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.

Instructions for the assignment

1.YOU HAVE TO DOWNLOAD ONLY THESE NOTEBOOKS(check the drive link attached), WRITE YOUR CODE IN THE SAME NOTEBOOKS AND UPLOAD AS YOUR SUBMISSION.

1. There are two tasks of KNN clearly mentioned in the ipynb. One is to apply Brute force KNN and other is KD-tree version of KNN. You have to perform both these tasks on all 4 vectorizers. (BOW, TFIDF, AVG-W2V, TFIDF-AVG_W2V)
2. If you have 4GB of RAM then consider 50k points as sample size for brute force algorithm and 20k as sample size for kd-tree algorithm. If your RAM is 8GB then consider a minimum sample size of 100k datapoints for brute force and 20k datapoints for kd-tree algorithm. And if your RAM is less than 4GB then please upgrade your RAM to a minimum of 8GB.
3. You can use sparse matrices for brute force algorithm of KNN.
4. For kd-tree algorithm you have to use dense matrices. Please note that if you pass sparse matrix as input to kd-tree algorithm then by default it will run in brute-force. So please use dense matrices for kd-tree.
5. Use AUC as a metric for hyperparameter tuning.
6. Properly document the results according to the instructions provided in the corresponding ipynb.
7. If you want to further increase the performance of the model, you can experiment with the feature engineering section mentioned in the ipynb.

Steps

1. Import data

2. Preprocessing the data
3. Split data into train and test data sets
4. Take care of data leakage by not fitting - transform the entrire data
5. Apply the knn brute force algorithm
6. Apply the kd tree algorithm

Blogs to read

- sklearn doc on nn
- knn classifier knn and kdtree
- SO CV Very good explanation on importance of cv
- How to Train a Final Machine Learning Model puts light on CV

[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 [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

```
import sqlite3

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import nltk
import string

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
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 collections import Counter

# ============================== loading libraries ====================
=======================

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_score

from sklearn.preprocessing import StandardScaler

from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc

from sklearn.feature_extraction.text import CountVectorizer
```

```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\gensim\utils.py:1197: UserWarning: detected Windows; aliasing chunkiz
e to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

In [2]:

```
import os
print(os.listdir("."))
```

```
['.ipynb_checkpoints', '01 adv py template.ipynb', '03 Amazon Fine Food
Reviews Analysis_KNN.ipynb', '04 Amazon Fine Food Reviews Analysis_Naiv
eBayes.ipynb', '3d_plot.JPG', 'Amazon knn  resubmission.ipynb', 'Amazon
KNN-Copy1.ipynb', 'Amazon KNN.ipynb', 'Assignment 22 SQL', 'Comparing g
ridsearch and randomizedsearch for finding hyperparameter.ipynb', 'conf
usion_matrix.png', 'database.sqlite', 'demo_data', 'finalized_df.sav',
'finalized_model.sav', 'Functions for knn.ipynb', 'heat_map.JPG', 'Iter
tools tutorial.ipynb', 'kfold.ipynb', 'knn', 'knn practice 1- kd.ipyn
b', 'knn practice 1.ipynb', 'knn-20190220T090416Z-001.zip', 'knn.ipyn
b', 'pickle.ipynb', 'preprocessed_final', 'python collections.ipynb',
'summary.JPG', 'train_cv_auc.JPG', 'train_test_auc.JPG', 'Untitled.ipyn
b']
```

Applying KNN Brute Force: Data Import and Preprocessing

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 50
0000 data points
# you can change the number to any other number based on your computing
 power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points
```

In [4]:
```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 50000""", con)
```

In [5]:
```
# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1
```

In [6]:
```
#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 (50000, 10)
```

Out[6]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [7]:

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

In [8]:

```
print(display.shape)
display.head()
```

(80668, 7)

Out[8]:

	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

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
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 [9]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[9]:

	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 [10]:
```
display['COUNT(*)'].sum()
```

Out[10]: 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 [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[11]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
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 [12]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [13]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[13]:
```
(46072, 10)
```

In [14]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[14]:
```
92.144
```

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 [15]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[15]:

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

In [16]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [17]:
```
final.head()
```

Out[17]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDe

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDe
22620	24750	2734888454	A13ISQV0U9GZIC	Sandikaye	1	
22621	24751	2734888454	A1C298ITT645B6	Hugh G. Pritchard	0	
2546	2774	B00002NCJC	A196AJHU9EASJN	Alex Chaffee	0	
2547	2775	B00002NCJC	A13RRPGE79XFFH	reader48	0	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	

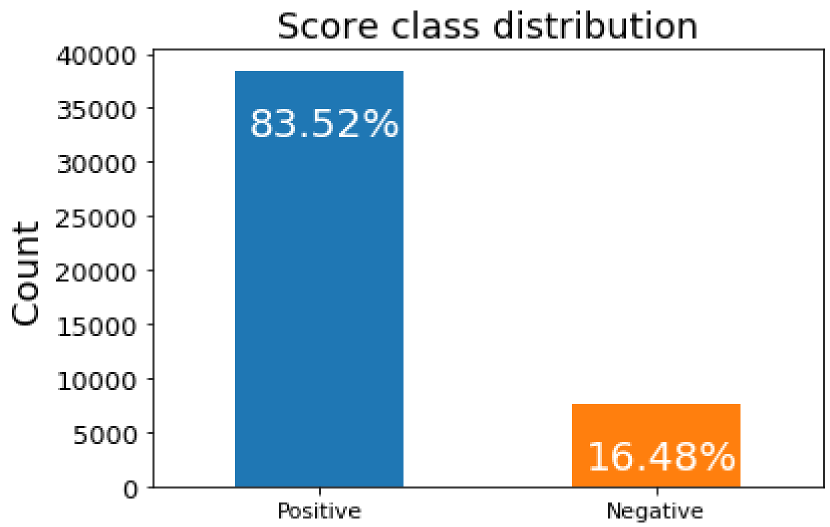
In [18]:

```
#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()
```

```
(46071, 10)
```

Out[18]:
```
1    38479
0     7592
Name: Score, dtype: int64
```

In [19]:
```
# Code referred from https://stackoverflow.com/questions/31749448/how-t
o-add-percentages-on-top-of-bars-in-seaborn
ax = final['Score'].value_counts().plot(kind='bar',
                                        fontsize=13);
ax.set_alpha(0.8)
ax.set_title("Score class distribution", fontsize=18)
ax.set_ylabel("Count", fontsize=18);
#ax.set_yticks([0, 5, 10, 15, 20])
ax.set_xticklabels(['Positive', 'Negative'], rotation=0, fontsize=11)

# create a list to collect the plt.patches data
totals = []

# find the values and append to list
for i in ax.patches:
    totals.append(i.get_height())

# set individual bar lables using above list
total = sum(totals)

# set individual bar lables using above list
for i in ax.patches:
    # Decreasing the i.get_x()+.12 will shift the text to left side and
 decreasing the i.get_height()-14 will bring the text down
    ax.text(i.get_x()+.04, i.get_height()-6000, \
            str(round((i.get_height()/total)*100, 2))+'%', fontsize=20,
                color='white')
```



Observation: This is an imbalance dataset. There are roughly 84% Positive review and 16% Negative reviews.

Checkpoint 1: Imported data and some basic eda

In [20]:
```
# Filtering 1 (positive) and 0 (negative) reviews
#pos_reviews = final[final['Score'] == 1].sample(n=10000, random_state=
507)
#neg_reviews = final[final['Score'] == 0].sample(n=10000, random_state=
507)

# Combining the above dataframes into one
#final = pd.concat([pos_reviews, neg_reviews])
```

In [21]:
```
# Converting Time to time format in seconds using a unix epoch time
# We will arrange the entire final dataframe in ascending order for tim
e based splitting

final["Time"] = pd.to_datetime(final["Time"], origin='unix', unit = "s"
```

```
)
final = final.sort_values(by = "Time")
```

In [22]:

```
final.size
```

Out[22]:

```
460710
```

[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 [23]:

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

sent_1000 = final['Text'].values[1000]
print(sent_1000)
```

```python
print("="*50)

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

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

```
This was a really good idea and the final product is outstanding. I use
the decals on my car window and everybody asks where i bought the decal
s i made.  Two thumbs up!
==================================================
Speaking as another Texan, I think the first rule for these delicious t
reats is to NOT order them during spring or summer. In fact, your safes
t bet is to ONLY order them in the dead of winter.  LOL!  As long as yo
u do that, be prepared for a truly amazing treat!  This package comes w
ith 12 bite-sized delicacies.  The chocolate is high-quality, the nuts
are crunchy, and the overall taste couldn't be better.  Definitely wort
h the price!
==================================================
Fast, easy and definitely delicious.  Makes a great cup of coffee and v
ery easy to make.  Good purchase.  Will continue to order from here.<br
/>Thanx...
==================================================
Naturally this review is based upon my cat's intake of Petite Cuisine.
She's not a particular picky eater, so I can't say much about that. How
ever, she looks to really enjoy this brand of cat food. I have tried so
me brands of wet food in the past that have made her sick (I know cats
seem to have digestive systems that are prone to upsetting!) Petite Cui
sine did not have any effect there, and she really enjoyed all the flav
ors. I don't feed her wet food often, usually just some tuna fish now a
nd then. So, although this food is expensive if you used it at every me
al, it is priced about the same as tuna, so it fits my needs perfectly.
I'm sure my cat will enjoy the rest of this case, and I can keep the ca
nned tuna to myself for now :-)
==================================================
```

In [24]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
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)
```

```
This was a really good idea and the final product is outstanding. I use
the decals on my car window and everybody asks where i bought the decal
s i made.  Two thumbs up!
```

In [25]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
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)
```

```
This was a really good idea and the final product is outstanding. I use
the decals on my car window and everybody asks where i bought the decal
s i made.  Two thumbs up!
```

```
==================================================
Speaking as another Texan, I think the first rule for these delicious t
reats is to NOT order them during spring or summer. In fact, your safes
t bet is to ONLY order them in the dead of winter.  LOL!  As long as yo
u do that, be prepared for a truly amazing treat!  This package comes w
ith 12 bite-sized delicacies.  The chocolate is high-quality, the nuts
are crunchy, and the overall taste couldn't be better.  Definitely wort
h the price!
==================================================
Fast, easy and definitely delicious.  Makes a great cup of coffee and v
ery easy to make.  Good purchase.  Will continue to order from here.Tha
nx...
==================================================
Naturally this review is based upon my cat's intake of Petite Cuisine.
She's not a particular picky eater, so I can't say much about that. How
ever, she looks to really enjoy this brand of cat food. I have tried so
me brands of wet food in the past that have made her sick (I know cats
seem to have digestive systems that are prone to upsetting!) Petite Cui
sine did not have any effect there, and she really enjoyed all the flav
ors. I don't feed her wet food often, usually just some tuna fish now a
nd then. So, although this food is expensive if you used it at every me
al, it is priced about the same as tuna, so it fits my needs perfectly.
I'm sure my cat will enjoy the rest of this case, and I can keep the ca
nned tuna to myself for now :-)
```

In [26]:

```python
# 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)
```

```python
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [27]:
```python
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Fast, easy and definitely delicious.  Makes a great cup of coffee and v
ery easy to make.  Good purchase.  Will continue to order from here.<br
/>Thanx...
==================================================
```

In [28]:
```python
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
This was a really good idea and the final product is outstanding. I use
the decals on my car window and everybody asks where i bought the decal
s i made.  Two thumbs up!
```

In [29]:
```python
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Fast easy and definitely delicious Makes a great cup of coffee and very
easy to make Good purchase Will continue to order from here br Thanx
```

In [30]:
```python
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <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', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [31]:

```
# 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████████████████████
█████████████████████████████████████████████████████████| 46071/46071
[00:13<00:00, 3488.12it/s]
```

In [32]:
```
preprocessed_reviews[1500]
```

Out[32]:
```
'fast easy definitely delicious makes great cup coffee easy make good p
urchase continue order thanx'
```

[3.2] Preprocessing Review Summary

In [33]:
```
## Similartly you can do preprocessing for review summary also.
from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
for sentence in tqdm(final['Summary'].values):
    sentence = re.sub(r"http\S+", "", sentence)
    sentence = BeautifulSoup(sentence, 'lxml').get_text()
    sentence = decontracted(sentence)
    sentence = re.sub("\S*\d\S*", "", sentence).strip()
    sentence = re.sub('[^A-Za-z]+', ' ', sentence)
    # https://gist.github.com/sebleier/554280
    sentence = ' '.join(e.lower() for e in sentence.split() if e.lower
() not in stopwords)
    preprocessed_summary.append(sentence.strip())
```

```
 57%|██████████████████████████████████████████████████████████████████
███                                                      | 26170/46071
[00:04<00:03, 5640.67it/s]C:\Users\Nit-prj1010\AppData\Local\Continuum
\anaconda3\lib\site-packages\bs4\__init__.py:273: UserWarning: "b'...'"
looks like a filename, not markup. You should probably open this file a
nd pass the filehandle into Beautiful Soup.
```

```
  ' Beautiful Soup.' % markup)
100%|██████████████████████████████████████████████████████████████████████| 46071/46071
[00:08<00:00, 5555.36it/s]
```

In [34]:
```python
final.head()
```

Out[34]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	H
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	
28086	30629	B00008RCMI	A19E94CF5O1LY7	Andrew Arnold	0	
28087	30630	B00008RCMI	A284C7M23F0APC	A. Mendoza	0	
38740	42069	B0000EIEQU	A1YMJX4YWCE6P4	Jim Carson "http://www.jimcarson.com"	12	

In [35]:
```python
final['CleanedText']= preprocessed_reviews
final['CleanedSummary']= preprocessed_summary
```

In [36]:
```python
final.CleanedText.isnull().sum()
```

Out[36]: 0

In [37]:
```python
final.head()
```

Out[37]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10
28086	30629	B00008RCMI	A19E94CF5O1LY7	Andrew Arnold	0
28087	30630	B00008RCMI	A284C7M23F0APC	A. Mendoza	0
38740	42069	B0000EIEQU	A1YMJX4YWCE6P4	Jim Carson "http://www.jimcarson.com"	12

In [38]:

```
import pickle
```

In [39]:

```
file_Name = "preprocessed_final"
# open the file for writing
fileObject = open(file_Name,'wb')

# this writes the object a to the
# file named 'testfile'
pickle.dump(final,fileObject)
```

Checkpoint 2: Data is now sorted based on Time and preprocessed.

In [40]:
```
# Create X and Y variable
X = final['CleanedText'].values
y= final['Score'].values
```

In [41]:
```
type(X)
```

Out[41]:
```
numpy.ndarray
```

In [42]:
```
type(y)
```

Out[42]:
```
numpy.ndarray
```

In [43]:
```
# ss
from sklearn.model_selection import train_test_split

# Splitting into train and test in the ratio 70:30
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3
0,shuffle=False, random_state=507)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_
size=0.30, shuffle=False, random_state=507)
```

In [44]:
```
# ss
print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)

print("="*100)
```

```
(22574,) (22574,)
(9675,) (9675,)
(13822,) (13822,)
========================================================================
=============================
```

In [45]:
```
print("Train Set:",X_train.shape, y_train.shape[0])
print("Test Set:",X_test.shape, y_test.shape[0])
```

```
Train Set: (22574,) 22574
```

```
Test Set: (13822,) 13822
```

Checkpoint 3: Data has been partioned into train, cv and test

[4.1] BAG OF WORDS

In [46]:
```
# ss
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer()
vectorizer.fit(X_train) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.transform(X_test)

print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22574, 28400) (22574,)
(9675, 28400) (9675,)
(13822, 28400) (13822,)
=======================================================================
=============================
```

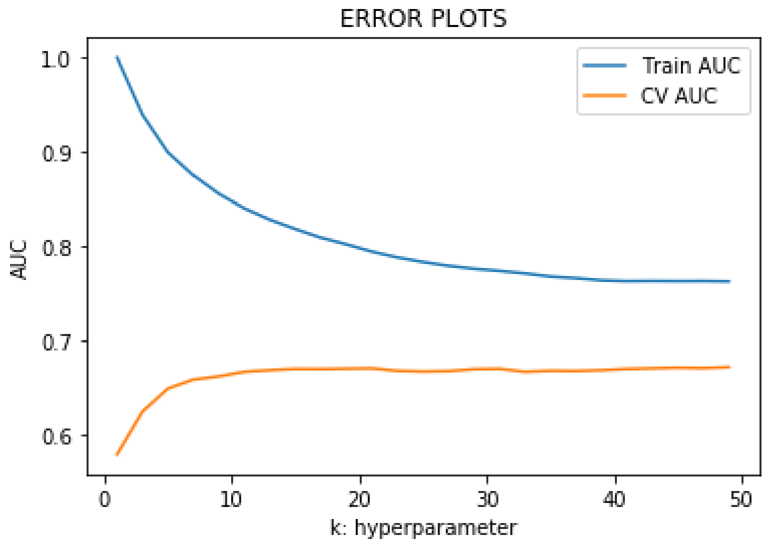
In [47]:
```
print("the type of count vectorizer ",type(X_train_bow))
print("the shape of cut text BOW vectorizer ",X_train_bow.get_shape())
print("the number of unique words: ", X_train_bow.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of cut text BOW vectorizer  (22574, 28400)
the number of unique words:  28400
```

1. KNN Brute Force algorithm implementation on BOW

In [48]:
```
# ss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive clas
s, confidence values, or non-thresholded measure of
decisions (as returned by “decision_function” on some classifiers).
For binary y_true, y_score is supposed to be the score of the class wit
h greater label.

"""

train_auc = []
cv_auc = []

# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm='brute')
    neigh.fit(X_train_bow, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(X_train_bow)[:,1]
    y_cv_pred =  neigh.predict_proba(X_cv_bow)[:,1]
```

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

plt.plot(neighbors, train_auc, label='Train AUC')
plt.plot(neighbors, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("k: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

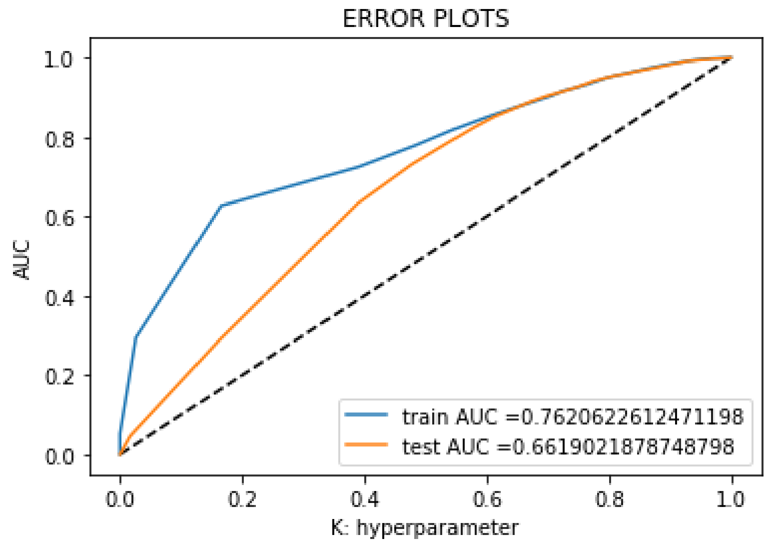


In [49]:

```
# ss
# changing to misclassification error
MSE = [1 - x for x in cv_auc]


# determining best k
optimal_k_bow_bf = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_bow_bf)
```

```
The optimal number of neighbors is 49.
```

In [50]:
```
## ss

# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_bow_bf, algorithm='b
rute')
neigh.fit(X_train_bow, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(X_train_bow)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
X_test_bow)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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(X_train_bow)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(X_test_bow)))
```




```
================================================================================================================
Train confusion matrix
[[  183  3156]
 [   98 19137]]
Test confusion matrix
[[  150  2379]
 [   80 11213]]
```

In [51]:
```
auc_train_bow_bf = auc(train_fpr, train_tpr)
auc_test_bow_bf = auc(test_fpr, test_tpr)
```

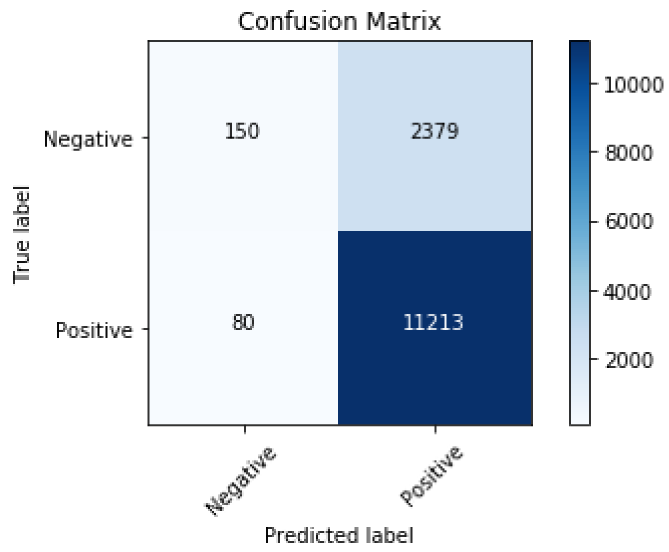
In [52]:
```
# Get the confusion matrix
from sklearn.metrics import classification_report


# Code modified from sklearn tutorial: https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html

import itertools
def plot_confusion_matrix(cm, classes,
```

```
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    #if normalize:
     #   cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
     #   print("Normalized confusion matrix")
    #else:
      #  print('Confusion matrix')

    #print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1
])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

In [53]:

```
cnf_matrix = confusion_matrix(y_test, neigh.predict(X_test_bow))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
```

```
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```



[4.2] Bi-Grams and n-Grams.

In [54]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.
org/stable/modules/generated/sklearn.feature_extraction.text.CountVecto
rizer.html

# you can choose these numebrs min_df=10, max_features=5000, of your ch
oice
#count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_feature
s=5000)
#final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
#print("the type of count vectorizer ",type(final_bigram_counts))
```

```
#print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
#print("the number of unique words including both unigrams and bigrams ", final_bigram_counts.get_shape()[1])
```

[4.3] TF-IDF

In [55]:

```
# ss
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_train) # fit has to happen only on train data

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

print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22574, 13749) (22574,)
(9675, 13749) (9675,)
(13822, 13749) (13822,)
========================================================================
============================
```

In [56]:

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

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of cut text BOW vectorizer  (22574, 13749)
the number of unique words:  13749
```

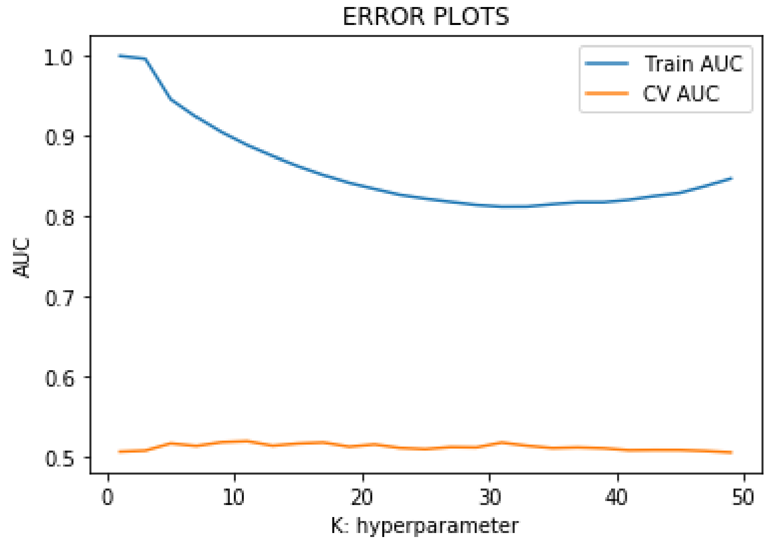
```
the number of unique words:  13749
```

2. KNN Brute Force algorithm implementation on TF-IDF

In [57]:

```python
# ss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive clas
s, confidence values, or non-thresholded measure of
decisions (as returned by “decision_function” on some classifiers).
For binary y_true, y_score is supposed to be the score of the class wit
h greater label.

"""

train_auc = []
cv_auc = []

# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm='brute')
    neigh.fit(X_train_tfidf, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(X_train_tfidf)[:,1]
    y_cv_pred =  neigh.predict_proba(X_cv_tfidf)[:,1]
```

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

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

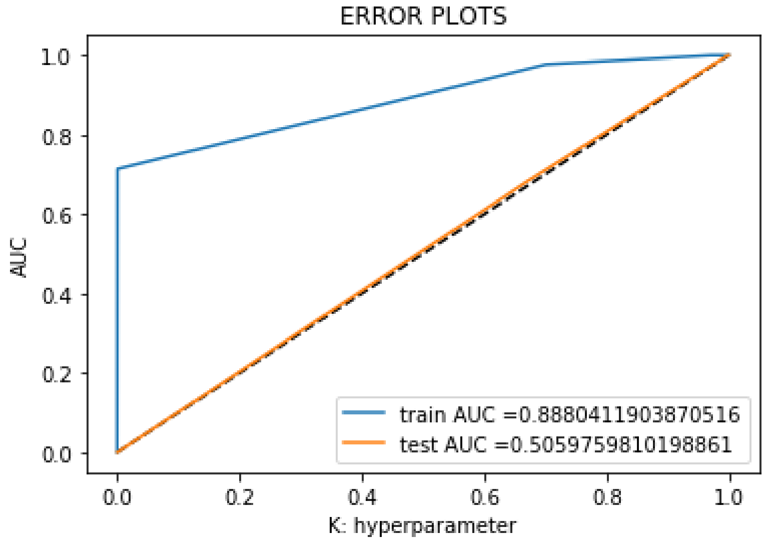


In [58]:
```
# changing to misclassification error
MSE= [1 - x for x in cv_auc]

# determining best k
optimal_k_tfidf_bf = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_tfidf_bf)
```

```
The optimal number of neighbors is 11.
```

In [59]:
```
## ss
```

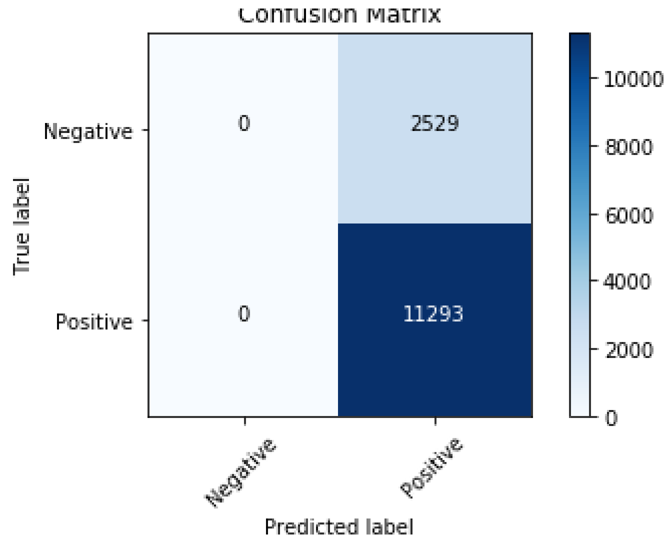
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_tfidf_bf, algorithm=
'brute')
neigh.fit(X_train_tfidf, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(X_train_tfidf)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
X_test_tfidf)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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(X_train_tfidf)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(X_test_tfidf)))
```




```
======================================================================================================
Train confusion matrix
[[    1  3338]
 [    0 19235]]
Test confusion matrix
[[    0  2529]
 [    0 11293]]
```

In [60]:
```
auc_train_tfidf_bf = auc(train_fpr, train_tpr)
auc_test_tfidf_bf = auc(test_fpr, test_tpr)
```

In [61]:
```
cnf_matrix = confusion_matrix(y_test, neigh.predict(X_test_tfidf))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```



H. Observations:

1. For the TF-IDF vectorizer , using the brute force implementation, the optimal k used was 9 and it gave a test accuracy of 83.51%
2. As the number of k reached 9, the MSE came down sharply.
3. The confusion matrix shows poor classification of our model.
4. The AUC for train and test is quite far away from each other and also the auc test is poor.

[4.4] Word2Vec

In [62]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
```

In [63]:
```
print(list_of_sentance_train[0])
```

```
['really', 'good', 'idea', 'final', 'product', 'outstanding', 'use', 'd
ecals', 'car', 'window', 'everybody', 'asks', 'bought', 'decals', 'mad
e', 'two', 'thumbs']
```

In [64]:

```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, work
ers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors
-negative300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
[('awesome', 0.8231831789016724), ('good', 0.809023916721344), ('fantas
tic', 0.8033546209335327), ('wonderful', 0.8007094264030457), ('excelle
nt', 0.7858836650848389), ('terrific', 0.7624676823616028), ('perfect',
0.7576509714126587), ('amazing', 0.7421754598617554), ('decent', 0.6955
416798591614), ('nice', 0.6583067178726196)]
==================================================
[('best', 0.8094383478164673), ('tastiest', 0.7711542844772339), ('nast
iest', 0.7426066398620605), ('ever', 0.7398572564125061), ('greatest',
0.733481228351593), ('softest', 0.7298107147216797), ('closest', 0.7284
467220306396), ('ive', 0.7268621921539307), ('hottest', 0.7198749780654
907), ('eaten', 0.6891652345657349)]
```

In [65]:

```
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  9128
sample words  ['really', 'good', 'idea', 'final', 'product', 'outstandi
ng', 'use', 'car', 'window', 'everybody', 'asks', 'bought', 'made', 'tw
o', 'thumbs', 'received', 'shipment', 'could', 'hardly', 'wait', 'try',
'love', 'call', 'instead', 'stickers', 'removed', 'easily', 'daughter',
'designed', 'signs', 'printed', 'reverse', 'windows', 'beautifully', 'p
rint', 'shop', 'program', 'going', 'lot', 'fun', 'everywhere', 'like',
'tv', 'computer', 'nothing', 'bother', 'link', 'top', 'page', 'buy']
```

Converting train text data

In [66]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stor
ed in this list
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, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|██████████████████████████████████████████████████████████████████
█████████████████████████████████████████████████████████| 22574/22574
[00:27<00:00, 822.56it/s]
```

```
(22574, 50)
[-0.37  0.09  0.27  0.15  0.41  0.24 -0.46  0.02  0.31 -0.07  0.07  0.3
6
 -0.09 -0.32  0.2  -0.14 -0.41  0.35  0.13 -0.59  0.3   0.6  -0.13  0.0
4
  0.27  0.36 -0.04  0.06 -0.07 -0.44  0.63 -0.08 -0.64 -0.17 -0.18 -0.3
7
 -0.32  0.4  -0.24  0.32  0.2  -0.47  0.07 -0.06 -0.14  0.46  0.2  -0.4
7
 -0.07  0.19]
```

Converting cv text data

In [67]:

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

In [68]:

```
# 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
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
sent_vectors_cv = np.array(sent_vectors_cv)
print(sent_vectors_cv.shape)
print(sent_vectors_cv[0])
```

```
100%|██████████████████████████████████████████████████| 9675/9675
[00:11<00:00, 823.46it/s]
```

```
(9675, 50)
[-0.11  0.43 -0.04  0.25  0.44  0.15 -0.33  0.21  0.48 -0.04 -0.06  0.5
1
 -0.31  0.08 -0.01 -0.45 -0.41  0.1  -0.1  -0.38  0.45  0.78 -0.04  0.3
2
  0.5   0.14 -0.17  0.17 -0.18 -0.04  0.38  0.36 -0.62 -0.2  -0.38 -0.5
3
 -0.72  0.16 -0.43  0.11 -0.06 -0.42 -0.15 -0.12 -0.09  0.6   0.05 -0.4
7
 -0.    0.3 ]
```

Converting test text data

In [69]:

```
i=0
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
```

In [70]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is store
d 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, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
```

```
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
print(sent_vectors_test.shape)
print(sent_vectors_test[0])
```

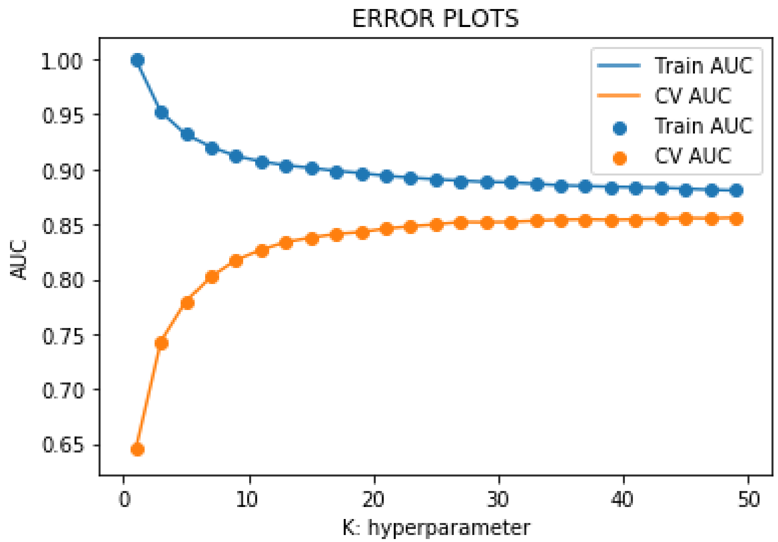
```
100%|██████████████████████████████████████████████████████████████████████████████████████████████████████████| 13822/13822
[00:16<00:00, 860.52it/s]
```

```
(13822, 50)
[-0.08  0.07  0.37  0.28  0.23 -0.49 -0.85  0.24  0.67 -0.59 -0.61  0.9
3
 -0.88  0.64 -0.22 -0.85 -0.14 -0.18  0.09 -0.63  0.38  1.38 -0.15  0.2
5
  0.41 -0.48  0.37  0.96 -0.31 -0.22  0.7   0.42 -0.91 -0.44  0.2  -1.3
4
 -0.87 -0.48 -0.45 -0.23 -0.06 -0.84 -0.22  0.17 -0.66  0.76  0.5  -0.9
5
 -0.05 -0.08]
```

In [71]:

```
train_auc = []
cv_auc = []

myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm = 'brute')
    neigh.fit(sent_vectors_train, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(sent_vectors_train)[:,1]
    y_cv_pred =  neigh.predict_proba(sent_vectors_cv)[:,1]

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

```
plt.plot(neighbors, train_auc, label='Train AUC')
plt.scatter(neighbors, train_auc, label='Train AUC')
plt.plot(neighbors, cv_auc, label='CV AUC')
plt.scatter(neighbors, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

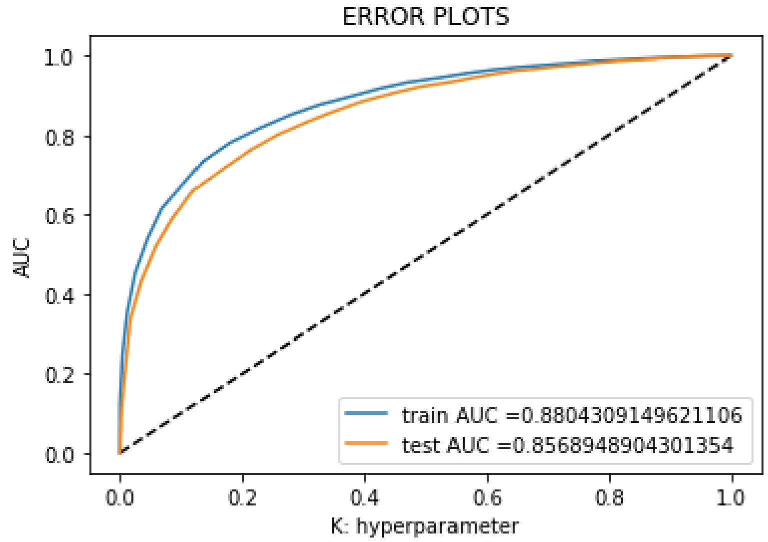


3. KNN Brute Force algorithm implementation on Avg-W2V

In [72]:
```
# changing to misclassification error
MSE = [1 - x for x in cv_auc]

# determining best k
optimal_k_avgw2v_bf = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_avgw2v_bf)
```

```
The optimal number of neighbors is 49.
```

In [73]:
```
## ss

# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_avgw2v_bf, algorithm
='brute')
neigh.fit(sent_vectors_train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(sent_vectors_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
sent_vectors_test)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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)))
```

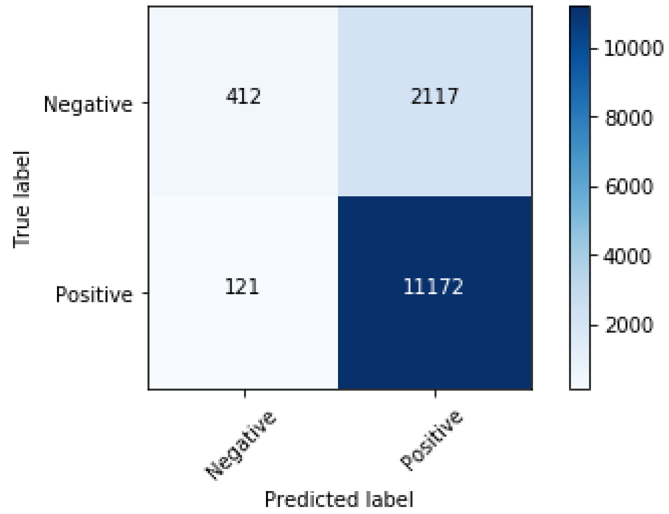



```
==========================================================================
==============================
Train confusion matrix
[[  547  2792]
 [  168 19067]]
Test confusion matrix
[[  412  2117]
 [  121 11172]]
```

In [74]:
```
auc_train_avgw2v_bf = auc(train_fpr, train_tpr)  #auc_train_avgw2v_bf
auc_test_avgw2v_bf = auc(test_fpr, test_tpr)
```

In [75]:
```
cnf_matrix = confusion_matrix(y_test, neigh.predict(sent_vectors_test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```

Confusion Matrix



[4.4.1.2] TFIDF weighted W2v

In [76]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
X_train_tf_idf_w2v = model.fit_transform(X_train)
X_test_tf_idf_w2v = model.transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [77]:
```
# TF-IDF weighted Word2Vec for sentences in X_train
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review
 is stored in this list
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/r
```

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

```
100%|██████████████████████████████████████████████████████████████| 22574/22574
[04:08<00:00, 90.68it/s]
```

In [78]:

```
# TF-IDF weighted Word2Vec for sentences in X_test
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is
 stored in this list
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/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
```

```
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1
```

```
100%|████████████████████████████████████████████████████████| 9675/9675 [01:41<00:00, 95.47it/s]
```

In [79]:

```
# TF-IDF weighted Word2Vec for sentences in X_test
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 this list
row=0;
for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

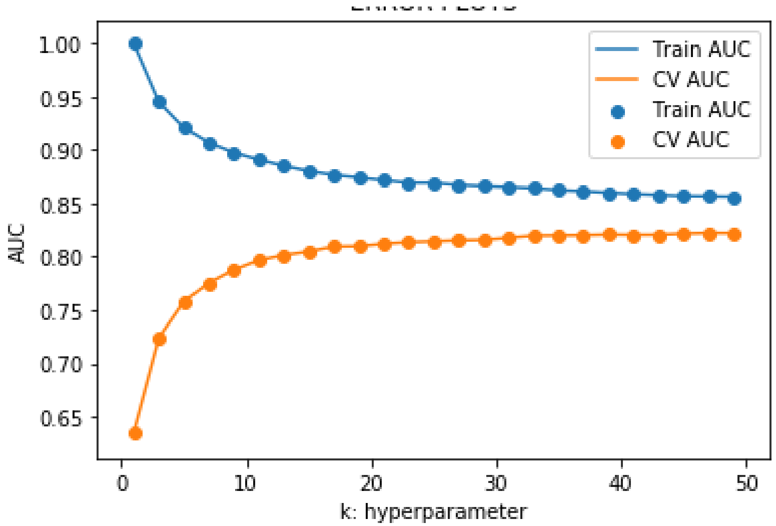
```
100%|████████████████████████████
```

```
| 13822/13822
[02:32<00:00, 90.85it/s]
```

4. KNN Brute Force algorithm implementation on TFIDF-W2V

In [80]:
```
train_auc = []
cv_auc = []

myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm = 'brute')
    neigh.fit(tfidf_sent_vectors_train, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(tfidf_sent_vectors_train)[:,1]
    y_cv_pred =  neigh.predict_proba(tfidf_sent_vectors_cv)[:,1]

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

plt.plot(neighbors, train_auc, label='Train AUC')
plt.scatter(neighbors, train_auc, label='Train AUC')
plt.plot(neighbors, cv_auc, label='CV AUC')
plt.scatter(neighbors, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("k: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

ERROR PLOTS



In [81]:

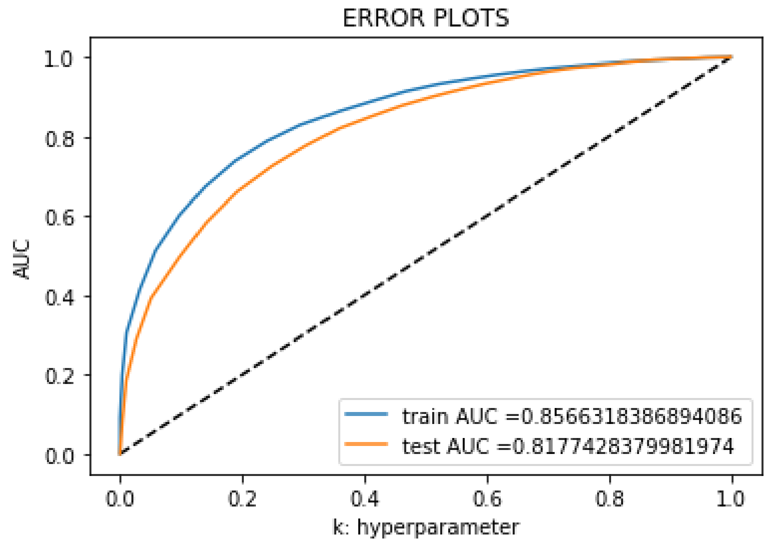
```
# changing to misclassification error
MSE= [1 - x for x in cv_auc]

# determining best k
optimal_k_tfidfavgw2v_bf = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_tfidfavgw2
v_bf)
```

```
The optimal number of neighbors is 47.
```

In [82]:

```
## ss

# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_tfidfavgw2v_bf, algo
rithm='brute')
neigh.fit(tfidf_sent_vectors_train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
```

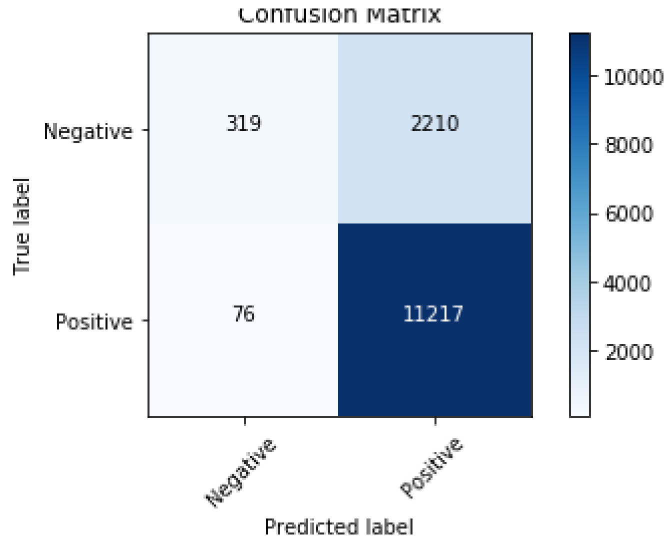
```
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(tfidf_sent_vectors_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
tfidf_sent_vectors_test)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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
[[  399  2940]
 [  131 19104]]
Test confusion matrix
[[  319  2210]
 [   76 11217]]
```

In [83]:
```
auc_train_tfidfw2v_bf = auc(train_fpr, train_tpr)
auc_test_tfidfw2v_bf = auc(test_fpr, test_tpr)
```

In [84]:
```
cnf_matrix = confusion_matrix(y_test, neigh.predict(tfidf_sent_vectors_
test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```



Applying KNN kd tree: Data Import and Preprocessing

Free-up variables that are occupying space and are not needed

In [85]:
```
del final, preprocessed_reviews

del X, y, sorted_data, sent_vectors_cv, sent_vectors_test, sent_vectors
_train

del tfidf_sent_vectors_train, tfidf_sent_vectors_cv, tfidf_sent_vectors
_test

del list_of_sentance_cv, list_of_sentance_test, list_of_sentance_train

del dictionary, filtered_data, actualScore, sent_0, sent_1000, sent_150
, sent_1500, sent_4900, stopwords, tfidf_feat, w2v_words
```

In [86]:
```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 20000""", con)
```

In [87]:
```
def partition(x):
    if x < 3:
        return 0
    return 1
```

In [88]:
```
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[88]:

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

In [89]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=Tr
ue, inplace=False, kind='quicksort', na_position='last')
```

In [90]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time"
,"Text"}, keep='first', inplace=False)
final.shape
```

Out[90]: (19354, 10)

In [91]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[91]: 96.77

In [92]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [93]:
```
print(final.shape)

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

```
(19354, 10)
```

Out[93]:
```
1    16339
0     3015
Name: Score, dtype: int64
```

In [94]:
```
final["Time"] = pd.to_datetime(final["Time"], origin='unix', unit = "s"
)
final = final.sort_values(by = "Time")
```

In [95]:
```
final.size
```

Out[95]: 193540

In [96]:
```
# 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)

# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
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)
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)
```

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

```
This was a really good idea and the final product is outstanding. I use
the decals on my car window and everybody asks where i bought the decal
s i made.  Two thumbs up!
==================================================
THIS COFFEE IS REALLY DELICIOUS.A COOL LATIN FLAVOR.EXCELLENT.5 STARS I
GIVE TO THIS COFFEE.I HOPE AMAZON NEVER GET RID OF IT BECAUSE THIS COFF
EE IS REALLY HARD TO FIND IN MY LOCAL SUPERMARKETS.AND I HPE ALWAYS THE
Y GOT THE SAME LOW PRICE FOR 6 PACKETS.THE LESS I GET THIS COFFEE BAGS
IS $2.49 PER PACKET.GOOD DEAL,AMAZON.HURRAY FOR YOU.
==================================================
I use this product frequently.  Like most tofu, you need to press it (b
etween paper towels with a heavy skillet on top works fine) to get the
excess water out.  The more water you can remove, the less you'll have
to deal with sloppiness when cooking, something the previous reviewer d
id not like.<br /><br />As for a blank slate on taste, that's exactly w
hat makes tofu great.  It will take on any flavor you want to impart.
Our most common marinade is placing the pressed, cubed tofu in a Ziploc
with a mix of soy, honey, and lemon or lime juice.  A quick search onli
ne for a marinade will give you ideas (many also include minced garlic,
ginger, etc).  You can also purchase a premade marinade, like a teriyak
i sauce.  The more liquid the marinade (and the more water removed from
pressing), the better it will penetrate the tofu.  Even a half hour in
the bag works fine.<br /><br />We saute it right in the pan with the st
ir fry veggies (add tofu last--it just needs to get warm; or, for a fir
mer style, you can bake or "brown" it separately first) and pour in the
remaining marinade as the final sauce (you can thicken with cornstarch
if desired).  Handle the tofu cubes gently as they are not firm like mo
st meats, but broken up pieces taste just fine too.<br /><br />Marinate
d tofu cubes also do well on kebabs with veggies on the grill.<br /><br
/>Plain tofu "creams" well and is often good in a dish that requires th
ickness.  We've made chocolate mousse with it as well as scrambling it
like eggs.<br /><br />We have great success breading pressed cubes of t
his tofu just like you would the chicken in a General Tso recipe.  Gene
ral Tso's Tofu is AWESOME.  The flavor comes from the sauce so you do
n't need to marinate first.<br /><br />Some people also freeze tofu--ge
nerally remove from packaging and press first--to give it a firmer cons
```

istency.

Tofu is all about how you prepare it. Most people
will NOT like it plain, so don't expect to just dig a fork into it.

This particluar product is great because of its all-purpose nat
ure (firm is definitely better than soft for saute, etc) and its shelf
life. I would have given it five stars but the must-be-refrigerated ve
rsions packaged in fluid do seem to be firmer. They don't last as long
in the house, though, so this is a perfect choice to keep in the pantry
(usually dated a few to several months out).

==

I ordered three different kinds of Yogi tea based on the great reviews
-- lemon ginger, stomach ease, and green tea super antioxident. Unfortu
nately, they all taste exactly the same -- like licorice. If you like l
icorice flavor, you'll like this tea. If you're looking for something t
hat actually tastes like lemon and ginger, look elsewhere.

==

This was a really good idea and the final product is outstanding. I use
the decals on my car window and everybody asks where i bought the decal
s i made. Two thumbs up!
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==

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GIVE TO THIS COFFEE.I HOPE AMAZON NEVER GET RID OF IT BECAUSE THIS COFF
EE IS REALLY HARD TO FIND IN MY LOCAL SUPERMARKETS.AND I HPE ALWAYS THE
Y GOT THE SAME LOW PRICE FOR 6 PACKETS.THE LESS I GET THIS COFFEE BAGS
IS $2.49 PER PACKET.GOOD DEAL,AMAZON.HURRAY FOR YOU.

==

I use this product frequently. Like most tofu, you need to press it (b
etween paper towels with a heavy skillet on top works fine) to get the
excess water out. The more water you can remove, the less you'll have
to deal with sloppiness when cooking, something the previous reviewer d
id not like.As for a blank slate on taste, that's exactly what makes to
fu great. It will take on any flavor you want to impart. Our most com
mon marinade is placing the pressed, cubed tofu in a Ziploc with a mix
of soy, honey, and lemon or lime juice. A quick search online for a ma
rinade will give you ideas (many also include minced garlic, ginger, et
c). You can also purchase a premade marinade, like a teriyaki sauce.
The more liquid the marinade (and the more water removed from pressin

```
g), the better it will penetrate the tofu.  Even a half hour in the bag
works fine.We saute it right in the pan with the stir fry veggies (add
tofu last--it just needs to get warm; or, for a firmer style, you can b
ake or "brown" it separately first) and pour in the remaining marinade
as the final sauce (you can thicken with cornstarch if desired).  Handl
e the tofu cubes gently as they are not firm like most meats, but broke
n up pieces taste just fine too.Marinated tofu cubes also do well on ke
babs with veggies on the grill.Plain tofu "creams" well and is often go
od in a dish that requires thickness.  We've made chocolate mousse with
it as well as scrambling it like eggs.We have great success breading pr
essed cubes of this tofu just like you would the chicken in a General T
so recipe.  General Tso's Tofu is AWESOME.  The flavor comes from the s
auce so you don't need to marinate first.Some people also freeze tofu--
generally remove from packaging and press first--to give it a firmer co
nsistency.Tofu is all about how you prepare it.  Most people will NOT l
ike it plain, so don't expect to just dig a fork into it.This particlua
r product is great because of its all-purpose nature (firm is definitel
y better than soft for saute, etc) and its shelf life.  I would have gi
ven it five stars but the must-be-refrigerated versions packaged in flu
id do seem to be firmer.  They don't last as long in the house, though,
so this is a perfect choice to keep in the pantry (usually dated a few
to several months out).
==================================================
I ordered three different kinds of Yogi tea based on the great reviews
-- lemon ginger, stomach ease, and green tea super antioxident. Unfortu
nately, they all taste exactly the same -- like licorice. If you like l
icorice flavor, you'll like this tea. If you're looking for something t
hat actually tastes like lemon and ginger, look elsewhere.
```

In [97]:

```
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)
```

```python
    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 [98]:
```python
stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [99]:
```
# 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████
██████████████████████████████████████████| 19354/19354
[00:05<00:00, 3370.89it/s]
```

In [100]:
```
final['CleanedText']= preprocessed_reviews
```

In [101]:
```
final.CleanedText.isnull().sum()
```

Out[101]:
```
0
```

In [102]:
```
# Create X and Y variable
X = final['CleanedText'].values
y= final['Score'].values
```

In [103]:
```
from sklearn.model_selection import train_test_split
# Splitting into train and test in the ratio 70:30
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3
0,shuffle=False, random_state=507)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_
size=0.30, shuffle=False, random_state=507)
```

In [104]:
```
print("Train Set:",X_train.shape[0], y_train.shape[0])
```

```
print("CV Set:",X_cv.shape[0], y_cv.shape[0])
print("Test Set:",X_test.shape[0], y_test.shape[0])
```

```
Train Set: 9482 9482
CV Set: 4065 4065
Test Set: 5807 5807
```

5. KNN KD-Tree implementation on BoW

In [105]:

```
# ss
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(min_df=10, max_features=500)
vectorizer.fit(X_train) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.transform(X_test)

print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(9482, 500) (9482,)
(4065, 500) (4065,)
(5807, 500) (5807,)
=======================================================================
=============================
```

In [106]:

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

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

the shape of cut text BOW vectorizer  (9482, 500)
```

```
the shape of cut text BOW vectorizer  (9482, 500)
the number of unique words:  500
```

In [107]:

```
# Converting sparse matrix to dense
X_train_bow = X_train_bow.todense()
X_cv_bow = X_cv_bow.todense()
X_test_bow = X_test_bow.todense()
```

In [108]:

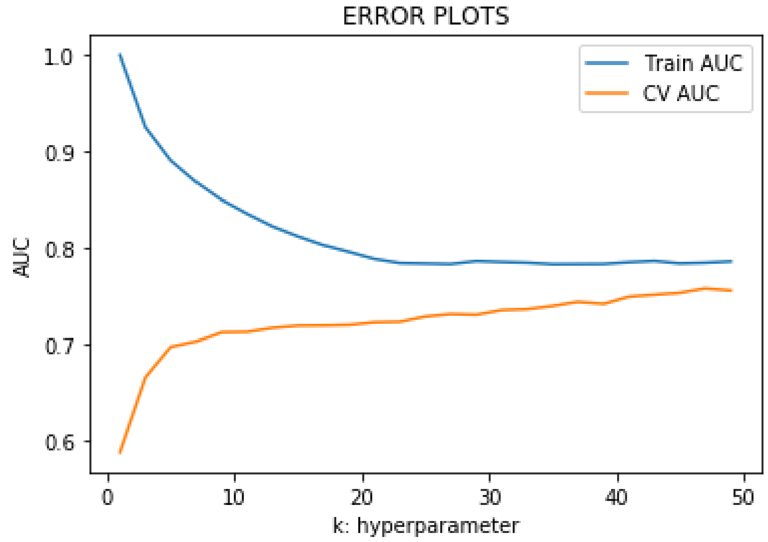
```
print("the type of count vectorizer ",type(X_train_bow))
```

```
the type of count vectorizer  <class 'numpy.matrixlib.defmatrix.matri
x'>
```

In [109]:

```
# ss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive clas
s, confidence values, or non-thresholded measure of
decisions (as returned by “decision_function” on some classifiers).
For binary y_true, y_score is supposed to be the score of the class wit
h greater label.

"""

train_auc = []
cv_auc = []

# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
```

```
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm='kd_tree')
    neigh.fit(X_train_bow, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(X_train_bow)[:,1]
    y_cv_pred =  neigh.predict_proba(X_cv_bow)[:,1]

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

plt.plot(neighbors, train_auc, label='Train AUC')
plt.plot(neighbors, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("k: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [110]:

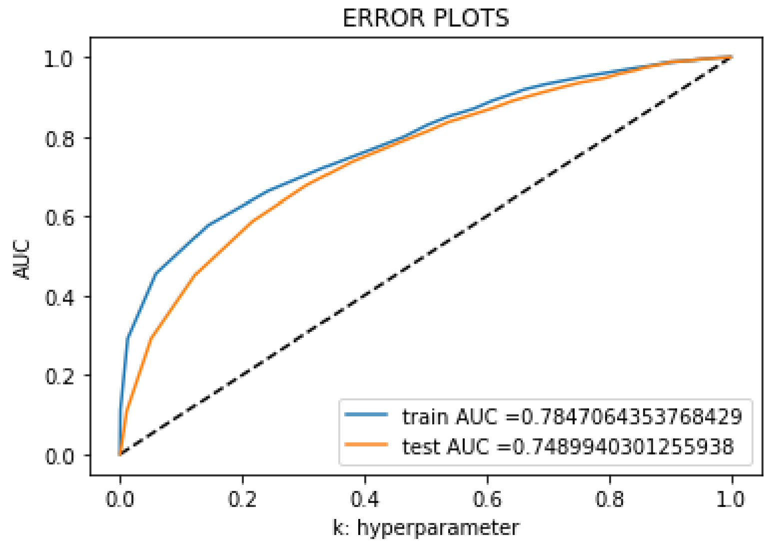
```
# ss
# changing to misclassification error
MSE = [1 - x for x in cv_auc]
```

```
# determining best k
optimal_k_bow_kd = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_bow_kd)
```

```
The optimal number of neighbors is 47.
```

In [111]:

```
neigh = KNeighborsClassifier(n_neighbors=optimal_k_bow_kd, algorithm='k
d_tree')
neigh.fit(X_train_bow, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(X_train_bow)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
X_test_bow)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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(X_train_bow)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(X_test_bow)))
```

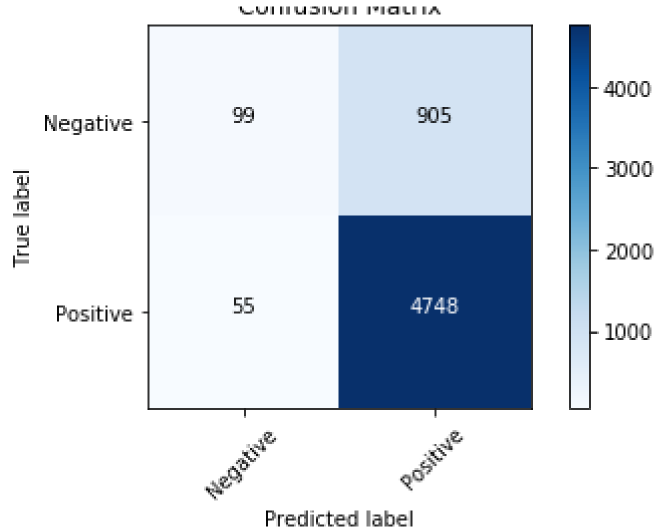



```
=======================================================================
=============================
Train confusion matrix
[[ 135 1223]
 [ 103 8021]]
Test confusion matrix
[[  99  905]
 [  55 4748]]
```

In [112]:
```python
auc_train_bow_kd = auc(train_fpr, train_tpr)
auc_test_bow_kd = auc(test_fpr, test_tpr)
```

In [113]:
```python
cnf_matrix = confusion_matrix(y_test, neigh.predict(X_test_bow))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```

Confusion Matrix



6. KNN KD-Tree implementation on TF-IDF

In [114]:
```
# ss
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_feature
s=500)
tf_idf_vect.fit(X_train) # fit has to happen only on train data

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

print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(9482, 500) (9482,)
```

```
(4065, 500) (4065,)
(5807, 500) (5807,)
========================================================================
==============================
```

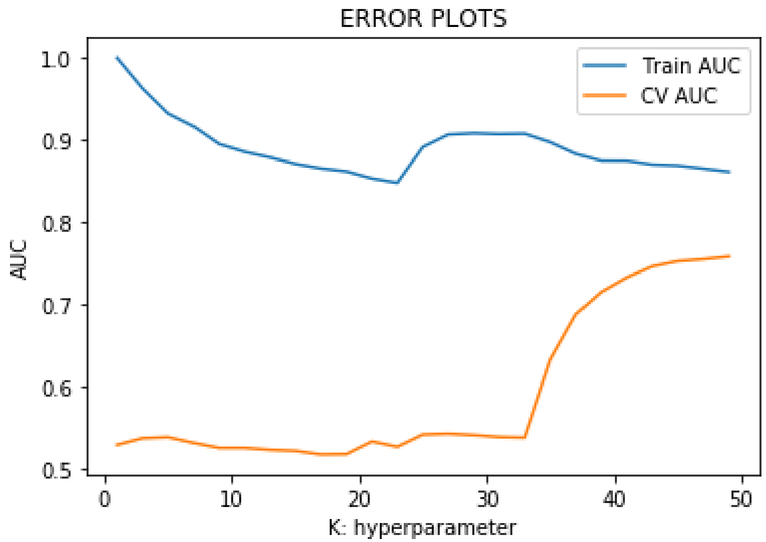
In [115]:
```
# Converting sparse matrix to dense
X_train_tfidf = X_train_tfidf.todense()
X_cv_tfidf = X_cv_tfidf.todense()
X_test_tfidf = X_test_tfidf.todense()
```

In [116]:
```
type(X_train_tfidf)
```

Out[116]:
```
numpy.matrixlib.defmatrix.matrix
```

In [117]:
```
# ss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
"""
y_true : array, shape = [n_samples] or [n_samples, n_classes]
True binary labels or binary label indicators.

y_score : array, shape = [n_samples] or [n_samples, n_classes]
Target scores, can either be probability estimates of the positive clas
s, confidence values, or non-thresholded measure of
decisions (as returned by “decision_function” on some classifiers).
For binary y_true, y_score is supposed to be the score of the class wit
h greater label.

"""

train_auc = []
cv_auc = []

# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))
```

```python
#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm='kd_tree')

    neigh.fit(X_train_tfidf, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(X_train_tfidf)[:,1]
    y_cv_pred =  neigh.predict_proba(X_cv_tfidf)[:,1]

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

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



In [118]:

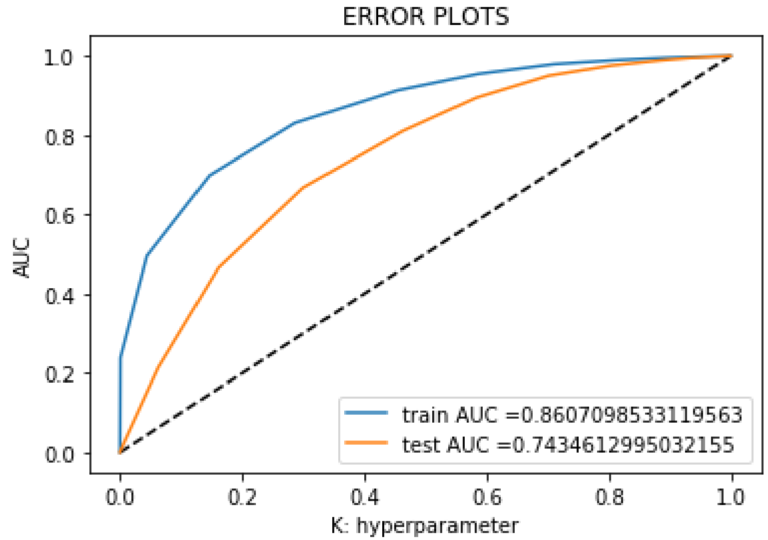
```
# changing to misclassification error
MSE= [1 - x for x in cv_auc]

# determining best k
optimal_k_tfidf_kd = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_tfidf_kd)
```

```
The optimal number of neighbors is 49.
```

In [119]:

```
## ss

# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_tfidf_kd, algorithm=
'kd_tree')
neigh.fit(X_train_tfidf, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(X_train_tfidf)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
X_test_tfidf)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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(X_train_tfidf)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(X_test_tfidf)))
```




```
====================================================================================================
Train confusion matrix
[[   0 1358]
 [   0 8124]]
Test confusion matrix
[[   0 1004]
 [   0 4803]]
```

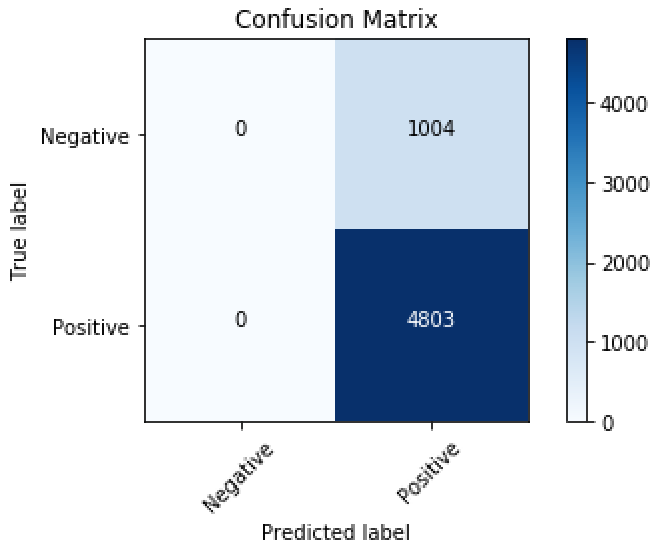
In [120]:

```
auc_train_tfidf_kd = auc(train_fpr, train_tpr)
auc_test_tfidf_kd = auc(test_fpr, test_tpr)
```

In [121]:

```
cnf_matrix = confusion_matrix(y_test, neigh.predict(X_test_tfidf))
np.set_printoptions(precision=2)
```

```
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```



[4.4] Word2Vec

In [122]:

```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
```

In [123]:

```
print(list_of_sentance_train[0])
```

```
['really', 'good', 'idea', 'final', 'product', 'outstanding', 'use', 'd
ecals', 'car', 'window', 'everybody', 'asks', 'bought', 'decals', 'mad
e', 'two', 'thumbs']
```

In [124]:

```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, work
ers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors
-negative300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
[('good', 0.8621622323989868), ('excellent', 0.8588515520095825), ('won
derful', 0.7883070111274719), ('quick', 0.7698708772659302), ('awesom
e', 0.7666758298873901), ('especially', 0.7547547221183777), ('makes',
0.7517443895339966), ('super', 0.7501925826072693), ('fantastic', 0.738
4480237960815), ('tasty', 0.7362213134765625)]
==================================================
[('hooked', 0.9825462102890015), ('amongst', 0.9818435311317444), ('abs
olute', 0.9788781404495239), ('dunkin', 0.9782604575157166), ('shortbre
ad', 0.9753953814506531), ('varieties', 0.9747499823570251), ('among',
0.9743835926055908), ('favorites', 0.9742165207862854), ('hands', 0.970
3830480575562), ('decadence', 0.9692540764808655)]
```

In [125]:

```
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  5964
```

```
sample words  ['really', 'good', 'idea', 'final', 'product', 'outstandi
ng', 'use', 'car', 'window', 'everybody', 'asks', 'bought', 'made', 'tw
o', 'thumbs', 'received', 'shipment', 'could', 'hardly', 'wait', 'try',
'love', 'call', 'instead', 'stickers', 'removed', 'easily', 'daughter',
'designed', 'signs', 'printed', 'windows', 'beautifully', 'print', 'sho
p', 'program', 'going', 'lot', 'fun', 'everywhere', 'like', 'tv', 'comp
uter', 'chatchi', 'favorite', 'afternoon', 'treat', 'became', 'unavaila
ble', 'vending']
```

Converting train text data

In [126]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stor
ed in this list
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, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|████████████████████████████████████████████████████████████████████
██████████████████████████████████████████████████████████| 9482/9482
[00:08<00:00, 1148.83it/s]
```

```
(9482, 50)
[-0.19  0.01  0.19  0.02  0.24  0.32 -0.25  0.17  0.06 -0.18 -0.07  0.3
4
```

```
 -0.18 -0.15  0.08 -0.09 -0.15  0.19 -0.26 -0.27  0.3   0.7  -0.26  0.2
5
  0.35  0.15  0.04  0.24 -0.38 -0.25  0.57  0.24 -0.5  -0.21 -0.34 -0.4
3
 -0.46  0.28 -0.04  0.17  0.1  -0.29 -0.   -0.27  0.25  0.47  0.06 -0.6
2
 -0.24  0.06]
```

Converting cv text data

In [127]:

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

In [128]:

```
# 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
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
sent_vectors_cv = np.array(sent_vectors_cv)
print(sent_vectors_cv.shape)
print(sent_vectors_cv[0])
```

```
100%|██████████████████████████████████████████████████████████████████
████████████████████████████████████████████████████| 4065/4065
```

```
[00:03<00:00, 1183.42it/s]
```

```
(4065, 50)
[-0.19  0.08  0.12  0.07  0.24  0.3  -0.36  0.12  0.39 -0.36 -0.19  0.4
4
 -0.22 -0.19 -0.18 -0.58 -0.33 -0.21 -0.18 -0.46  0.5   1.06 -0.24  0.2
7
  0.37  0.16 -0.09  0.25 -0.47 -0.34  0.64  0.71 -0.73 -0.16 -0.45 -0.7
6
 -0.68 -0.12 -0.19  0.19  0.05 -0.48 -0.04 -0.43  0.3   0.32  0.39 -0.8
1
 -0.48  0.15]
```

Converting test text data

In [129]:

```
i=0
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
```

In [130]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is store
d 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, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
```

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

```
100%|████████████████████████████████████████████████████████████
██████████████████████████████████████████████████| 5807/5807
[00:04<00:00, 1227.73it/s]
```

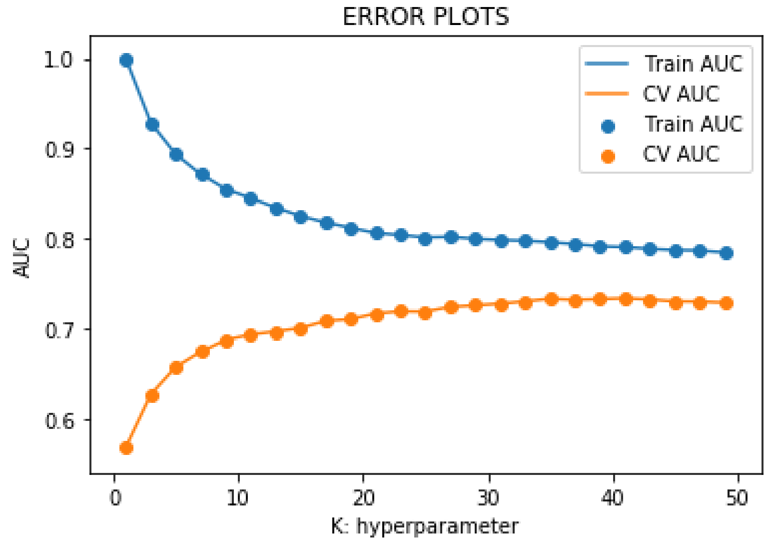
```
(5807, 50)
[ 0.03  0.1  -0.08  0.06  0.42  0.39 -0.77  0.27 -0.17 -0.04  0.13  0.5
4
 -0.18 -0.22  0.03 -0.54 -0.4  -0.18 -0.29 -0.08  0.21  1.23 -0.14  0.2
  0.53  0.22 -0.34  0.11 -0.4  -0.49  0.8   0.49 -0.72  0.02 -0.95 -0.6
1
 -0.86  0.25 -0.14  0.52 -0.11 -0.38 -0.01 -0.17  0.17  0.76  0.19 -0.8
1
 -0.23  0.07]
```

7. KNN KD-Tree implementation on AVG W2V

In [131]:

```
train_auc = []
cv_auc = []

myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm = 'kd_tree')
    neigh.fit(sent_vectors_train, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
ility estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(sent_vectors_train)[:,1]
    y_cv_pred =  neigh.predict_proba(sent_vectors_cv)[:,1]

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

```
plt.plot(neighbors, train_auc, label='Train AUC')
plt.scatter(neighbors, train_auc, label='Train AUC')
plt.plot(neighbors, cv_auc, label='CV AUC')
plt.scatter(neighbors, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

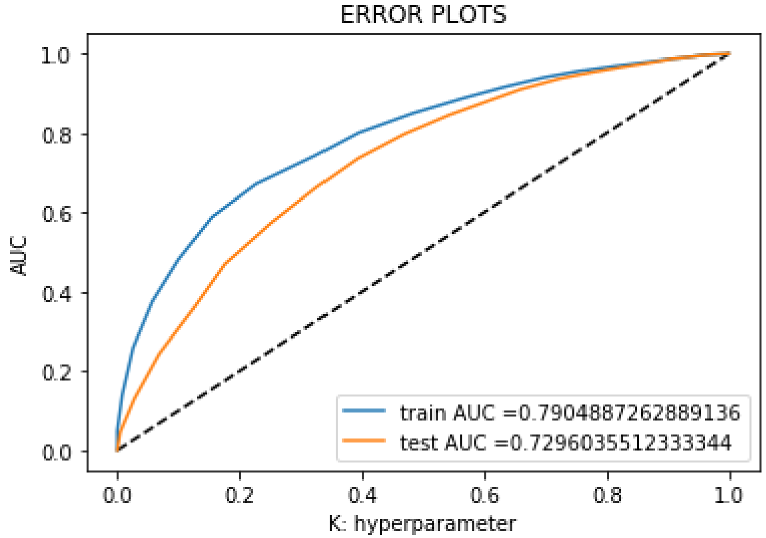


In [132]:
```
# changing to misclassification error
MSE = [1 - x for x in cv_auc]

# determining best k
optimal_k_avgw2v_kd = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_avgw2v_kd)
```

```
The optimal number of neighbors is 41.
```

In [133]:
```
## ss

# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
```

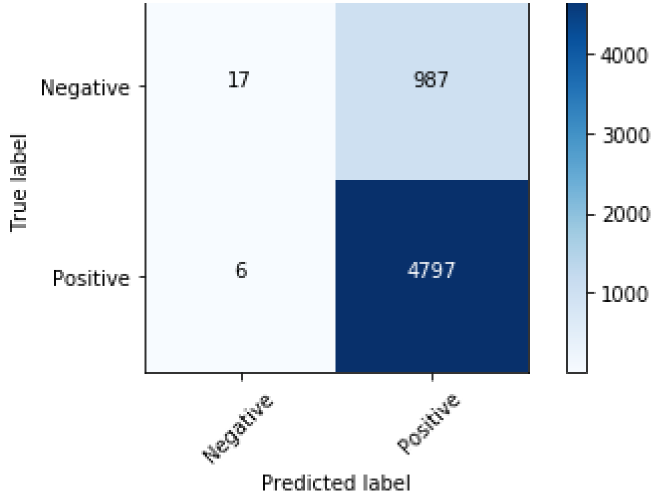
```
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_avgw2v_kd, algorithm
='kd_tree')
neigh.fit(sent_vectors_train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(sent_vectors_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
sent_vectors_test)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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
[[  27 1331]
 [  15 8109]]
Test confusion matrix
[[  17  987]
 [   6 4797]]
```

In [134]:
```
auc_train_avgw2v_kd = auc(train_fpr, train_tpr)
auc_test_avgw2v_kd = auc(test_fpr, test_tpr)
```

In [135]:
```
cnf_matrix = confusion_matrix(y_test, neigh.predict(sent_vectors_test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```



8. KNN KD-Tree implementation on TFIDF-W2V

In [136]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
X_train_tf_idf_w2v = model.fit_transform(X_train)
X_test_tf_idf_w2v = model.transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [137]:
```
# TF-IDF weighted Word2Vec for sentences in X_train
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review
 is stored in this list
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/r
```

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

```
100%|██████████████████████████████████████████████████████████████████████████████████████| 9482/9482
[00:56<00:00, 166.55it/s]
```

In [138]:

```
# TF-IDF weighted Word2Vec for sentences in X_test
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is
 stored in this list
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/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
```

```
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████| 4065/4065
[00:22<00:00, 176.76it/s]
```

In [139]:

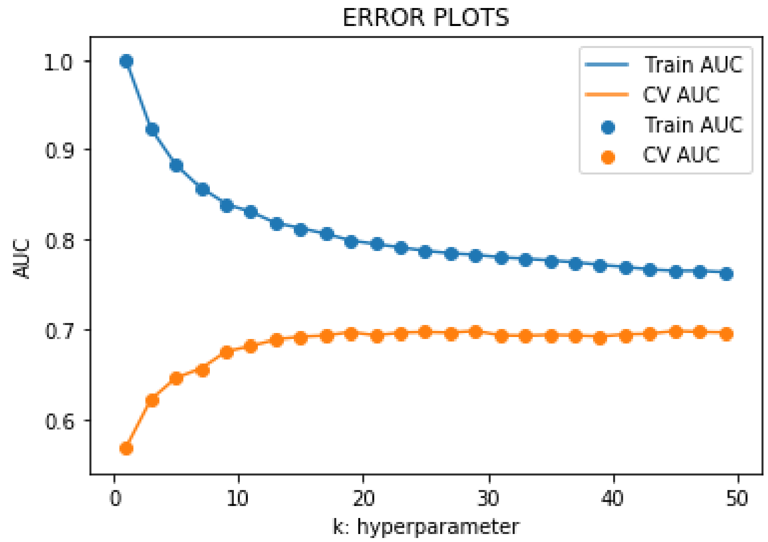
```
# TF-IDF weighted Word2Vec for sentences in X_test
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review
 is stored in this list
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/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████
```

```
| 5807/5807
[00:32<00:00, 180.48it/s]
```

In [140]:

```
train_auc = []
cv_auc = []

myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

#K = [1, 5, 10, 15, 21, 31, 41, 51]
for i in neighbors:
    neigh = KNeighborsClassifier(n_neighbors=i, algorithm = 'kd_tree')
    neigh.fit(tfidf_sent_vectors_train, y_train)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
    # not the predicted outputs
    y_train_pred =  neigh.predict_proba(tfidf_sent_vectors_train)[:,1]
    y_cv_pred =  neigh.predict_proba(tfidf_sent_vectors_cv)[:,1]

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

plt.plot(neighbors, train_auc, label='Train AUC')
plt.scatter(neighbors, train_auc, label='Train AUC')
plt.plot(neighbors, cv_auc, label='CV AUC')
plt.scatter(neighbors, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("k: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

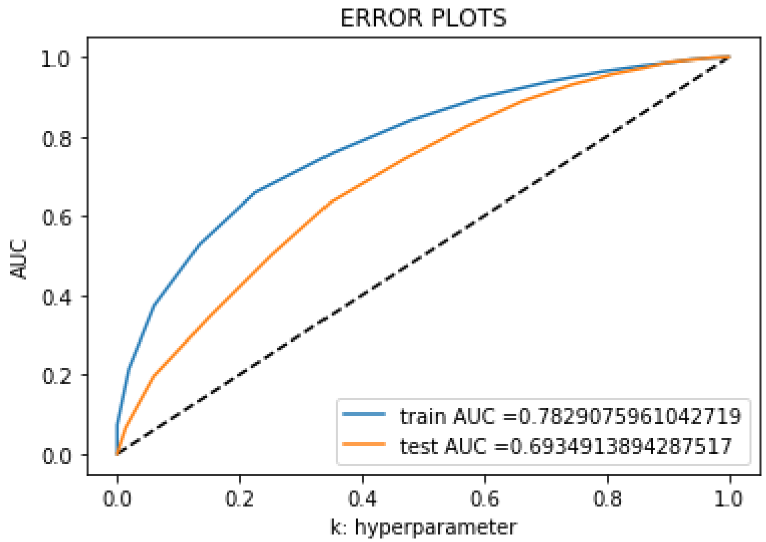


In [141]:
```
# changing to misclassification error
MSE= [1 - x for x in cv_auc]

# determining best k
optimal_k_tfidfavgw2v_kd = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k_tfidfavgw2
v_kd)
```

```
The optimal number of neighbors is 29.
```

In [142]:
```
## ss

# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=optimal_k_tfidfavgw2v_kd, algo
rithm='kd_tree')
neigh.fit(tfidf_sent_vectors_train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
```

```
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_pro
ba(tfidf_sent_vectors_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(
tfidf_sent_vectors_test)[:,1])

plt.plot([0,1],[0,1],'k--')
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
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)))
```



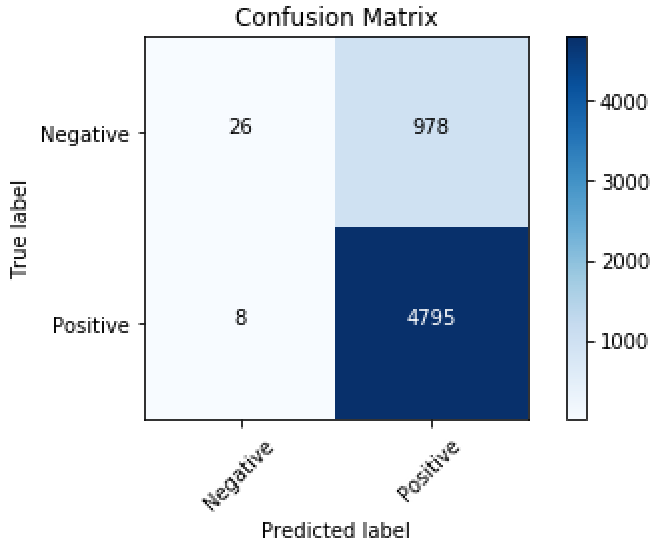

```
============================================================================
==============================
Train confusion matrix
[[  30 1328]
 [  15 8109]]
Test confusion matrix
[[  26  978]
 [   8 4795]]
```

In [143]:

```
auc_train_tfidfw2v_kd = auc(train_fpr, train_tpr)
auc_test_tfidfw2v_kd = auc(test_fpr, test_tpr)
```

In [144]:

```
cnf_matrix = confusion_matrix(y_test, neigh.predict(tfidf_sent_vectors_
test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion
 Matrix');
```



Conclusions

In [145]:
```
from prettytable import PrettyTable
```

In [146]:
```
t1 = PrettyTable()
```

In [147]:
```
t2 = PrettyTable()
```

In [148]:
```
t1.field_names = ['Sr. No', 'Algorithm','k-fold cv','Number of Data Poi
nts']
t1.add_row([1, 'Brute Force', 5, 50000])
t1.add_row([2, 'KD Tree', 5, 20000])
print(t1)
```

```
+--------+-------------+-----------+----------------------+
| Sr. No |  Algorithm  | k-fold cv | Number of Data Points |
+--------+-------------+-----------+----------------------+
|   1    | Brute Force |     5     |        50000         |
```

```
|   2    |   KD Tree    |     5     |         20000         |
+--------+-------------+-----------+----------------------+
```

In [149]:
```
t2.field_names = ['Sr. No', 'Vectorizer', 'Algorithm', 'Optimal K', 'AU
C Train','AUC Test']
```

In [150]:
```
t2.add_row([1, 'BoW', 'brute force', optimal_k_bow_bf, auc_train_bow_bf
,auc_test_bow_bf])
t2.add_row([2, 'TF-IDF', 'brute force', optimal_k_tfidf_bf,  auc_train_
tfidf_bf, auc_test_tfidf_bf])
t2.add_row([3, 'Avg W2V', 'brute force', optimal_k_avgw2v_bf, auc_train
_avgw2v_bf,auc_test_avgw2v_bf])
t2.add_row([4, 'TFIDF-W2V', 'brute force', optimal_k_tfidfavgw2v_bf, au
c_train_tfidfw2v_bf, auc_test_tfidfw2v_bf])

t2.add_row([5, 'BoW', 'kd-tree', optimal_k_bow_kd, auc_train_bow_kd,auc
_test_bow_kd])
t2.add_row([6, 'TF-IDF', 'kd-tree', optimal_k_tfidf_kd, auc_train_tfidf
_kd, auc_test_tfidf_kd])
t2.add_row([7, 'Avg W2V', 'kd-tree', optimal_k_avgw2v_kd, auc_train_avg
w2v_kd, auc_test_avgw2v_kd])
t2.add_row([8, 'TFIDF-W2V', 'kd-tree', optimal_k_tfidfavgw2v_kd,auc_tra
in_tfidfw2v_kd, auc_test_tfidfw2v_kd])
```

In [151]:
```
print(t2)
```

```
+--------+------------+-------------+-----------+--------------------+-
-------------------+
| Sr. No | Vectorizer |  Algorithm  | Optimal K |     AUC Train      |
     AUC Test       |
+--------+------------+-------------+-----------+--------------------+-
-------------------+
|   1    |    BoW     | brute force |     49    | 0.7620622612471198 |
0.6619021878748798 |
|   2    |   TF-IDF   | brute force |     11    | 0.8880411903870516 |
0.5059759810198861 |
|   3    |  Avg W2V   | brute force |     49    | 0.8804309149621106 |
0.8568948904301354 |
```

4	TFIDF-W2V	brute force	47	0.8566318386894086	0.8177428379981974
5	BoW	kd-tree	47	0.7847064353768429	0.7489940301255938
6	TF-IDF	kd-tree	49	0.8607098533119563	0.7434612995032155
7	Avg W2V	kd-tree	41	0.7904887262889136	0.7296035512333344
8	TFIDF-W2V	kd-tree	29	0.7829075961042719	0.6934913894287517

Summary

1. Using unbalanced dataset impacts the performance of the model(s). The number of positive reviews(~84%) were greater than the negative(~16%) ones. The accuracy measure, as seen in the models, can be misleading if unbalanced data is used.
2. Before partitioning into training(70%) and test set(30%), the data sorted based on Time.
3. Brute force accepts sparse matrix but when given to kd-tree algorithm, it gave warning. So kd-tree requires dense matrix.
4. The results given by kd-tree implementation are more or less similar to the results given by brute force implementation of knn. kd-tree models performed better than the brute force models of knn.
5. The kd-tree implementation was faster than brute force. But we also have to consider the number of data point that we took for kd-tree was 20k and that for brute force was 50k.
6. We can get better accuracy results if we take into account all the datapoints as we can then have larger set of words to train our models on.
7. One should always refer to other performance metrices such as confusion metrics, AUC-ROC curve etc before concluding results about the model.