03 Amazon Fine Food Reviews Analysis_KNN

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1 Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

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

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

2 [1]. Reading Data

2.1 [1.1] Loading the data

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

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

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

In [139]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve, auc
from bs4 import BeautifulSoup
from sklearn.model_selection import GridSearchCV
from prettytable import PrettyTable
```

2.2 As we need different data points for different implementations of KNN.

1. For Brute Force method I have tried taking varity of data points ranging from 100k to 40k, system was freezing at some point or other till I used only 30k points.

2. For KD-Tree method I'm using 20k data points.

In [64]:
```
# using SQLite Table to read data
# con_b is for brute force data

con_b = sqlite3.connect('database.sqlite')

# I used 30k points while running brute force first and then
# reduced the number of data points to 20k for kd tree implementation

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 negati
def partition(x):
    if x < 3:
        return 0
    return 1

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

```
Number of data points in our data (20000, 10)
```

Out[64]:
```
   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 [65]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
```

```
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con_b)
```

In [66]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[66]:
```
                  UserId   ProductId             ProfileName        Time  Score  \
0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
2  #oc-R11DNU2NBKQ23Z  B007Y59HVM         Kim Cieszykowski  1348531200      1
3  #oc-R11O5J5ZVQE25C  B005HG9ET0            Penguin Chick  1346889600      5
4  #oc-R12KPBODL2B5ZD  B007OSBE1U    Christopher P. Presta  1348617600      1

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

In [67]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[67]:
```
              UserId   ProductId                    ProfileName        Time  \
80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

       Score                                               Text  COUNT(*)
80638      5  I was recommended to try green tea extract to ...         5
```

In [68]:
```
display['COUNT(*)'].sum()
```

Out[68]:
```
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 [69]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
```

```
        ORDER BY ProductID
        """, con_b)
        display.head(3)
```

Out[69]:
```
           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

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

                                     Summary  \
        0  LOACKER QUADRATINI VANILLA WAFERS
        1  LOACKER QUADRATINI VANILLA WAFERS
        2  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 ...
```

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 [70]:
```
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal
```

In [71]:
```
# Deduplication of entries
final = sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, kee
final.shape
```

Out[71]:
```
(19354, 10)
```

In [72]:
```
# Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[72]: 96.77

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 [73]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con_b)

display.head()
```

Out[73]:
```
      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 [74]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [75]:
```
# 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()
```

```
(19354, 10)
```

Out[75]:
```
1    16339
0     3015
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

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

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

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

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

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

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

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

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

```
Our dogs just love them.  I saw them in a pet store and a tag was attached regarding them being
==================================================
It's Branston pickle, what is there to say. If you've never tried it you most likely wont like
==================================================
First Impression: The friendly folks over at "Exclusively Dog" heard about my website and sent
==================================================
It is hard to find candy that is overly sweet. My wife and Granddaughter both love Pink Grapefr
==================================================
```

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

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

print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victo
```

In [14]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
from bs4 import BeautifulSoup

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

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

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

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

```
Our dogs just love them.  I saw them in a pet store and a tag was attached regarding them being
==================================================
When I ordered these, I thought they were a bit pricey, but I decided to give them a try anyway
==================================================
This was my favorite stevia product and I had it on subscribe and save until I queried customer
==================================================
TOTALLY ORGASMIC.  these chips are the best spicy chip i have ever tasted.  signed up for the s
```

In [76]:
```
# 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 [15]: sent_1500 = decontracted(sent_1500)
         print(sent_1500)
         print("="*50)
```

```
This was my favorite stevia product and I had it on subscribe and save until I queried custome
==================================================
```

```
In [22]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
         sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
         print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br  /><br />The Victor
```

```
In [23]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
         sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
         print(sent_1500)
```

```
Wow So far two two star reviews One obviously had no idea what they were ordering the other wa
```

```
In [77]: # https://gist.github.com/sebleier/554280
         # we are removing the words from the stop words list: 'no', 'nor', 'not'
         # <br /><br /> ==> after the above steps, we are getting "br br"
         # we are including them into stop words list
         # instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

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

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

```
In [78]: # Combining all the above stundents

         preprocessed_reviews_b = []       # preprocessed reviews for brute force implementati
         # tqdm is for printing the status bar

         for sentance in tqdm(final['Text'].values):
             sentance = re.sub(r"http\S+", "", sentance)
             sentance = BeautifulSoup(sentance, 'lxml').get_text()
             sentance = decontracted(sentance)
             sentance = re.sub("\S*\d\S*", "", sentance).strip()
             sentance = re.sub('[^A-Za-z]+', ' ', sentance)
             # https://gist.github.com/sebleier/554280
             sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopw
             preprocessed_reviews_b.append(sentance.strip())
```

```
100%|| 19354/19354 [00:07<00:00, 2495.83it/s]
```

```
In [79]: len(preprocessed_reviews_b)
```

```
Out[79]: 19354
```

```
In [80]: len(final["Score"])
```

```
Out[80]: 19354
```

5 [4] Splitting the data

Here before doing any vectorization we'll first split the data i.e (X,Y) in train data, cross validation data and test data.

```
In [52]: #final['Score'].value_counts().plot(kind='bar')
```

```
In [81]: X = preprocessed_reviews_b
         Y = final['Score'].values
```

```
In [82]: print(X[0])
```

```
used victor fly bait seasons ca not beat great product
```

Now we are splitting the data in three parts 1. Train data
2. Cross validation data 3. Test data

```
In [83]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_tes

         x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.30) # this is r
         x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.30) # t
```

```
In [85]: print(len(x_train))
         print(len(x_cv))
         print(len(x_test))
```

```
9482
4065
5807
```

6 [5] Featurization

6.1 [5.1] BAG OF WORDS

```
In [86]: # BoW using scikit-learn

         count_vect = CountVectorizer(min_df=10, max_features=10000)     # count_vect_b for br
         count_vect.fit(x_train)
         print("some feature names ", count_vect.get_feature_names()[:10])
         print('='*50)

         # we use the fitted CountVectorizer to convert the text to vector
         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("After vectorizations")
         print(x_train_bow.shape, y_train.shape)
         print(x_cv_bow.shape, y_cv.shape)
         print(x_test_bow.shape, y_test.shape)
         print("="*50)

         print("the type of count vectorizer ",type(x_train_bow))
         print("the type of count vectorizer ",type(x_cv_bow))
         print("the type of count vectorizer ",type(x_test_bow))
```

```
some feature names  ['ability', 'able', 'absolute', 'absolutely', 'absorb', 'acceptable', 'acc
==================================================
After vectorizations
(9482, 3442) (9482,)
(4065, 3442) (4065,)
(5807, 3442) (5807,)
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

6.2 [5.2] TF-IDF

In [87]:
```python
# TF-IDF for brute force

tf_idf_vect = TfidfVectorizer( min_df=10, max_features=10000)                #in scik
tf_idf_vect.fit(x_train)
print("some sample features",tf_idf_vect.get_feature_names()[0:10])
print('='*50)

# we use the fitted TfidfVectorizer to convert the text to vector

x_train_tf = tf_idf_vect.transform(x_train)
x_cv_tf    = tf_idf_vect.transform(x_cv)
x_test_tf  = tf_idf_vect.transform(x_test)

print("After vectorizations")
print(x_train_tf.shape, y_train.shape)
print(x_cv_tf.shape, y_cv.shape)
print(x_test_tf.shape, y_test.shape)
print("="*50)

print("the type of tf-idf vectorizer ",type(x_train_tf))
```

```
some sample features ['ability', 'able', 'absolute', 'absolutely', 'absorb', 'acceptable', 'ac
==================================================
After vectorizations
(9482, 3442) (9482,)
(4065, 3442) (4065,)
(5807, 3442) (5807,)
==================================================
the type of tf-idf vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

6.3 [5.3] Word2Vec

In [88]:
```python
# 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())
```

6.4 Training w2v model

In [89]:
```
# this line of code trains your w2v model on the given list of sentances

w2v_model = Word2Vec(list_of_sentance_train, min_count = 5, size = 50, workers = -1)
```

In [90]:
```
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  5758
sample words  ['haribo', 'gummi', 'strawberries', 'tastiest', 'candy', 'available', 'may', 'bia
```

7 Converting Reviews into Numerical Vectors using W2V vectors

7.1 Algorithm: Avg W2V

Converting Training data text

In [91]:
```
# average Word2Vec
# compute average word2vec for each review.

sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this lis

for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
```

```
100%|| 9482/9482 [00:10<00:00, 912.22it/s]


(9482, 50)
```

Converting Cross validation data text

In [92]:
```
list_of_sentance_cv = []

for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())
```

In [93]:
```
# average Word2Vec
# compute average word2vec for each review.

sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list

for sent in tqdm(list_of_sentance_cv):  # for each review/sentence
    sent_vec = np.zeros(50)             # as word vectors are of zero length 50, yo
    cnt_words =0;                       # num of words with a valid vector in the s
    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)
```

```
100%|| 4065/4065 [00:04<00:00, 847.81it/s]


(4065, 50)
```

Converting Test data text

In [94]:
```
list_of_sentance_test = []

for sentance in x_test :
    list_of_sentance_test.append(sentance.split())
```

In [95]:
```
# average Word2Vec
# compute average word2vec for each review.

sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list

for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
```

```
100%|| 5807/5807 [00:06<00:00, 870.01it/s]
```

7.2 Algorithm: TFIDF Weighted W2V

Converting Training data

```
In [96]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
         model = TfidfVectorizer()
         tf_idf_matrix_train = model.fit_transform(x_train)
         # we are converting a dictionary with word as a key, and the idf as a value
         dictionary_train = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
In [97]: # TF-IDF weighted Word2Vec
         tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

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

```
100%|| 9482/9482 [01:26<00:00, 117.87it/s]
```

```
In [98]: # TF-IDF weighted Word2Vec
         tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

         tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is stored in thi
         row=0;
         for sent in tqdm(list_of_sentance_cv): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length
             weight_sum =0; # num of words with a valid vector in the sentence/review
```

```
        for word in sent: # for each word in a review/sentence
            if word in w2v_words and word in tfidf_feat:
                vec = w2v_model.wv[word]
#               tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary_train[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors_cv.append(sent_vec)
        row += 1
```

```
100%|| 4065/4065 [00:37<00:00, 108.16it/s]
```

In [99]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

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

```
100%|| 5807/5807 [00:52<00:00, 110.19it/s]
```

8 [6] Assignment 3: KNN

Apply Knn(brute force version) on these feature sets

```
    <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>Apply Knn(kd tree version) on these feature sets</strong>
    <br><font color='red'>NOTE: </font>sklearn implementation of kd-tree accepts only dense ma
    <ul>
        <li><font color='red'>SET 5:</font>Review text, preprocessed one converted into vector
        <pre>
        count_vect = CountVectorizer(min_df=10, max_features=500)
        count_vect.fit(preprocessed_reviews)
        </pre>
        </li>
        <li><font color='red'>SET 6:</font>Review text, preprocessed one converted into vector
        <pre>
            tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
            tf_idf_vect.fit(preprocessed_reviews)
        </pre>
        </li>
        <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>The hyper paramter tuning(find best K)</strong>
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li>
<strong>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.
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
```

```
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

Note: Data Leakage

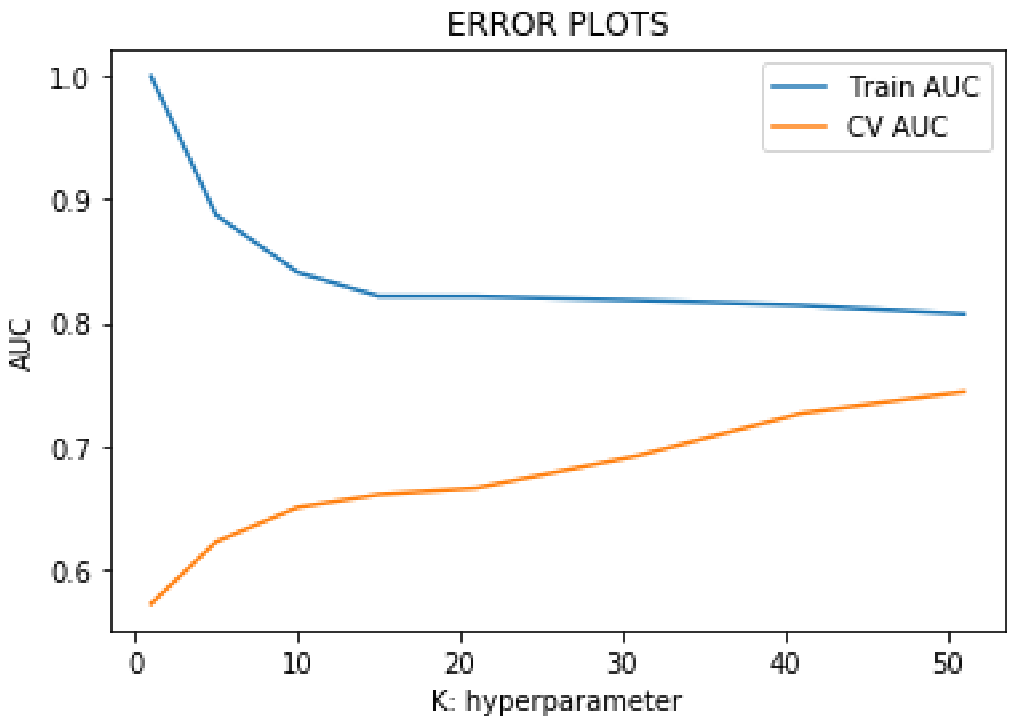
1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply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

8.1 [6.1] Applying KNN brute force

8.1.1 [6.1.1] Applying KNN brute force on BOW, SET 1

Starting with Hyperparameter tuning using simple for loop Finding optimal K using Grid Search hyper parameter tuning

In [38]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearc

K = [1, 5, 10, 15, 21, 31, 41, 51]
knn = KNeighborsClassifier(algorithm= 'brute', n_jobs= -1)
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
grid = GridSearchCV(knn, parameters, cv=3, scoring='roc_auc', n_jobs=-1)
grid.fit(x_train_bow, y_train)

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

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

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



In [39]: grid.best_estimator_

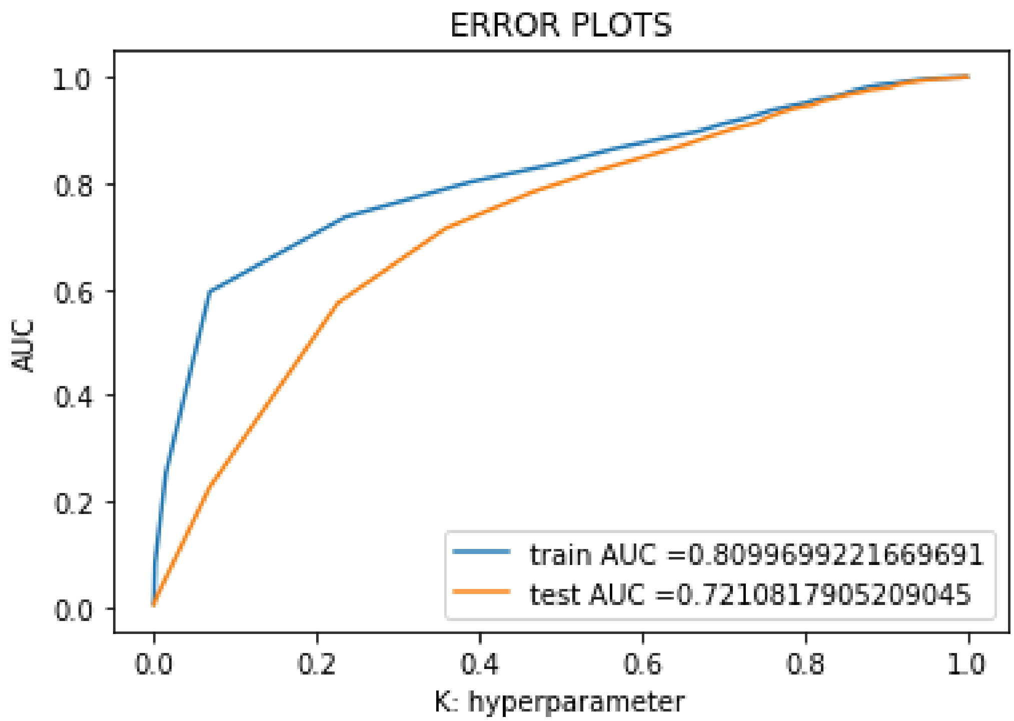
Out[39]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                      metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
                      weights='uniform')

In [40]: best_k_bow = 51

Testing with Test data

In [41]:
```
knn = KNeighborsClassifier(n_neighbors = best_k_bow, algorithm= 'brute')
knn.fit(x_train_bow, y_train)

train_fpr_bow, train_tpr_bow, thresholds_bow = roc_curve(y_train, knn.predict_proba(x_
test_fpr_bow, test_tpr_bow, thresholds_bow = roc_curve(y_test, knn.predict_proba(x_tes

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

```
print("="*50)

print("Train confusion matrix")
print(confusion_matrix(y_train, knn.predict(x_train_bow)))
print("Test confusion matrix")
print(confusion_matrix(y_test, knn.predict(x_test_bow)))
```



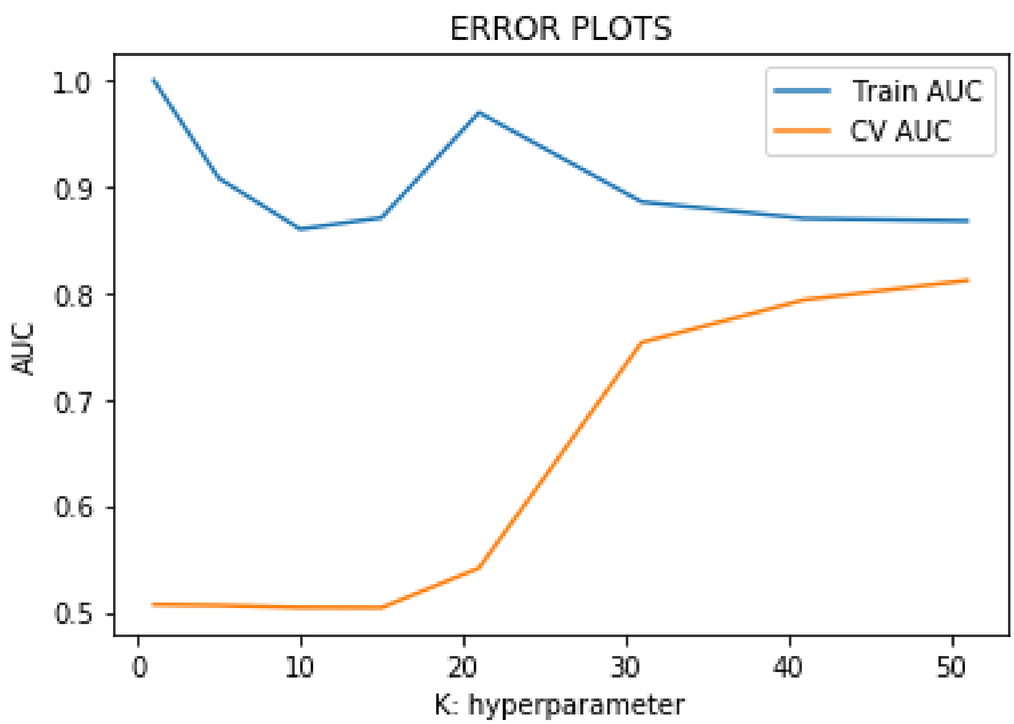

```
==================================================
Train confusion matrix
[[  164  2000]
 [   98 11493]]
Test confusion matrix
[[  96 1211]
 [  74 7041]]
```

8.1.2 [5.1.2] Applying KNN brute force on TFIDF, SET 2

Starting with hyperparameter tuning.

```
In [43]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearc

         knn = KNeighborsClassifier(algorithm= 'brute', n_jobs= -1)
         parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
```

```
grid = GridSearchCV(knn, parameters, cv=3, scoring='roc_auc', n_jobs = -1)
grid.fit(x_train_tf, y_train)

train_auc_tf = grid.cv_results_['mean_train_score']
cv_auc_tf    = grid.cv_results_['mean_test_score']


plt.plot(K, train_auc_tf, label='Train AUC')

plt.plot(K, cv_auc_tf, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



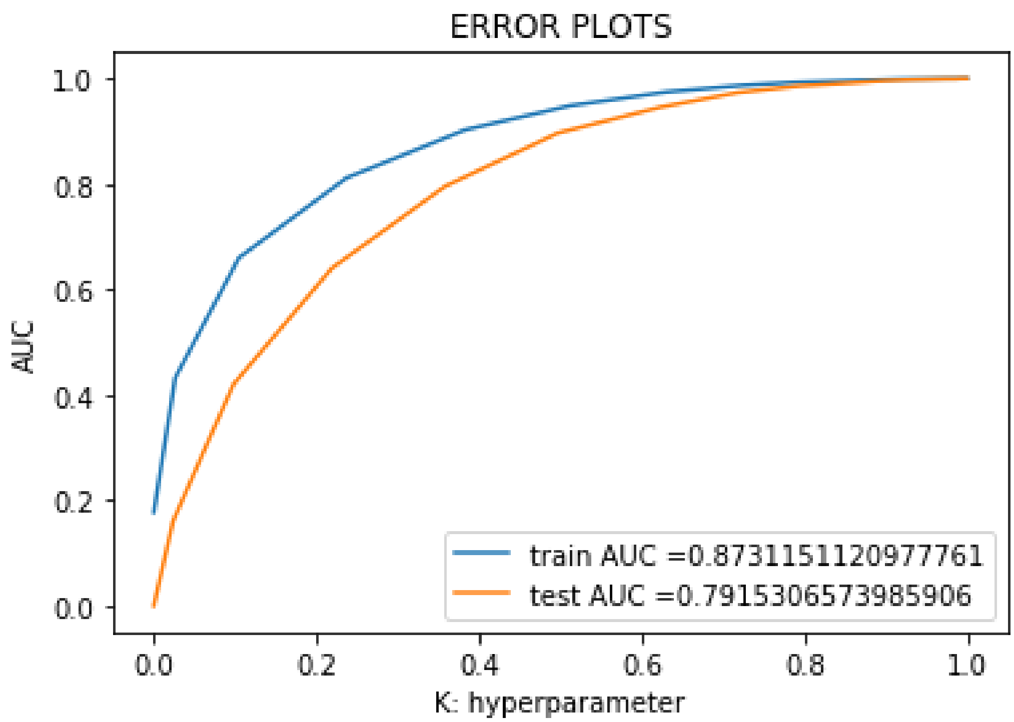
In [44]:
```
grid.best_estimator_
```

Out[44]:
```
KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
           weights='uniform')
```

In [45]:
```
best_k_tf = 51
```

Testing with Test data

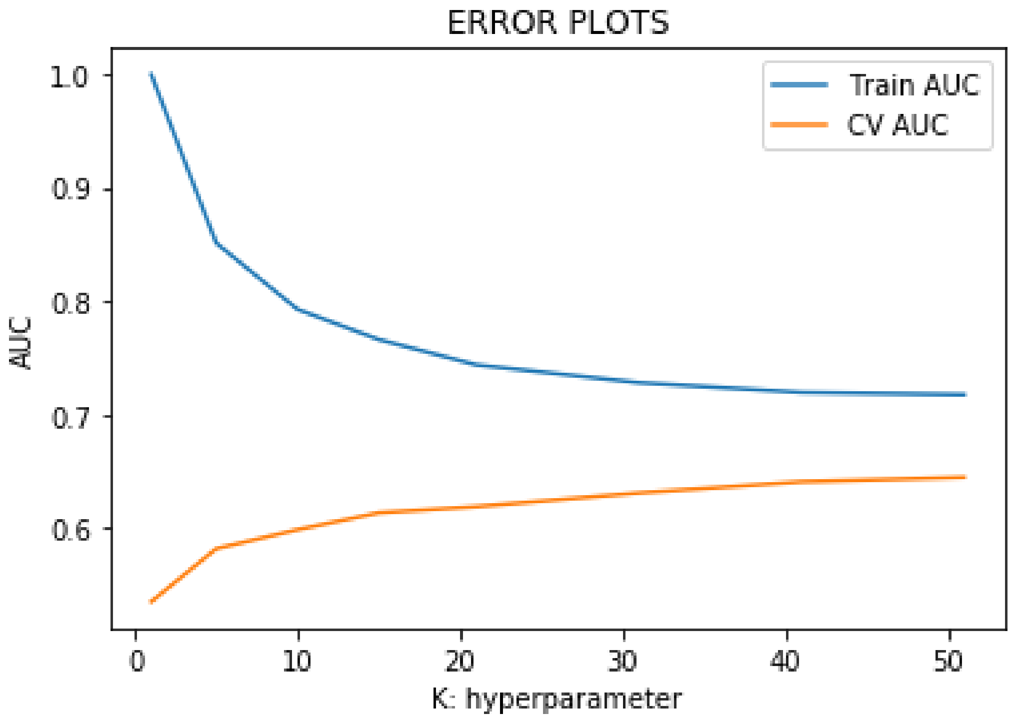
In [55]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_tf, algorithm= 'brute', n_jobs= -1)
neigh.fit(x_train_tf, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
# not the predicted outputs

train_fpr_b_tfidf, train_tpr_b_tfidf, thresholds_b_tfidf = roc_curve(y_train, neigh.pr
test_fpr_b_tfidf, test_tpr_b_tfidf, thresholds_b_tfidf = roc_curve(y_test, neigh.pred

plt.plot(train_fpr_b_tfidf, train_tpr_b_tfidf, label="train AUC ="+str(auc(train_fpr_b
plt.plot(test_fpr_b_tfidf, test_tpr_b_tfidf, label="test AUC ="+str(auc(test_fpr_b_tfi
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(x_train_tf)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(x_test_tf)))
```



```
================================================================================
Train confusion matrix
[[    0  2164]
 [    0 11591]]
Test confusion matrix
[[   0 1307]
 [   0 7115]]
```

8.1.3 [5.1.3] Applying KNN brute force on AVG W2V, SET 3

In [56]:
```python
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearc

neigh = KNeighborsClassifier(algorithm= 'brute', n_jobs= -1)
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
clf.fit(sent_vectors_train, y_train)

train_auc_b_aw2v  = clf.cv_results_['mean_train_score']
cv_auc_b_aw2v     = clf.cv_results_['mean_test_score']

plt.plot(K, train_auc_b_aw2v, label='Train AUC')
plt.plot(K, cv_auc_b_aw2v, label='CV AUC')

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



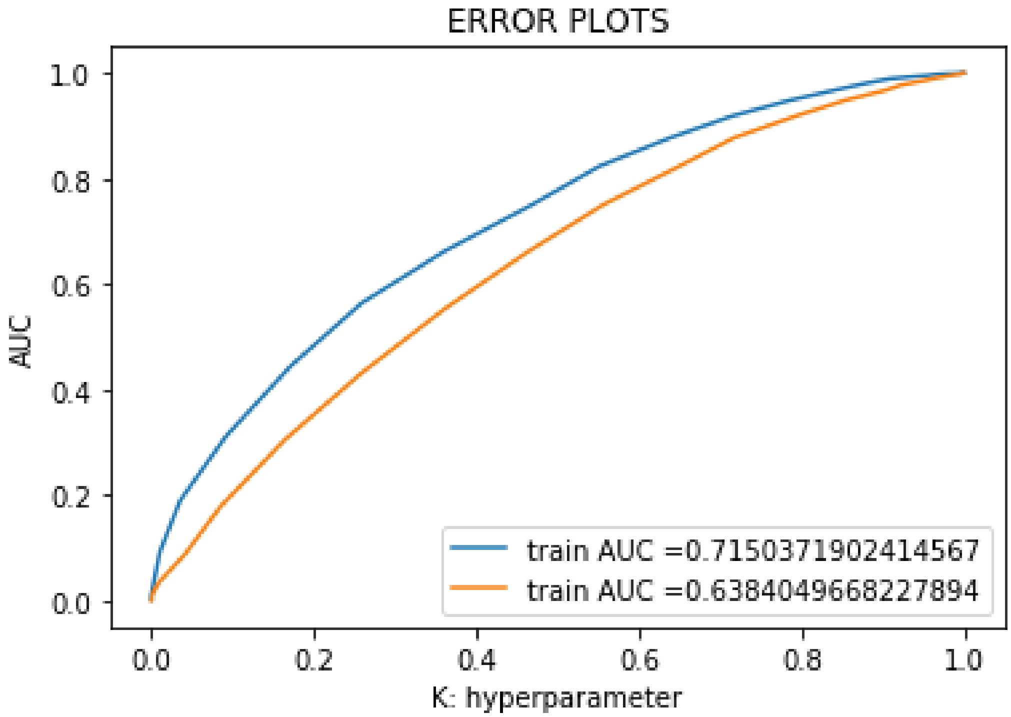
In [57]:
```
grid.best_estimator_
```

Out[57]:
```
KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
           weights='uniform')
```

In [58]:
```
best_k_b_aw2v = 51
```

In [59]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_b_aw2v, algorithm='brute', n_jobs=-
neigh.fit(sent_vectors_train, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
# not the predicted outputs

train_fpr_b_aw2v, train_tpr_b_aw2v, thresholds_b_aw2v = roc_curve(y_train, neigh.predi
test_fpr_b_aw2v, test_tpr_b_aw2v, thresholds_b_aw2v   = roc_curve(y_test, neigh.predic

plt.plot(train_fpr_b_aw2v, train_tpr_b_aw2v, label="train AUC ="+str(auc(train_fpr_b_a
plt.plot(test_fpr_b_aw2v, test_tpr_b_aw2v, label="train AUC ="+str(auc(test_fpr_b_aw2v
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

```
print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(sent_vectors_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(sent_vectors_test)))
```

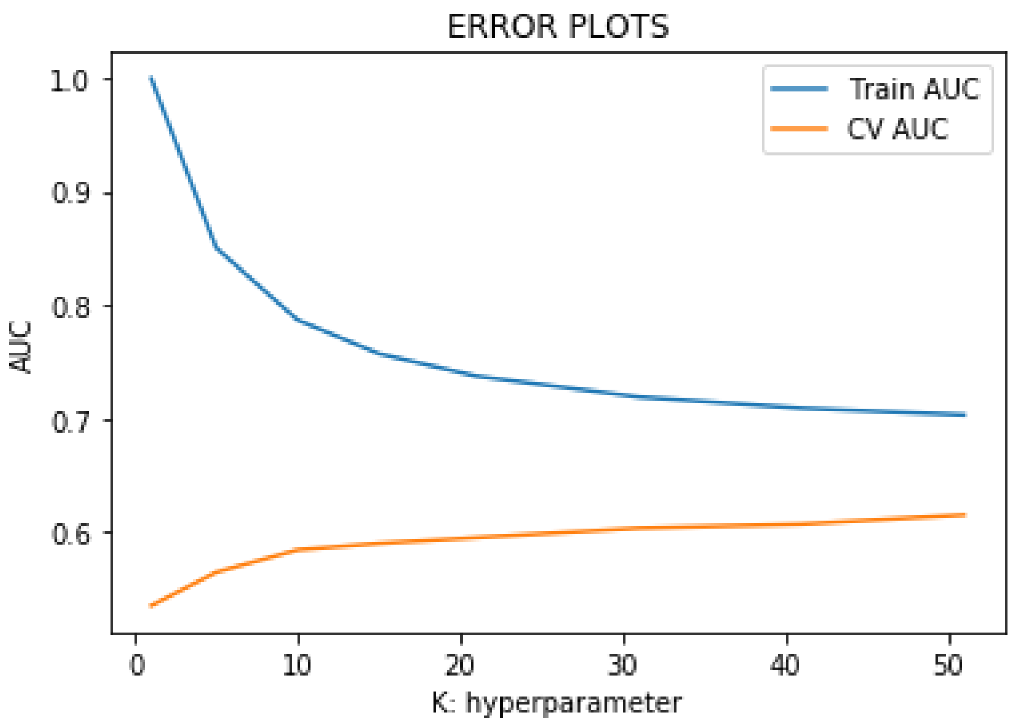



```
====================================================================================================
Train confusion matrix
[[    5  2159]
 [    2 11589]]
Test confusion matrix
[[   1 1306]
 [   0 7115]]
```

8.1.4 [5.1.4] Applying KNN brute force on TFIDF W2V, SET 4

```
In [3]: # Please write all the code with proper documentation

In [60]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearc
```

```
neigh = KNeighborsClassifier(algorithm= 'brute', n_jobs= -1)
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
clf.fit(tfidf_sent_vectors_train, y_train)

train_auc_b_tfw2v  = clf.cv_results_['mean_train_score']
cv_auc_b_tfw2v     = clf.cv_results_['mean_test_score']

plt.plot(K, train_auc_b_tfw2v, label='Train AUC')
plt.plot(K, cv_auc_b_tfw2v, label='CV AUC')

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

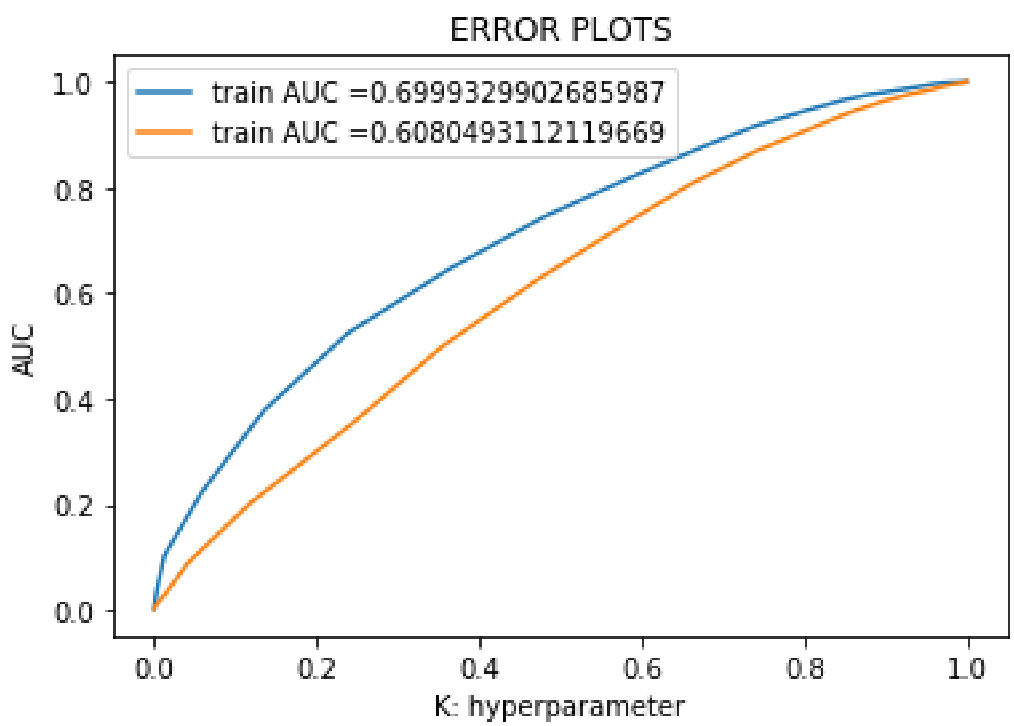


In [61]:
```
grid.best_estimator_
```

Out[61]:
```
KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
           weights='uniform')
```

In [62]:
```
best_k_b_tfw2v = 51
```

In [63]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_b_tfw2v, algorithm='brute', n_jobs=
neigh.fit(tfidf_sent_vectors_train, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
# not the predicted outputs

train_fpr_b_tfw2v, train_tpr_b_tfw2v, thresholds_b_tfw2v = roc_curve(y_train, neigh.p
test_fpr_b_tfw2v, test_tpr_b_tfw2v, thresholds_b_tfw2v   = roc_curve(y_test, neigh.pr

plt.plot(train_fpr_b_tfw2v, train_tpr_b_tfw2v, label="train AUC ="+str(auc(train_fpr_
plt.plot(test_fpr_b_tfw2v, test_tpr_b_tfw2v, label="train AUC ="+str(auc(test_fpr_b_t
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(tfidf_sent_vectors_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(tfidf_sent_vectors_test)))
```



```
==================================================================================
Train confusion matrix
[[    1  2163]
 [    0 11591]]
Test confusion matrix
[[   0 1307]
 [   1 7114]]
```

8.2 [5.2] Applying KNN kd-tree

8.2.1 [5.2.1] Applying KNN kd-tree on BOW, SET 5

First we need to convert sparse vectors formed by bow to dense metrices converting sparse metrice to dense metrices using todense() function

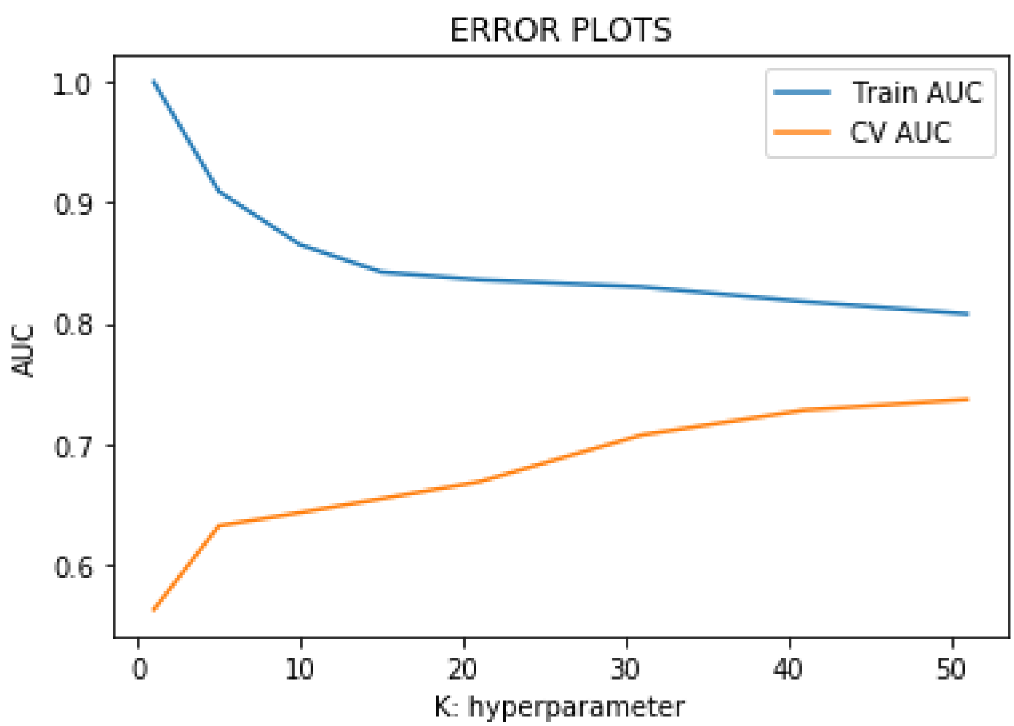
```
In [102]: # converting sparse metrices to dense metrices using todense()
          x_train_bow_dense = x_train_bow.todense()
          x_cv_bow_dense    = x_cv_bow.todense()
          x_test_bow_dense  = x_test_bow.todense()

          print("After converting these sparse metrices to dense metrices")

          print(x_train_bow_dense.shape, y_train.shape)
          print(x_cv_bow_dense.shape,          y_cv.shape)
          print(x_test_bow_dense.shape,  y_test.shape)

          print("="*50)

          print("the type of count vectorizer ",type(x_train_bow_dense))
          print("the type of count vectorizer ",type(x_cv_bow_dense))
          print("the type of count vectorizer ",type(x_test_bow_dense))
```

```
After converting these sparse metrices to dense metrices
(9482, 3442) (9482,)
(4065, 3442) (4065,)
(5807, 3442) (5807,)
==================================================
the type of count vectorizer  <class 'numpy.matrix'>
the type of count vectorizer  <class 'numpy.matrix'>
the type of count vectorizer  <class 'numpy.matrix'>
```

Hyperparameter tuning using Grid Search, which seems to work better as compared to for loop we use

```
In [105]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSear

          neigh = KNeighborsClassifier(algorithm= 'kd_tree', n_jobs= -1)
```

```
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
clf.fit(x_train_bow_dense, y_train)

train_auc_bow_kd      = clf.cv_results_['mean_train_score']
cv_auc_bow_kd         = clf.cv_results_['mean_test_score']

plt.plot(K, train_auc_bow_kd, label='Train AUC')
plt.plot(K, cv_auc_bow_kd, label='CV AUC')

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

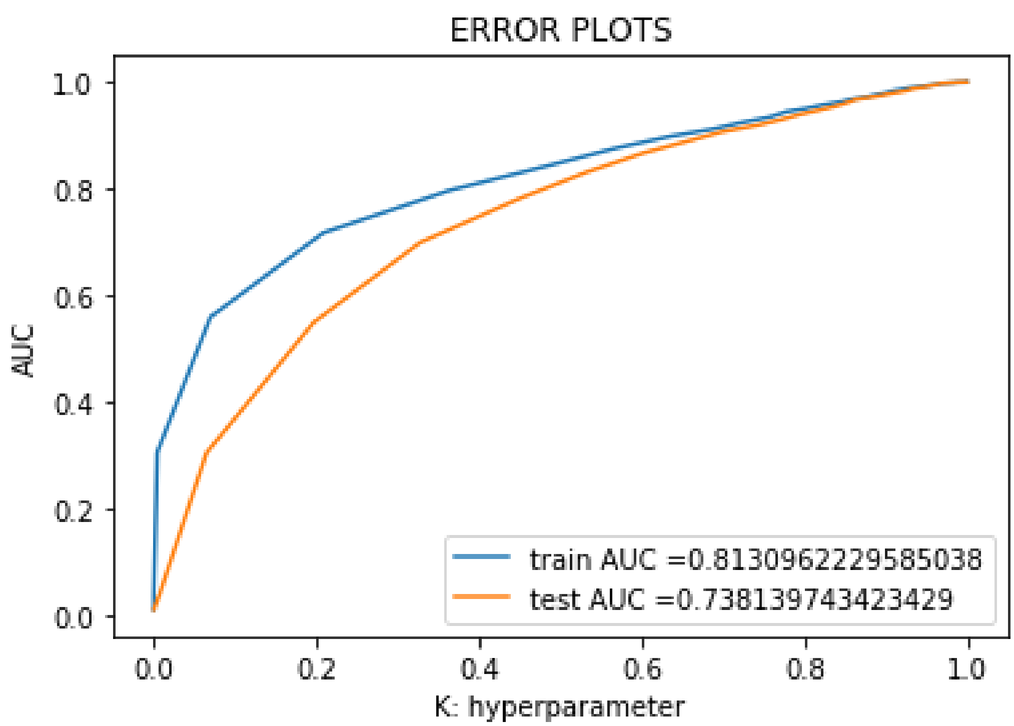


Hyperparameter tuning using simple for loops which consumes alot of memory as well as takes alot of time to compute the results

```
In [106]: clf.best_estimator_

Out[106]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
                     weights='uniform')
```

In [107]:
```
best_k_kd_bow =51
```

In [108]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_kd_bow, algorithm='kd_tree')
neigh.fit(x_train_bow_dense, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates o
# not the predicted outputs

train_fpr_bow_kd, train_tpr_bow_kd, thresholds_bow_kd = roc_curve(y_train, neigh.pred
test_fpr_bow_kd, test_tpr_bow_kd, thresholds_bow_kd = roc_curve(y_test, neigh.predict

plt.plot(train_fpr_bow_kd, train_tpr_bow_kd, label="train AUC ="+str(auc(train_fpr_bo
plt.plot(test_fpr_bow_kd, test_tpr_bow_kd, label="test AUC ="+str(auc(test_fpr_bow_kd
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(x_train_bow_dense)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(x_test_bow_dense)))
```



```
==================================================
Train confusion matrix
[[  63 1385]
 [  47 7987]]
Test confusion matrix
[[  36  905]
 [  26 4840]]
```

8.2.2 [5.2.2] Applying KNN kd-tree on TFIDF, SET 6

converting sparse metrices from tfidf featurization to dense metrices before applying kd-tree knn

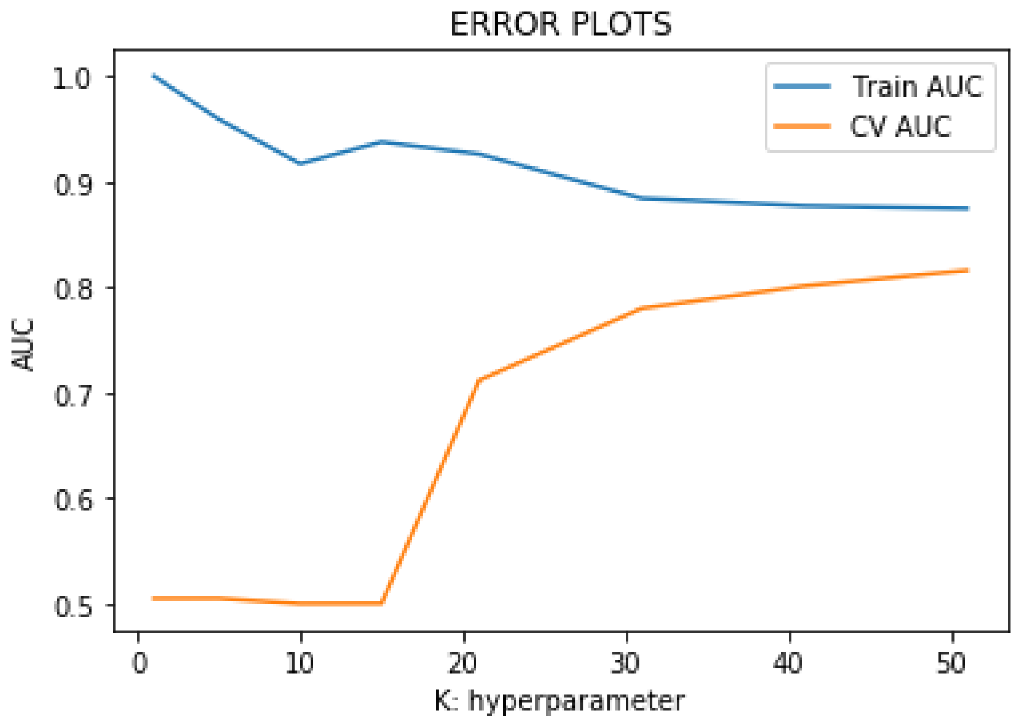
```
In [109]: # converting sparse metrices to dense metrices using todense()
          x_train_tf_dense = x_train_tf.todense()
          x_cv_tf_dense    = x_cv_tf.todense()
          x_test_tf_dense  = x_test_tf.todense()

          print("After converting these sparse metrices to dense metrices")

          print(x_train_tf_dense.shape, y_train.shape)
          print(x_cv_tf_dense.shape,    y_cv.shape)
          print(x_test_bow_dense.shape, y_test.shape)

          print("="*50)

          print("the type of count vectorizer ",type(x_train_tf_dense))
          print("the type of count vectorizer ",type(x_cv_tf_dense))
          print("the type of count vectorizer ",type(x_test_tf_dense))
```

```
After converting these sparse metrices to dense metrices
(9482, 3442) (9482,)
(4065, 3442) (4065,)
(5807, 3442) (5807,)
==================================================
the type of count vectorizer  <class 'numpy.matrix'>
the type of count vectorizer  <class 'numpy.matrix'>
the type of count vectorizer  <class 'numpy.matrix'>
```

Hyperparameter tuning using Grid Search

```
In [111]: # https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSear

          neigh = KNeighborsClassifier(algorithm= "kd_tree", n_jobs= -1)
          parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
          clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
          clf.fit(x_train_tf_dense, y_train)
```

```
train_auc_tfidf_kd      = clf.cv_results_['mean_train_score']
cv_auc_tfidf_kd         = clf.cv_results_['mean_test_score']

plt.plot(K, train_auc_tfidf_kd, label='Train AUC')
plt.plot(K, cv_auc_tfidf_kd, label='CV AUC')

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



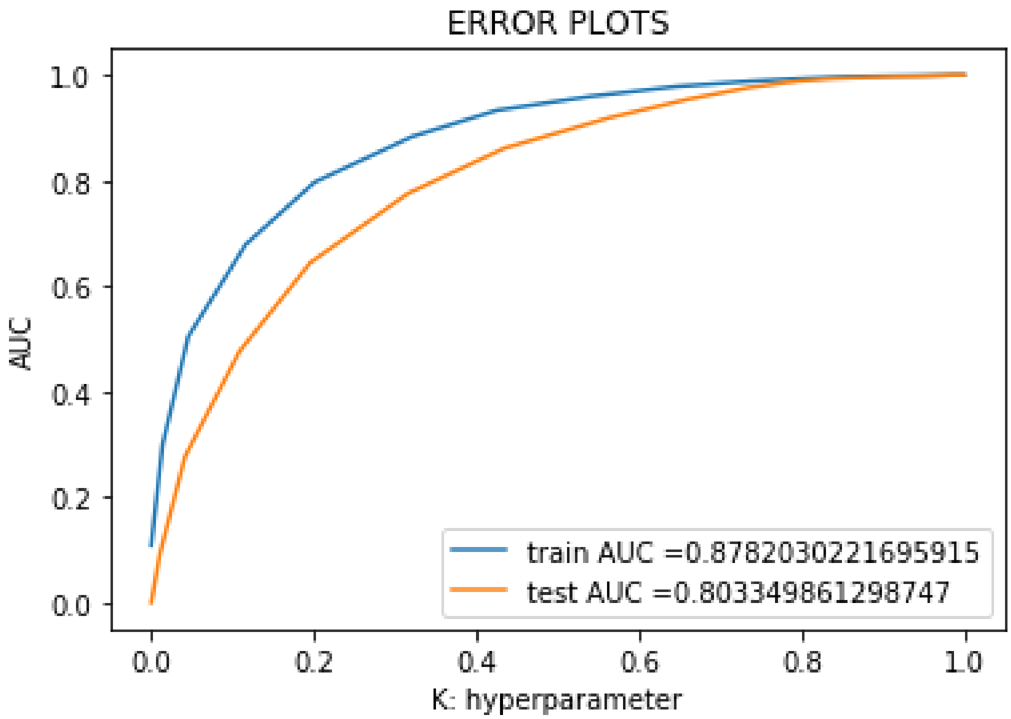
In [112]:
```
clf.best_estimator_
```

Out[112]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
           weights='uniform')
```

In [113]:
```
best_k_kd_tf = 51  # from grid search we take this value of K
```

In [114]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_kd_tf, algorithm= 'kd_tree', n_jobs
neigh.fit(x_train_tf_dense, y_train)

train_fpr_tfidf_kd, train_tpr_tfidf_kd, thresholds_tfidf_kd = roc_curve(y_train, neig
```

```
test_fpr_tfidf_kd, test_tpr_tfidf_kd, thresholds_tfidf_kd = roc_curve(y_test, neigh.p

plt.plot(train_fpr_tfidf_kd, train_tpr_tfidf_kd, label="train AUC ="+str(auc(train_fp
plt.plot(test_fpr_tfidf_kd, test_tpr_tfidf_kd, label="test AUC ="+str(auc(test_fpr_ti
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(x_train_tf_dense)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(x_test_tf_dense)))
```



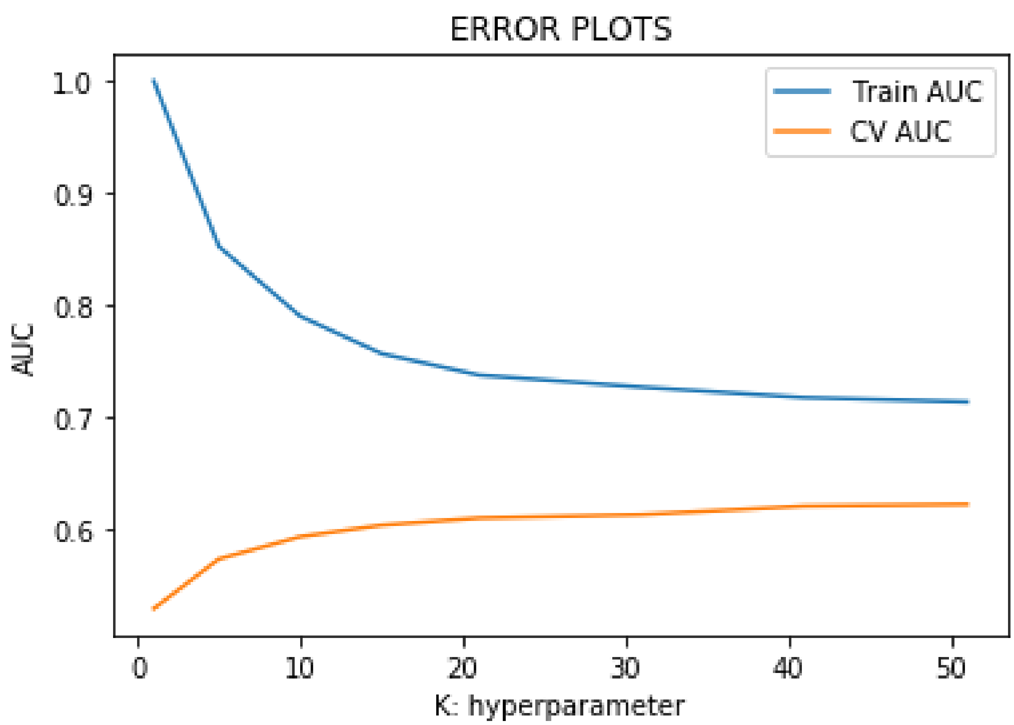

```
=====================================================================================
Train confusion matrix
[[   0 1448]
 [   0 8034]]
Test confusion matrix
[[   0  941]
```

```
[    0 4866]]
```

8.2.3 [5.2.3] Applying KNN kd-tree on AVG W2V, SET 3

In [3]:
```
# Please write all the code with proper documentation
```

In [115]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSear

neigh = KNeighborsClassifier(algorithm= 'kd_tree', n_jobs= -1)
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
clf.fit(sent_vectors_train, y_train)

train_auc_kd_aw2v  = clf.cv_results_['mean_train_score']
cv_auc_kd_aw2v     = clf.cv_results_['mean_test_score']

plt.plot(K, train_auc_kd_aw2v, label='Train AUC')
plt.plot(K, cv_auc_kd_aw2v, label='CV AUC')

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

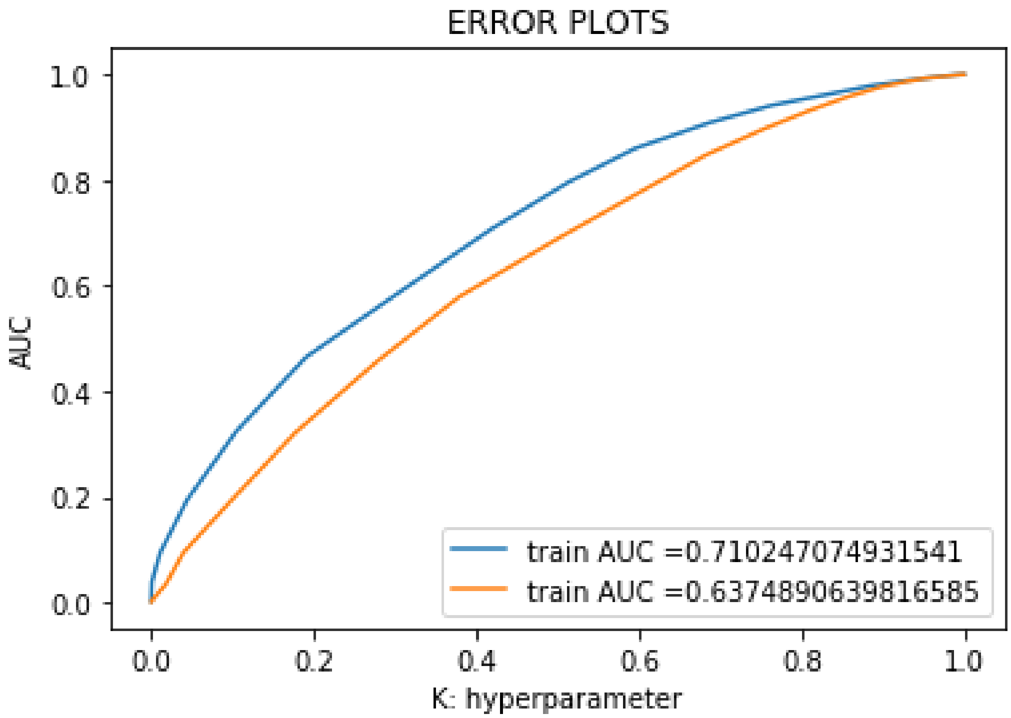


In [116]: clf.best_estimator_

Out[116]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
           weights='uniform')
```

In [117]:
```
best_k_kd_aw2v = 51
```

In [118]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_kd_aw2v, algorithm='kd_tree', n_jo
neigh.fit(sent_vectors_train, y_train)

train_fpr_kd_aw2v, train_tpr_kd_aw2v, thresholds_kd_aw2v = roc_curve(y_train, neigh.
test_fpr_kd_aw2v, test_tpr_kd_aw2v, thresholds_kd_aw2v   = roc_curve(y_test, neigh.p

plt.plot(train_fpr_kd_aw2v, train_tpr_kd_aw2v, label="train AUC ="+str(auc(train_fpr
plt.plot(test_fpr_kd_aw2v, test_tpr_kd_aw2v, label="train AUC ="+str(auc(test_fpr_kd

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

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(sent_vectors_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(sent_vectors_test)))
```



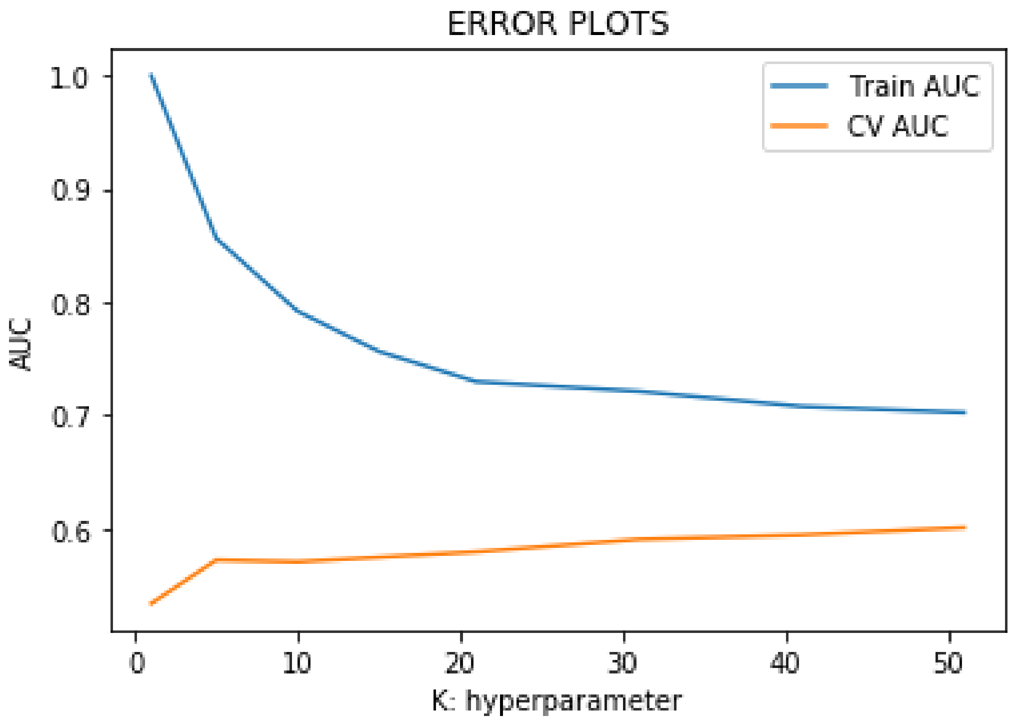

```
================================================================================================
Train confusion matrix
[[   1 1447]
 [   0 8034]]
Test confusion matrix
[[   1  940]
 [   0 4866]]
```

8.2.4 [5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 4

In [3]:
```
# Please write all the code with proper documentation
```

In [119]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSear

neigh = KNeighborsClassifier(algorithm= 'kd_tree', n_jobs= -1)
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
clf.fit(tfidf_sent_vectors_train, y_train)

train_auc_kd_tfw2v  = clf.cv_results_['mean_train_score']
cv_auc_kd_tfw2v     = clf.cv_results_['mean_test_score']

plt.plot(K, train_auc_kd_tfw2v, label='Train AUC')
```

```
plt.plot(K, cv_auc_kd_tfw2v, label='CV AUC')

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



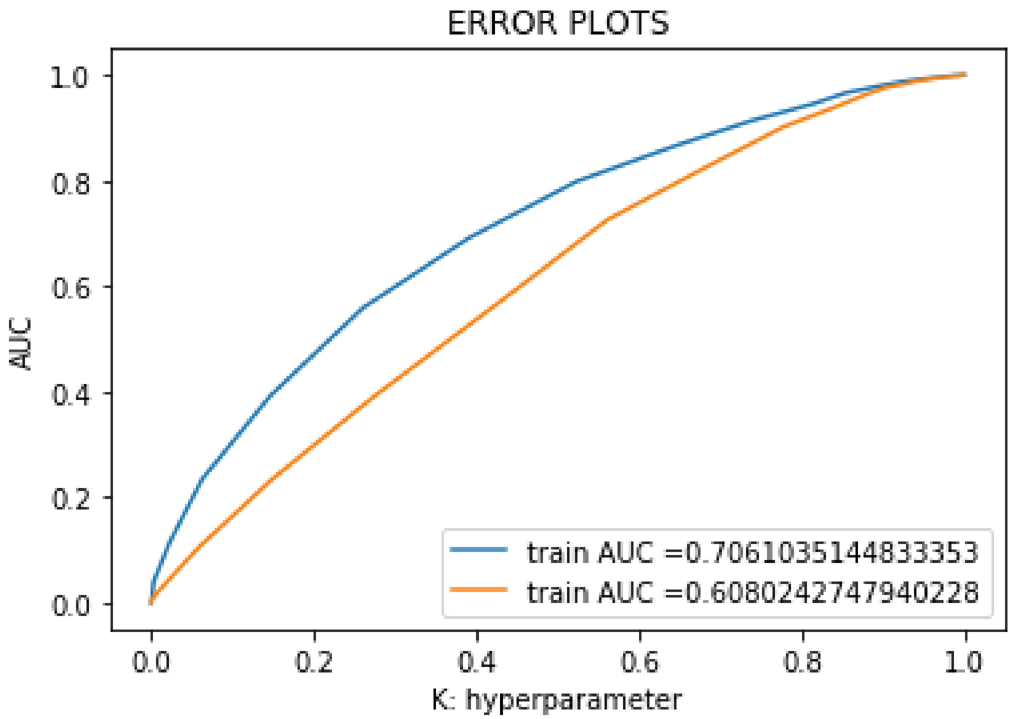
In [120]:
```
clf.best_estimator_
```

Out[120]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=51, p=2,
           weights='uniform')
```

In [121]:
```
best_k_kd_tfw2v = 51
```

In [122]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k_kd_tfw2v, algorithm='kd_tree', n_jo
neigh.fit(tfidf_sent_vectors_train, y_train)

train_fpr_kd_tfw2v, train_tpr_kd_tfw2v, thresholds_kd_tfw2v = roc_curve(y_train, neig
test_fpr_kd_tfw2v, test_tpr_kd_tfw2v, thresholds_kd_tfw2v   = roc_curve(y_test, neigh

plt.plot(train_fpr_kd_tfw2v, train_tpr_kd_tfw2v, label="train AUC ="+str(auc(train_fp
plt.plot(test_fpr_kd_tfw2v, test_tpr_kd_tfw2v, label="train AUC ="+str(auc(test_fpr_k
```

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

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(tfidf_sent_vectors_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(tfidf_sent_vectors_test)))
```




```
====================================================================================================
Train confusion matrix
[[   0 1448]
 [   0 8034]]
Test confusion matrix
[[   1  940]
 [   1 4865]]
```

9 [6] Conclusions

9.0.1 Number of data points used for different implementations :

1. We loaded the data from a splite3 database file using sql command.
2. For Brute Force implementation of K-NN I used 30k points to speed up the things.
3. I experimented alot by using various number of data points ranging from 100k to 40k.
4. But it was completely freezing the system that's why, then I used only 30k points.
5. And for kd-tree implementation of K-NN I used 20k points.

9.0.2 Data Cleaning and Preprocessing :

1. After loading the data we clean the data and preprocess it.
2. Remove duplicates and preprocessed text.
3. Which includes removing html tags, removing stop words etc.

9.0.3 Applying Featurization :

1. Before we applied any featurization on the data.
2. We split the data in three parts train data, cross validation data and test data.
3. Then after splitting the data we applied various vectorization techniques.
4. We used BoW, TF-IDF, Average w2v and TF-IDF w2v.

Then we applied KNN using two different algorithms. 1. Brute Force Algorithm 2. KD-Tree Algorithm

After using AUC curves we observed that > For Brute force implementation * kNN with BoW and TF-IDF vectors perform better as compared to Average w2v and tf-idf w2v. * And TF-IDF works even better when compared to BoW

> For KD-Tree implementation * As expected kd-tree implementation works better as compared to brute force method for all featurization. * And similarly like brute force algorithm, BoW and TF-IDF featurizations are performing better than Average w2v and tf-idf w2v. * Plus on comparing BoW and TF-IDF, we again observed that TF-IDF is working better and is more capable to classify the data points than any other vectorizer.

```
In [142]: names = ["KNN(Brute force) for BoW", "KNN(Brute force) for TF-IDF", "KNN(Brute force
          best_K = [ best_k_bow, best_k_tf, best_k_b_aw2v, best_k_b_tfw2v, best_k_kd_bow, best_

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

          # Initializing prettytable
          # Adding columns
          ptable = PrettyTable()
          ptable.add_column("S.NO.",number)
          ptable.add_column("MODEL",names)
          ptable.add_column("Best K",best_K)
          #ptable.add_column("Train Accuracy",train_AUC)
```

```python
#Printing the Table
print(ptable)
```

```
+--------+-----------------------------------+--------+
| S.NO. |               MODEL               | Best K |
+--------+-----------------------------------+--------+
|   1    |     KNN(Brute force) for BoW      |   51   |
|   2    |    KNN(Brute force) for TF-IDF    |   51   |
|   3    | KNN(Brute force) for Average w2v  |   51   |
|   4    | KNN(Brute force) for TF-IDF w2v   |   51   |
|   5    |       KNN(KD Tree) for BoW        |   51   |
|   6    |      KNN(KD Tree) for TF-IDF      |   51   |
|   7    |    KNN(KD Tree) for Average w2v   |   51   |
|   8    |    KNN(KD Tree) for TF-IDF w2v    |   51   |
+--------+-----------------------------------+--------+
```