:
```
best_C_avgw2v, best_gamma_avgw2v = find_best_Hyperparameters(sent_vectors_train_rb
```

```
Best Estimator:  SVC(C=10, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
Best cross-validation score: 0.88
Best C:  10
Best Gamma:  0.1
```

In [72]:
```
auc_avgw2v_rdf = test_rbf_kernel(sent_vectors_train_rbf, sent_vectors_test_rbf, be
```



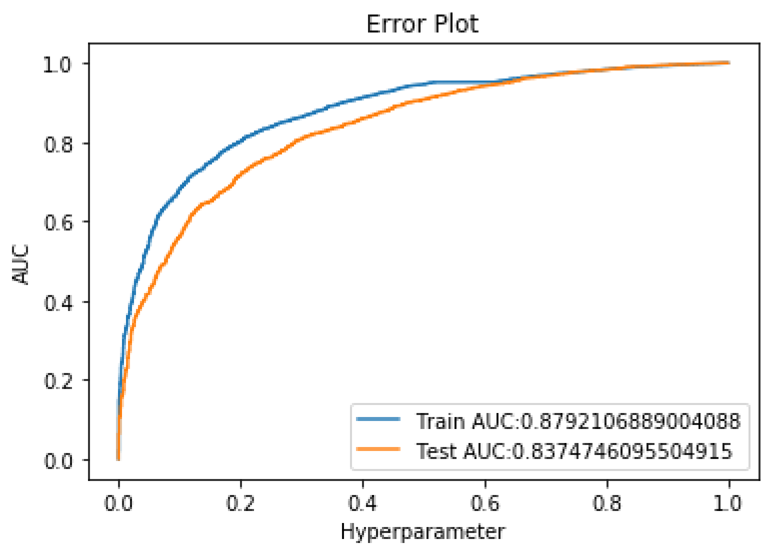


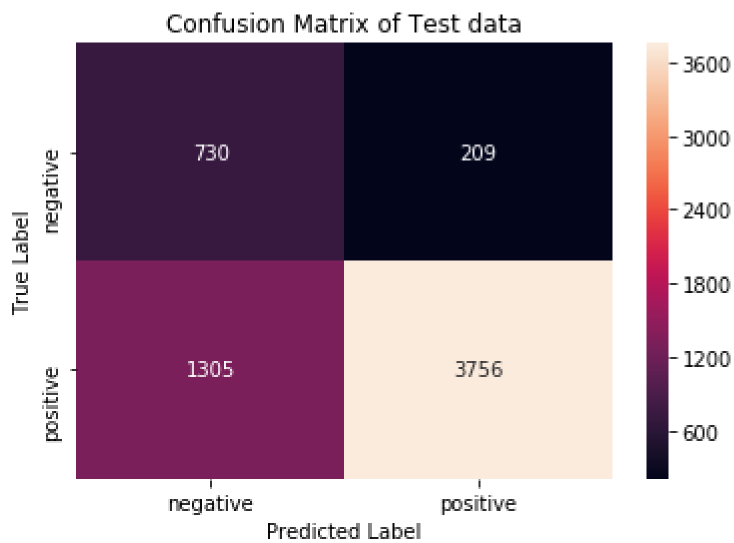
[5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

In [73]:
```
best_C_tfidfw2v, best_gamma_tfidfw2v = find_best_Hyperparameters(tfidf_sent_vector
```

```
Best Estimator:  SVC(C=1, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
Best cross-validation score: 0.85
Best C:  1
Best Gamma:  0.1
```

In [74]:
```
auc_tfidfw2v_rdf = test_rbf_kernel(tfidf_sent_vectors_train_rbf, tfidf_sent_vector
```





[6] Conclusions

In [76]:
```
models = pd.DataFrame({
'Vectorizer': ["BOW", "TFIDF", "W2V", "TFIDFW2V","BOW", "TFIDF", "W2V", "TFIDFW2V"
'Model' : ['LinearSVM', 'LinearSVM','LinearSVM','LinearSVM','KernalSVM','KernalSVM
'Hyper Para(Alpha, C & Gamma)': [{'alpha' : 1 },{'alpha' : 15},{'alpha' : 1}, {'al
                              {'C':best_C_bow,'gamma':best_gamma_bow}, {'C':best_C
                              {'C':best_C_avgw2v,'gamma':best_gamma_avgw2v}, {'C':
'AUC': [linearSVM_auc_bow, linearSVM_auc_tfidf, linearSVM_auc_avgw2v, linearSVM_au
        auc_bow_rdf, auc_tfidf_rdf, auc_avgw2v_rdf, auc_tfidfw2v_rdf]},
columns = ["Vectorizer", "Model", "Hyper Para(Alpha, C & Gamma)", "AUC"])
print(models)
```

```
  Vectorizer      Model Hyper Para(Alpha, C & Gamma)       AUC
0        BOW  LinearSVM                 {'alpha': 1}  0.922551
1      TFIDF  LinearSVM                {'alpha': 15}  0.950668
2        W2V  LinearSVM                 {'alpha': 1}  0.877456
3   TFIDFW2V  LinearSVM                 {'alpha': 1}  0.839230
4        BOW  KernalSVM     {'C': 10, 'gamma': 0.01}  0.840341
5      TFIDF  KernalSVM         {'C': 1, 'gamma': 1}  0.498660
6        W2V  KernalSVM      {'C': 10, 'gamma': 0.1}  0.875864
7   TFIDFW2V  KernalSVM       {'C': 1, 'gamma': 0.1}  0.837475
```