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 the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

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 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 id 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 os
import re
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sb
import pickle
```

```python
from sklearn import metrics
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer

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

from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.stem import PorterStemmer

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

from sklearn.preprocessing import StandardScaler
#TSNE
from sklearn.manifold import TSNE
from bs4 import BeautifulSoup
```

```
C:\ProgramData\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWa
rning: detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

In [2]:

```python
# Temporarily Suppressing Warnings
def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()
```

[1]. Reading Data

In [3]:

```python
# using the SQLite Table to read data.
```

```
# con = sqlite3.connect('./amazon-fine-food-reviews/database.sqlite')

con = sqlite3.connect('C:/Users/Saraswathi/Music/Appliedai/Data/amazon-
fine-food-reviews/database.sqlite')

#filetering only positve and negative reviews
#reviews not taking in to consideration with score = 3

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 20000""", con)

# Give reviews with Score>3 a positive rating, and reviews with a score
<3 a negative rating.
def partition( x ):
    if x > 3:
        return 1 #positive
#         return 1
    else:
        return 0 #negative

#changing reviews with score less than 3 to be positive and vice versa
actual_score = filtered_data['Score']
positivenegative = actual_score.map(partition)
filtered_data['Score']=positivenegative
print('Number of data point in our data',filtered_data.shape)
filtered_data.head(5)
```

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

Out[3]:

	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	
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	

Exploratory Data Analysis

[2] 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 [4]:
```
display = pd.read_sql_query("""
```

```
SELECT * FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""",con)
```

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

Out[5]:

	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 can be seen above the same user has multiple reviews of the with the 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 [6]:
```
#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 [7]:
```
#Duplication of entries
final = sorted_data.drop_duplicates(subset={'UserId','ProfileName','Time','Text'}, keep = 'first' , inplace= False)
final.shape
```

Out[7]:
```
(19354, 10)
```

In [8]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[8]:
```
96.77
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [9]:
```
display = pd.read_sql_query("""
SELECt *
FROM Reviews
WHERE Score !=3 AND Id=44737 OR Id=64422
ORDER BY ProductId
""",con)
display.head()
```

Out[9]:

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

In [10]:
```
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominato
r]
```

In [11]:
```
final.shape
final['Score'].value_counts()
```

Out[11]:
```
1    16339
0     3015
Name: Score, dtype: int64
```

Text Preprocessing.

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 [12]:
```
def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [13]:
```
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 [14]:
```
# 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):
for sentance in 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)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

In [15]:
```
# Add pre processed reviews in to final df
# final['preprocessed_reviews'] = preprocessed_reviews
```

In [16]:
```
preprocessed_reviews[1000]
```

Out[16]:
```
'received box great anticipation since not sell west coast got package
opened box extremely disappointed cookies looked like gorilla shook box
death left box filled crumbs rodent sized hole side box needless say no
t not reordering'
```

[3.2] Preprocess Summary

In [17]:
```
##preprocessing for review summary also.

# Combining all the above stundents
from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
# for sentance in tqdm(final['Summary'].values):
for sentance in (final['Summary'].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)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_summary.append(sentance.strip())
```

```
C:\ProgramData\Anaconda3\lib\site-packages\bs4\__init__.py:273: UserWar
ning: "b'...'" looks like a filename, not markup. You should probably o
pen this file and pass the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
```

Featurization

BAG OF WORDS, Bi-Grams and n-Grams, TF-IDF, Word2Vec, Converting text into vectors using wAvg W2V, TFIDF-W2V, Avg W2v, TFIDF weighted W2v

In [18]:
```
#storing label i.e positive and negative in another variable for tsne p
lot
labels = final['Score']
```

BAG OF WORDS

In [19]:
```
#BOW
count_vect = CountVectorizer()
count_vect.fit(preprocessed_reviews)
print('some feature names are',count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words",final_counts.get_shape()[1])
```

```
some feature names are ['aa', 'aaaa', 'aaaaa', 'aaaand', 'aafco', 'aahh
hs', 'aahs', 'ab', 'aback', 'abandon']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (19354, 25997)
the number of unique words 25997
```

Bi-Grams and n-Grams.

In [20]:
```
#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))
count_vect = CountVectorizer(ngram_range=(1,2),min_df=10,max_features=5
000)
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_sh
ape())
print("the number of unique words including both unigrams and bigrams",
final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (19354, 5000)
the number of unique words including both unigrams and bigrams 5000
```

TF-IDF

In [21]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df =10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[:10])
print('='*50)
final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape
())
print("the number of unique words including both unigrams and bigrams "
, final_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble buy', 'able eat', 'able find', 'able get', 'able give', 'able mak
e', 'able order', 'able purchase']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (19354, 11762)
the number of unique words including both unigrams and bigrams  11762
```

Word2Vec

In [22]:
```
# Train your own Word2Vec model using your own text corpus
# i = 0
list_of_sentance = []
for sentance in preprocessed_reviews:
#     list_of_sentance.append(sentance)
    list_of_sentance.append(sentance.split())
# print((list_of_sentance))
```

In [23]:
```
# Using Google News Word2Vectors
is_your_ram_gt_16gb = False
want_to_use_google_w2v = True
want_to_train_w2v = True

# print(list_of_sentance)

if want_to_train_w2v:
   # min_count = 5 considers only words that occured atleast 5 times
    w2v_model = Word2Vec(list_of_sentance,min_count = 5 ,size = 50 ,wor
kers = 4)
    print(type(w2v_model))
    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_16gb :
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model = KeyedVectors.load_word2vec_format('GoogleNews-vecto
rs-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 ")
```

```
<class 'gensim.models.word2vec.Word2Vec'>
[('good', 0.8307294249534607), ('awesome', 0.820031464099884), ('excell
```

```
ent', 0.8074917793273926), ('wonderful', 0.7911520004272461), ('amazin
g', 0.7876395583152771), ('fantastic', 0.7802572846412659), ('decent',
0.7413613200187683), ('perfect', 0.6911841034889221), ('super', 0.68569
97013092041), ('delicious', 0.685686469078064)]
==================================================
[('personal', 0.8410727381706238), ('closest', 0.8388027548789978), ('h
ottest', 0.8318940997123718), ('awful', 0.8056787252426147), ('hooked',
0.8014079928398132), ('socks', 0.7952672839164734), ('reminded', 0.7942
043542861938), ('disappointing', 0.7941983342170715), ('addicted', 0.79
33684587478638), ('greatest', 0.7886935472488403)]
```

In [24]:

```python
print(type(w2v_model))
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])
```

```
<class 'gensim.models.word2vec.Word2Vec'>
number of words that occured minimum 5 times  8370
sample words  ['used', 'fly', 'bait', 'seasons', 'ca', 'not', 'beat',
'great', 'product', 'available', 'traps', 'course', 'total', 'pretty',
'stinky', 'right', 'nearby', 'really', 'good', 'idea', 'final', 'outsta
nding', 'use', 'car', 'window', 'everybody', 'asks', 'bought', 'made',
'two', 'thumbs', 'received', 'shipment', 'could', 'hardly', 'wait', 'tr
y', 'love', 'call', 'instead', 'stickers', 'removed', 'easily', 'daught
er', 'designed', 'signs', 'printed', 'reverse', 'windows', 'beautifull
y']
```

Converting text into vectors using wAvg W2V, TFIDF-W2V

Avg W2v

In [25]:

```python
#average word2vec
#compute average word2 vec for each review
sent_vectors = [];
```

```
# for sent in tqdm(list_of_sentance):
for sent in (list_of_sentance):

    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;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec  /=cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
19354
50
```

TFIDF weighted W2v

In [26]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
model.fit(preprocessed_reviews)
# 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 [27]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names()

# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors = [] ; # the tfidf-w2v for each sentence/review is s
tored in this list
row = 0
```

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

In [ ]:

```python

```

[5] Assignment 3: KNN

1. **Apply Knn(brute force version) on these feature sets**
    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
    - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
    - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

2. **Apply Knn(kd tree version) on these feature sets**
   NOTE: sklearn implementation of kd-tree accepts only dense matrices, you need to convert the sparse matrices of CountVectorizer/TfidfVectorizer into dense matices. You can convert sparse matrices to dense using .toarray() attribute. For more information please visit this link

- SET 5:Review text, preprocessed one converted into vectors using (BOW) but with restriction on maximum features generated.

```
count_vect = CountVectorizer(min_df=10, max_features=500)
count_vect.fit(preprocessed_reviews)
```

- SET 6:Review text, preprocessed one converted into vectors using (TFIDF) but with restriction on maximum features generated.

```
tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
tf_idf_vect.fit(preprocessed_reviews)
```

- SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
- SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

3. **The hyper paramter tuning(find best K)**

- Find the best hyper parameter which will give the maximum AUC value
- Find the best hyper paramter using k-fold cross validation or simple cross validation data
- Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

4. **Representation of results**

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure
- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.

- Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points

5. **Conclusion**

- You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link

m

Note: Data Leakage

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

1.1 Applying KNN - Brute force

1.1.1 Applying KNN brute force on BOW, SET1

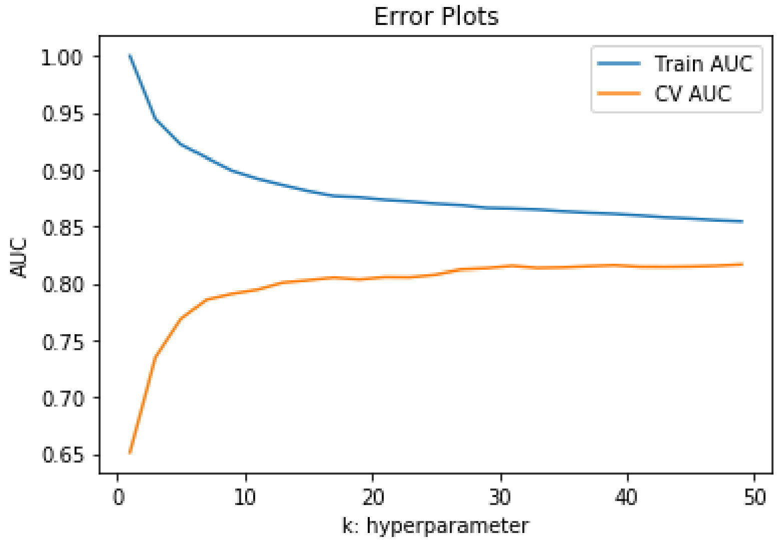
Hyper parameter Tuning using Simple for loop

In [28]:
```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score,auc
```

```
x = preprocessed_reviews
y = final['Score'].values

# print("shape of x is",type(x))
# print("shape of y is",type(y))

#tarin ,cv, test split
x1 , x_test, y1, y_test = train_test_split(x , y ,test_size =0.3,random
_state = 0)
x_train, x_cv, y_train, y_cv = train_test_split(x1, y1, test_size = 0.3
)
```

In [29]:
```
# Applying KNN brute force on BOW

cou_vec = CountVectorizer()
tran_x_train = cou_vec.fit_transform(x_train)
tran_x_cv = cou_vec.transform(x_cv)
tran_x_test = cou_vec.transform(x_test)

train_auc = []
cv_auc = []

k = list(range(1,50,2))
for i in k:
    knn = KNeighborsClassifier(n_neighbors = i, weights = 'uniform', al
gorithm = 'brute', leaf_size =30, p = 2, metric = 'cosine')
    knn.fit(tran_x_train,y_train)

    y_train_pred = knn.predict_proba(tran_x_train)[:,1]
    y_cv_pred = knn.predict_proba(tran_x_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(k, train_auc,label = 'Train AUC')
plt.plot(k, cv_auc,label = 'CV AUC')
plt.legend()
plt.xlabel('k: hyperparameter')
plt.ylabel('AUC')
```

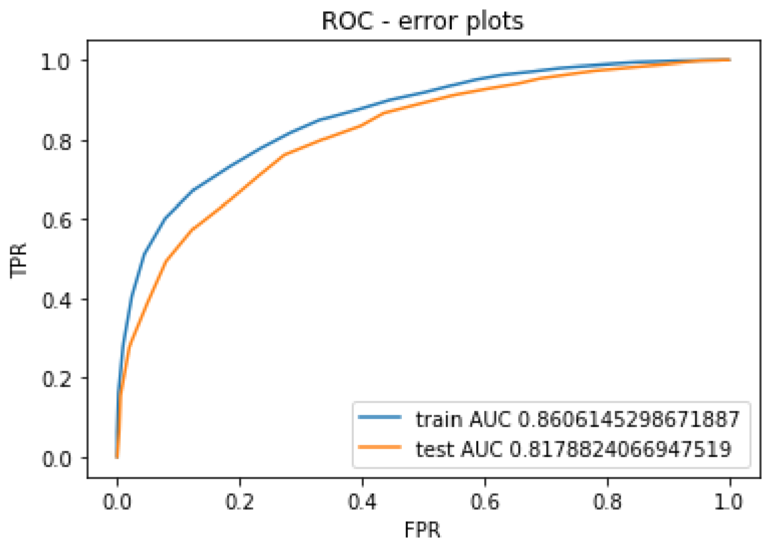
```
plt.title('Error Plots')
plt.show()
```



Testing with Test data

In [30]:
```
#ROC curve for k=40
#from above statistics we take k=49 as our best hyperparameter

knn = KNeighborsClassifier(n_neighbors= 40, weights= 'uniform',algorith
m= 'brute', leaf_size= 30, p = 2, metric= 'cosine')

knn.fit(tran_x_train,y_train)
train_prob =  knn.predict_proba(tran_x_train)[:,1]
test_prob = knn.predict_proba(tran_x_test)[:,1]

# print('----------train_prob---')
# print(train_prob)
# print('----------y-train------')
# print(y_train)

#convert the y_train and y_test string in to 0 and 1
```

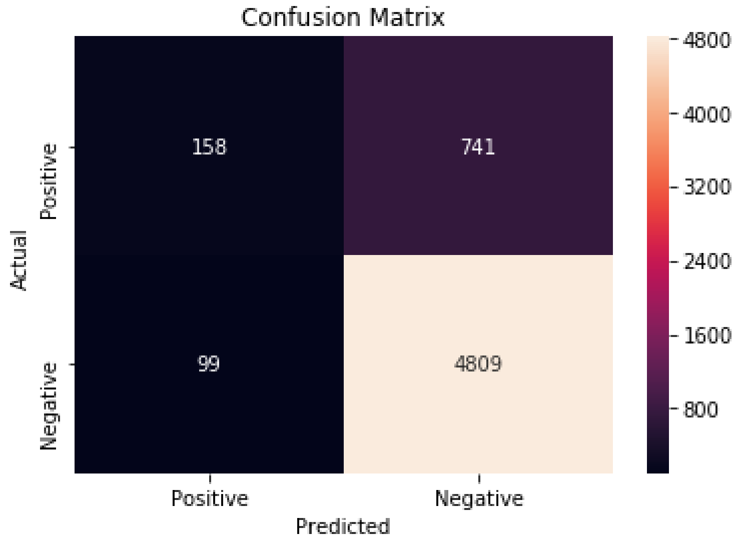
```
# y_train_labels = []
# for i in y_train:
#     if i == 'Positive':
#         y_train_labels.append(1)
#     else :
#         y_train_labels.append(0)



train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_pro
b )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

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

plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC - error plots')
plt.legend()
plt.show()
```



Confusion Matrix

In [31]:
```
#Confusion Matrix

print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(tran_x_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(tran_x_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(tran_x_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')


plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[ 334 1124]
 [ 111 7913]]
Test confusion matrix
[[ 158  741]
 [  99 4809]]
```

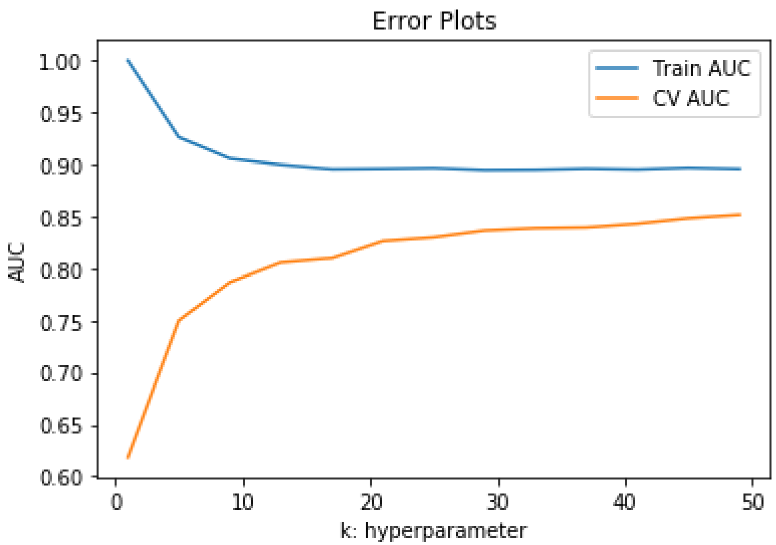


1.1.2 Applying KNN brute force on TFIDF

Hyper parameter Tuning using Simple for loop

In [32]:
```
# Applying KNN brute force on TFIDF

tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df = 10)

tran_x_train = tf_idf_vect.fit_transform(x_train)
tran_x_cv = tf_idf_vect.transform(x_cv)
tran_x_test = tf_idf_vect.transform(x_test)

train_auc = []
cv_auc = []

k = list(range(1,50,4))

for i in k:
    knn = KNeighborsClassifier(n_neighbors = i, weights = 'uniform', al
```

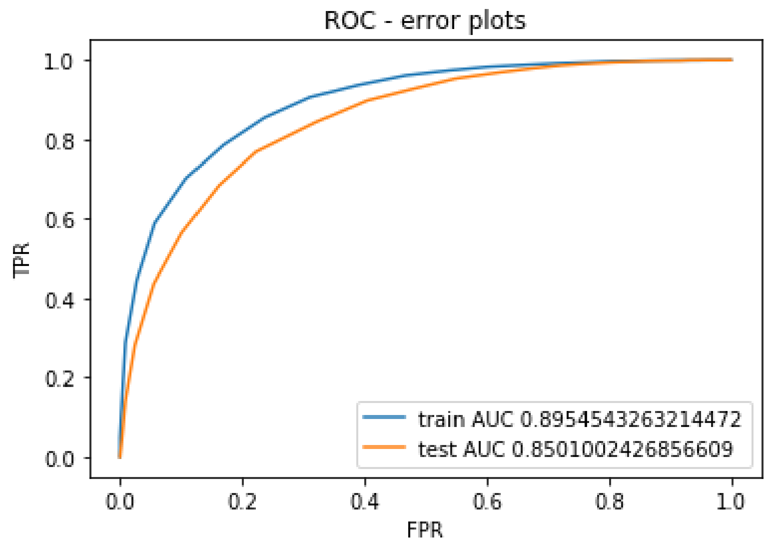
```
gorithm = 'brute', leaf_size =30, p = 2, metric = 'cosine')
    knn.fit(tran_x_train,y_train)

    y_train_pred = knn.predict_proba(tran_x_train)[:,1]
    y_cv_pred = knn.predict_proba(tran_x_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(k, train_auc,label = 'Train AUC')
plt.plot(k, cv_auc,label = 'CV AUC')
plt.legend()
plt.xlabel('k: hyperparameter')
plt.ylabel('AUC')
plt.title('Error Plots')
plt.show()
```



Testing with Test data

In [33]:
```
#ROC curve for k=39
#from above statistics we take k=49 as our best hyperparameter
```

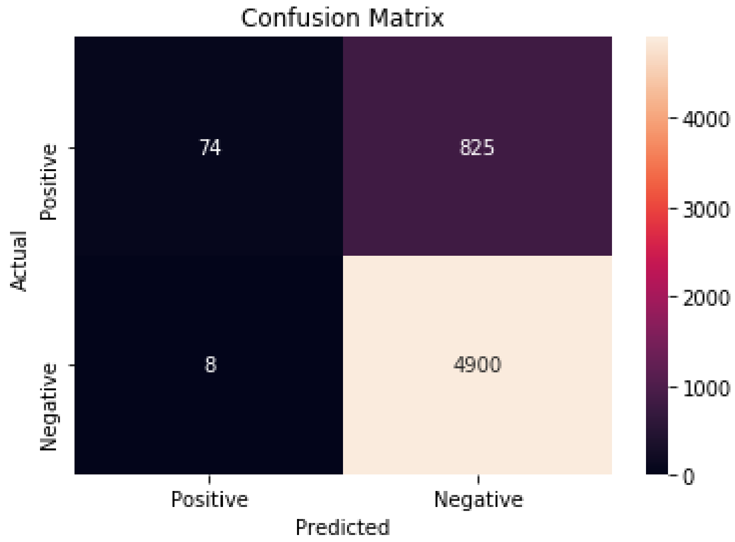
```
knn = KNeighborsClassifier(n_neighbors= 39, weights= 'uniform',algorith
m= 'brute', leaf_size= 30, p = 2, metric= 'cosine')

knn.fit(tran_x_train,y_train)
train_prob =  knn.predict_proba(tran_x_train)[:,1]
test_prob = knn.predict_proba(tran_x_test)[:,1]

train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_pro
b )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

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

plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC - error plots')
plt.legend()
plt.show()
```



Confusion Matrix

In [34]:
```
#Confusion Matrix

print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(tran_x_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(tran_x_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(tran_x_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')


plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[ 147 1311]
 [   8 8016]]
Test confusion matrix
[[  74  825]
 [   8 4900]]
```



1.1.3 Applying KNN brute force on avg W2V

Hyper parameter Tuning using Simple for loop

Training w2v model

In [35]:
```
# w2v for train

#Preparing Reviews for gensim model

list_of_sentance_train = []
for sentance in x_train :
    list_of_sentance_train.append(sentance.split())

# Training w2v model
w2v_model = Word2Vec(list_of_sentance_train , min_count = 5, size = 50,
 workers =4)
w2v_words = list(w2v_model.wv.vocab)
```

```
print('no of words occured min 5 times ',len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
no of words occured min 5 times  5849
sample words  ['taste', 'surprisingly', 'good', 'would', 'compare', 'cr
oss', 'sunflower', 'seeds', 'cashews', 'eat', 'plain', 'morning', 'foun
d', 'blend', 'oatmeal', 'well', 'sugar', 'salt', 'combo', 'season', 'ba
d', 'soaked', 'water', 'washed', 'canister', 'air', 'dried', 'tasty',
'not', 'buy', 'mix', 'liquid', 'create', 'fat', 'free', 'peanut', 'butt
er', 'bought', 'use', 'green', 'smoothies', 'protein', 'shakes', 'purpo
se', 'stuff', 'great', 'get', 'nice', 'added', 'yogurt']
```

Converting Train data text

In [36]:

```
# Converting Reviews into Numerical Vectors using W2V vectors
## Algorithm: Avg W2V

# compute average word2vec for each review.
sent_vectors = []; #the average word2vec for each sentance/review will
 store in this list
# for sent in tqdm(list_of_sentance_train):
for sent in (list_of_sentance_train):
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        if word in w2v_words:
            vec =  w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0 :
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
sent_vectors_train = np.array(sent_vectors)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
(9482, 50)
[-0.10015345 -0.13952778 -0.69643142 -0.22123822 -0.17367566 -0.2171626
4
```

```
  0.14167957  0.02430635  0.05191252  0.31244514 -0.1826644  -0.2322353
1
  0.25503365  0.81110474  0.03420242 -0.36973522  0.3336471  -0.0091980
6
 -0.36316538 -0.83581078  0.32639971  0.04406378  0.46400371  0.2771709
5
 -0.00772743  0.61218389 -0.09854228  0.3795618  -0.48292881  0.1361287
2
 -0.06617691  0.01175956 -0.76598121 -0.01519468 -0.03834009  0.1557205
8
 -0.29371912 -0.25373396  0.21663801 -0.21009477 -0.55682546 -0.4496064
2
  0.11176189 -0.73016817 -0.39343907  0.68043809  0.56688018 -0.4307608
7
 -0.14371563 -0.04545352]
```

Converting CV data text

In [37]:
```
list_of_sentance_cv = []
for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())
```

In [38]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; #the avg-w2v for each sentence/review is stored i
n this list
# for sent in tqdm(list_of_sentance_cv):
for sent in (list_of_sentance_cv):

    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent: #for each word in a review/sentance
        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])
```

```
(4065, 50)
[-0.56111266 -0.3301508  -0.49658867 -0.33143953 -0.03303619  0.0375997
5
  0.00461307  0.07727705 -0.16364837 -0.09558308  0.29497529 -0.0864339
4
  0.14915181  0.94391909 -0.21166885 -0.89522829  0.84734936 -0.4957740
4
 -0.62099049 -1.18628453 -0.12351938  0.08738138  0.45781254  0.0078997
  0.37790907  0.39231554  0.09007252  0.2302442  -0.52003445  0.1337631
7
  0.03520628 -0.01898587 -0.45706923  0.02258139 -0.01642686  0.1533716
7
 -0.56332976 -0.24369464  0.22561655 -0.09519706 -1.31305475 -0.2927077
4
 -0.44229863 -0.35368905 -0.49586512  0.4387508   0.23225555 -0.2837441
3
 -0.15746411 -0.70467384]
```

Testing with Test data

In [39]:
```
list_of_sentance_test = []
for sentance in x_test:
    list_of_sentance_test.append(sentance.split())
```

In [40]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; #the avg-w2v for each sentence/review is stored
 in this list
# for sent in tqdm(list_of_sentance_test):
for sent in (list_of_sentance_test):
```

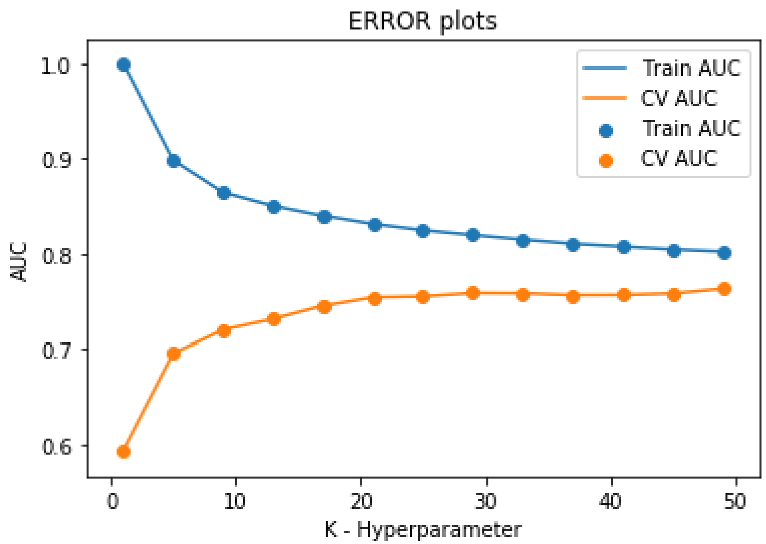
```
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent: #for each word in a review/sentance
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
print(sent_vectors_test.shape)
print(sent_vectors_test[0])
```

```
(5807, 50)
[-1.36685390e-01 -3.16162983e-01 -7.33962582e-01 -9.77356889e-02
 -1.47434362e-01 -2.47024420e-01  1.60562633e-01  6.06824044e-02
  5.00919787e-02  4.12182803e-01 -2.04726054e-01 -3.64262811e-01
  3.92061047e-01  1.06030562e+00 -1.39883657e-01 -4.88527705e-01
  2.90301900e-01  8.66909002e-02 -4.21208843e-01 -7.52164311e-01
  4.07807537e-01  9.10700036e-02  4.70599352e-01  1.29679959e-01
  2.70348833e-02  6.51796704e-01 -7.79308185e-02  3.69570275e-01
 -2.96529363e-01  1.74088216e-01 -9.34901494e-02  4.80122896e-02
 -6.68169109e-01 -1.07261927e-01  9.38937896e-04  6.21475880e-02
 -2.31186979e-01 -2.29142259e-01  2.26058979e-01 -2.54717535e-01
 -7.57863260e-01 -3.60096508e-01  3.71860920e-01 -9.30603580e-01
 -4.96191480e-01  7.95541171e-01  7.37504847e-01 -3.18548126e-01
 -1.76443904e-01 -7.12061148e-02]
```

appliying KNN on avg W2V

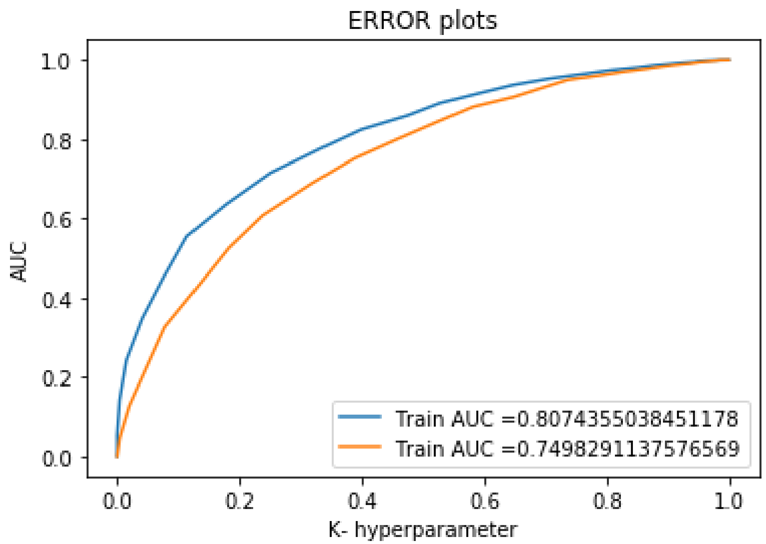
In [41]:
```
train_auc = []
cv_auc = []
k = range(1,50,4)

for i in k:
    knn = KNeighborsClassifier(n_neighbors= i, weights= 'uniform' ,algo
rithm='brute', leaf_size= 30, p = 2, metric= 'cosine')
```

```
    knn.fit(sent_vectors_train,y_train)
    y_train_pred = knn.predict_proba(sent_vectors_train)[:,1]
    y_cv_pred = knn.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(k, train_auc,label ='Train AUC')
plt.scatter(k, train_auc, label = 'Train AUC')
plt.plot(k, cv_auc , label = 'CV AUC')
plt.scatter(k, cv_auc ,label = 'CV AUC')
plt.legend()
plt.xlabel('K - Hyperparameter')
plt.ylabel('AUC')
plt.title('ERROR plots')
plt.show()
```



In [42]:
```
#from above statistics we take k=49 as our best hyperparameter
```

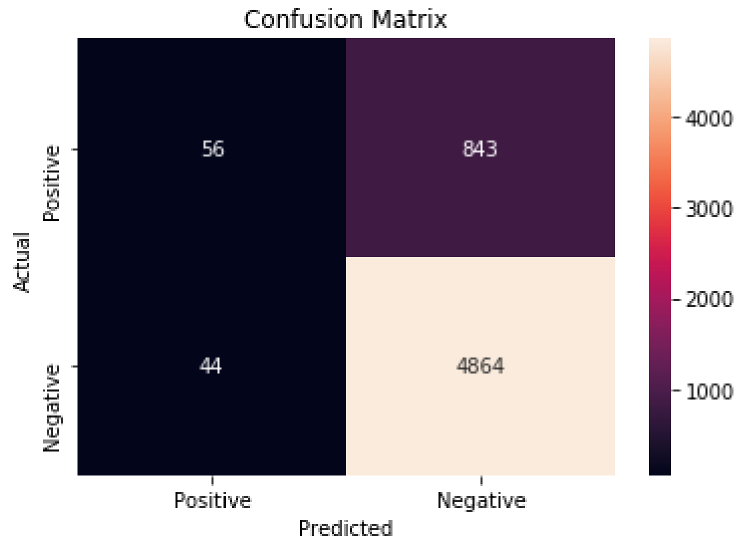
```
#ROC curve for k=41

knn = KNeighborsClassifier(n_neighbors= 41, weights= 'uniform', algorit
hm= 'brute',leaf_size= 30, p=2, metric= 'cosine')
knn.fit(sent_vectors_train,y_train)

train_fpr,train_tpr,tresholds = roc_curve(y_train, knn.predict_proba(se
nt_vectors_train)[:,1])
test_fpr,test_tpr,tresholds1 = roc_curve(y_test, knn.predict_proba(sent
_vectors_test)[:,1])

plt.plot(train_fpr, train_tpr, label = 'Train AUC ='+ str(auc(train_fpr
,train_tpr)))
plt.plot(test_fpr, test_tpr, label = 'Train AUC ='+ str(auc(test_fpr,te
st_tpr)))


plt.legend()
plt.xlabel('K- hyperparameter')
plt.ylabel('AUC')
plt.title('ERROR plots')
plt.show()
```



Confusion Matrix

In [43]:
```
#Confusion Matrix

print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(sent_vectors_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(sent_vectors_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(sent_vectors_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')


plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[ 109 1349]
 [  56 7968]]
Test confusion matrix
[[  56  843]
 [  44 4864]]
```



1.1.4 Applying KNN brute force on TFIDF W2V

Hyper parameter Tuning using Simple for loop

Training w2v model

In [44]:
```
# w2v for train
# Preparing Reviews for gensim model

list_of_sentance_train = []
for sentance in x_train:
    list_of_sentance_train.append(sentance.split())

w2v_model = Word2Vec(list_of_sentance_train , min_count = 5 ,size = 50,
 workers = 4)
w2v_words = list(w2v_model.wv.vocab)
```

In [45]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df= 10,max_features
= 500)

tf_idf_matrix = tf_idf_vect.fit_transform(x_train)
tfidf_feat = tf_idf_vect.get_feature_names()
dictionary = dict(zip(tf_idf_vect.get_feature_names(),list(tf_idf_vect.
idf_)))
```

Converting Train data text

In [46]:
```
tfidf_sent_vectors_train = []
row = 0

# for sent in tqdm(list_of_sentance_train):
for sent in (list_of_sentance_train):

    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum = tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

Converting CV data

In [47]:
```
list_of_sentance_cv = []
for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())

tfidf_sent_vectors_cv = []
```

```
row = 0

# for sent in tqdm(list_of_sentance_cv):
for sent in (list_of_sentance_cv):

    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum = tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1
```

Converting test data

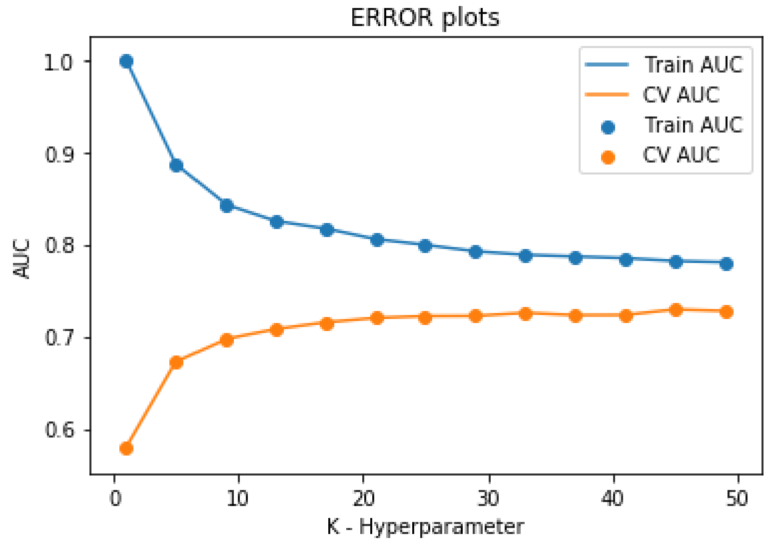
In [48]:
```
list_of_sentance_test = []
for sentance in x_test:
    list_of_sentance_test.append(sentance.split())

tfidf_sent_vectors_test = []
row = 0

# for sent in tqdm(list_of_sentance_test):
for sent in (list_of_sentance_test):

    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum = tf_idf
```

```
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

appliying KNN on tfidf W2V

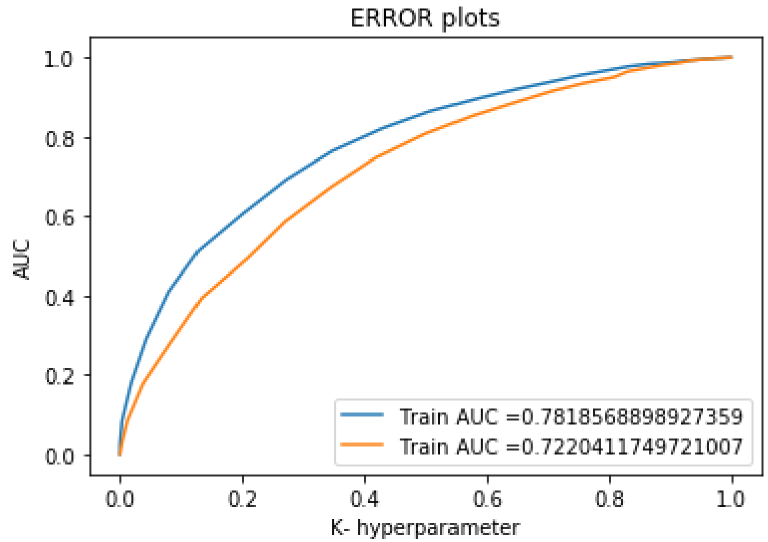
In [49]:

```
train_auc = []
cv_auc = []
k = range(1,50,4)

for i in k:
    knn = KNeighborsClassifier(n_neighbors= i, weights= 'uniform' ,algo
rithm='brute', leaf_size= 30, p = 2, metric= 'cosine')
    knn.fit(tfidf_sent_vectors_train,y_train)
    y_train_pred = knn.predict_proba(tfidf_sent_vectors_train)[:,1]
    y_cv_pred = knn.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(k, train_auc,label ='Train AUC')
plt.scatter(k, train_auc, label = 'Train AUC')
plt.plot(k, cv_auc , label = 'CV AUC')
plt.scatter(k, cv_auc ,label = 'CV AUC')
plt.legend()
plt.xlabel('K - Hyperparameter')
plt.ylabel('AUC')
plt.title('ERROR plots')
plt.show()
```



In [50]:
```
#from above statistics we take k=49 as our best hyperparameter
#ROC curve for k=45

knn = KNeighborsClassifier(n_neighbors= 45, weights= 'uniform', algorit
hm= 'brute',leaf_size= 30, p=2, metric= 'cosine')
knn.fit(tfidf_sent_vectors_train,y_train)

train_fpr,train_tpr,tresholds = roc_curve(y_train, knn.predict_proba(tf
idf_sent_vectors_train)[:,1])
test_fpr,test_tpr,tresholds1 = roc_curve(y_test, knn.predict_proba(tfid
f_sent_vectors_test)[:,1])

plt.plot(train_fpr, train_tpr, label = 'Train AUC ='+ str(auc(train_fpr
,train_tpr)))
plt.plot(test_fpr, test_tpr, label = 'Train AUC ='+ str(auc(test_fpr,te
st_tpr)))


plt.legend()
plt.xlabel('K- hyperparameter')
plt.ylabel('AUC')
```

```
plt.title('ERROR plots')
plt.show()
```

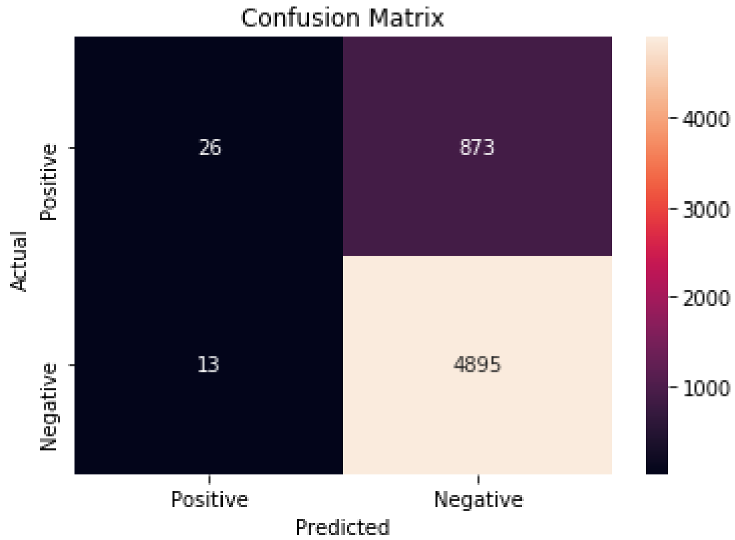


Confusion Matrix

In [51]:
```
#Confusion Matrix
knn = KNeighborsClassifier(n_neighbors= i, weights= 'uniform' ,algorith
m='brute', leaf_size= 30, p = 2, metric= 'cosine')
knn.fit(tfidf_sent_vectors_train,y_train)


print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(tfidf_sent_vectors_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(tfidf_sent_vectors_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(tfidf_sent_vectors_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')
```

```
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[  43 1415]
 [  16 8008]]
Test confusion matrix
[[  26  873]
 [  13 4895]]
```



1.2 Applying KNN kd-tree

1.2.1 Applying KNN kd-tree on BOW

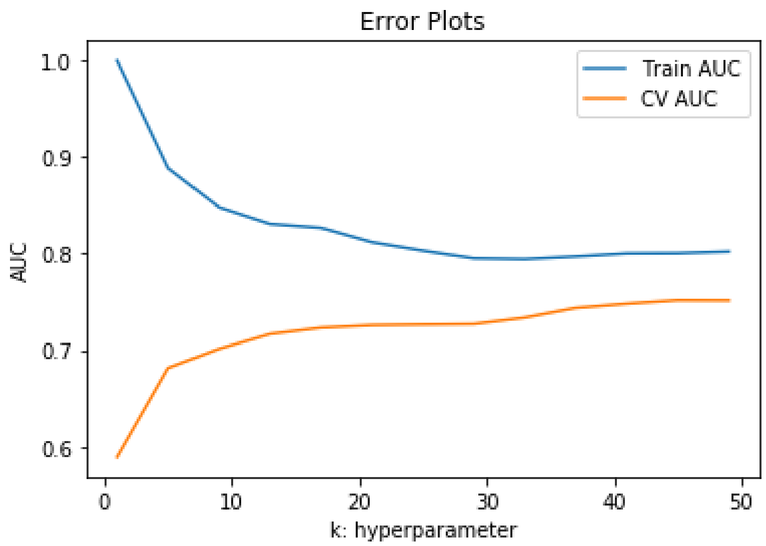
In [52]:
```
x = preprocessed_reviews
```

```
y = final['Score'].values

x = x[:20000]
y = y[:20000]

#tarin ,cv, test split
x1 , x_test, y1, y_test = train_test_split(x , y ,test_size =0.3,random
_state = 0)
x_train, x_cv, y_train, y_cv = train_test_split(x1, y1, test_size = 0.3
)
```

In [53]:

```
# Applying KNN brute force on BOW

cou_vec = CountVectorizer(min_df= 10 ,max_features= 500)
tran_x_train = cou_vec.fit_transform(x_train)
tran_x_cv = cou_vec.transform(x_cv)
tran_x_test = cou_vec.transform(x_test)

tran_x_train = tran_x_train.toarray()
tran_x_cv = tran_x_cv.toarray()
tran_x_test = tran_x_test.toarray()

train_auc = []
cv_auc = []

k = list(range(1,50,4))
for i in k:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'kd_tree')
    knn.fit(tran_x_train,y_train)

    y_train_pred = knn.predict_proba(tran_x_train)[:,1]
    y_cv_pred = knn.predict_proba(tran_x_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(k, train_auc,label = 'Train AUC')
plt.plot(k, cv_auc,label = 'CV AUC')
plt.legend()
```

```
plt.xlabel('k: hyperparameter')
plt.ylabel('AUC')
plt.title('Error Plots')
plt.show()
```

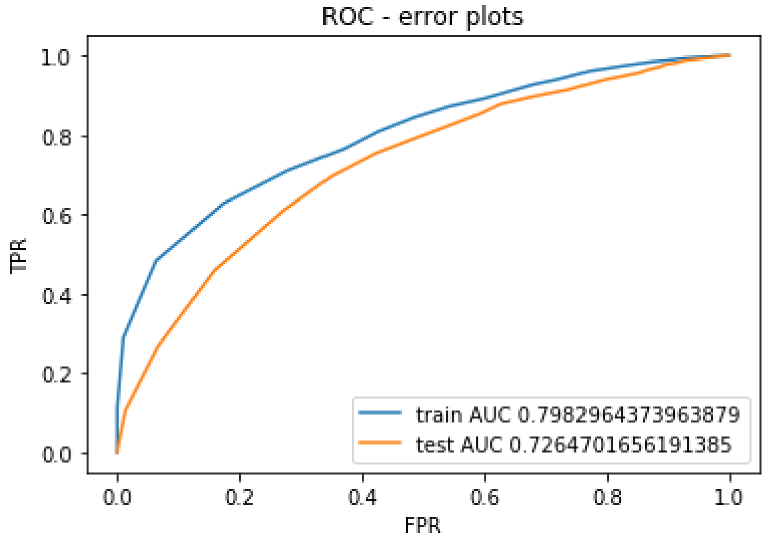


Testing with Test data

In [54]:

```
#ROC curve for k=40
#from above statistics we take k=40 as our best hyperparameter

knn = KNeighborsClassifier(n_neighbors= 40,algorithm= 'kd_tree')
knn.fit(tran_x_train,y_train)

train_prob =  knn.predict_proba(tran_x_train)[:,1]
test_prob = knn.predict_proba(tran_x_test)[:,1]

train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_pro
b )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

plt.plot(train_fpr ,train_tpr , label = 'train AUC '+str(auc(train_fpr,
```

```
 train_tpr)))
plt.plot(test_fpr, test_tpr , label = 'test AUC ' + str(auc(test_fpr,te
st_tpr)))

plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC - error plots')
plt.legend()
plt.show()
```

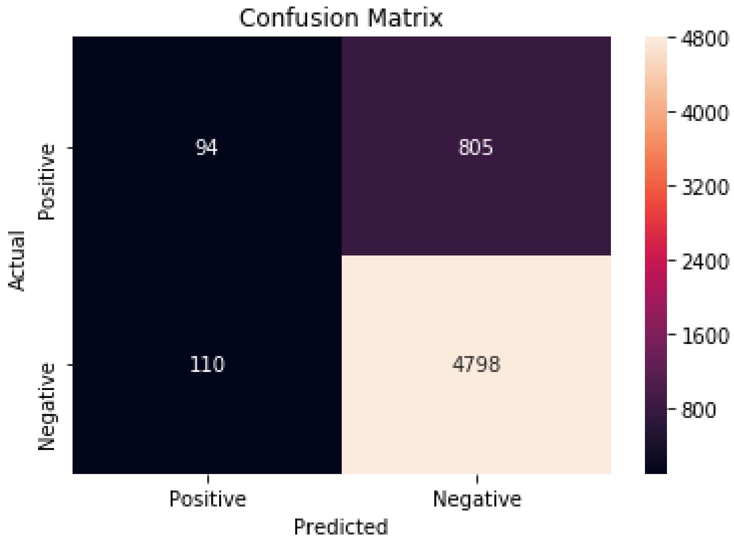


Confusion Matrix

In [55]:
```
#Confusion Matrix

print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(tran_x_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(tran_x_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(tran_x_test))
class_labels = ['Positive','Negative']
```

```
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')


plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

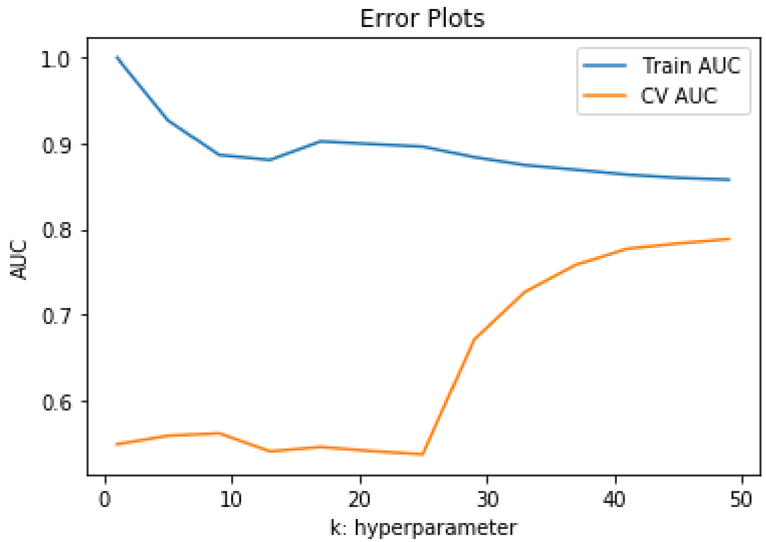
```
Train confusion matrix
[[ 192 1303]
 [ 130 7857]]
Test confusion matrix
[[  94  805]
 [ 110 4798]]
```



1.2.2 Applying KNN kd-tree on TFIDF

In [56]:
```
# Applying KNN brute force on BOW

cou_vec = TfidfVectorizer(ngram_range = (1,2), min_df= 10 ,max_features
```

```
= 500)
tran_x_train = cou_vec.fit_transform(x_train)
tran_x_cv = cou_vec.transform(x_cv)
tran_x_test = cou_vec.transform(x_test)

tran_x_train = tran_x_train.toarray()
tran_x_cv = tran_x_cv.toarray()
tran_x_test = tran_x_test.toarray()

train_auc = []
cv_auc = []

k = list(range(1,50,4))
for i in k:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'kd_tree')
    knn.fit(tran_x_train,y_train)

    y_train_pred = knn.predict_proba(tran_x_train)[:,1]
    y_cv_pred = knn.predict_proba(tran_x_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(k, train_auc,label = 'Train AUC')
plt.plot(k, cv_auc,label = 'CV AUC')
plt.legend()
plt.xlabel('k: hyperparameter')
plt.ylabel('AUC')
plt.title('Error Plots')
plt.show()
```

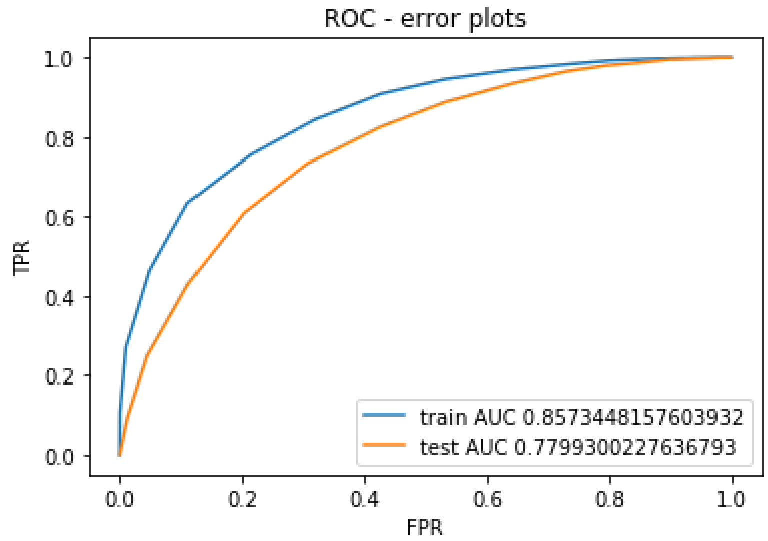


Testing with Test data

In [57]:

```
#ROC curve for k=49
#from above statistics we take k=49 as our best hyperparameter

knn = KNeighborsClassifier(n_neighbors= 49,algorithm= 'kd_tree')
knn.fit(tran_x_train,y_train)

train_prob =  knn.predict_proba(tran_x_train)[:,1]
test_prob = knn.predict_proba(tran_x_test)[:,1]

train_fpr, train_tpr, thresholds = metrics.roc_curve(y_train, train_pro
b )
test_fpr, test_tpr, thresholds1 = metrics.roc_curve(y_test,test_prob)

plt.plot(train_fpr ,train_tpr , label = 'train AUC '+str(auc(train_fpr,
 train_tpr)))
plt.plot(test_fpr, test_tpr , label = 'test AUC ' + str(auc(test_fpr,te
st_tpr)))
```

```
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC - error plots')
plt.legend()
plt.show()
```

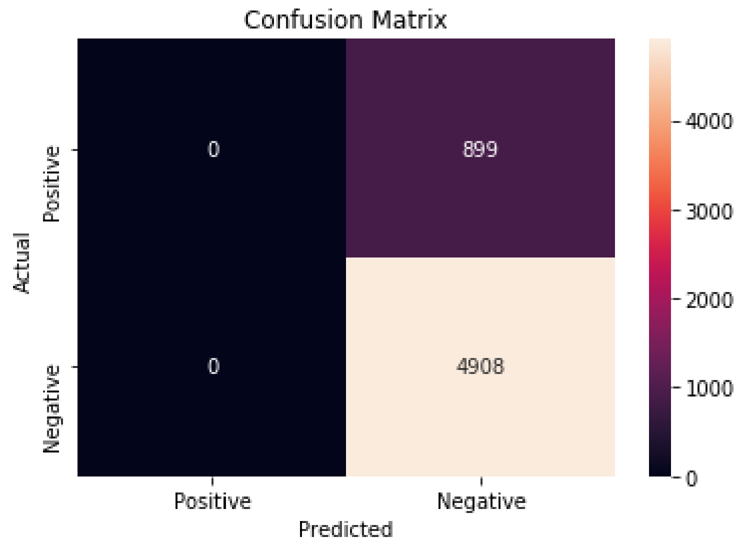


Confusion Matrix

In [58]:
```
#Confusion Matrix

print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(tran_x_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(tran_x_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(tran_x_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')
```

```
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[   0 1495]
 [   0 7987]]
Test confusion matrix
[[   0  899]
 [   0 4908]]
```



1.2.3 Applying KNN brute force on avg W2V

Hyper parameter Tuning using Simple for loop

Training w2v model

In [59]:
```
# w2v for train

#Preparing Reviews for gensim model

list_of_sentance_train = []
for sentance in x_train :
    list_of_sentance_train.append(sentance.split())

# Training w2v model
w2v_model = Word2Vec(list_of_sentance_train , min_count = 5, size = 50,
 workers =4)
w2v_words = list(w2v_model.wv.vocab)
print('no of words occured min 5 times ',len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
no of words occured min 5 times  5805
sample words  ['saw', 'soup', 'supermarket', 'bought', 'opened', 'heate
d', 'tasted', 'dumped', 'drain', 'rinsed', 'mouth', 'enough', 'said',
'one', 'time', 'favorite', 'guilty', 'pleasure', 'sadly', 'nothing', 'l
eft', 'enjoy', 'dry', 'flavorless', 'packing', 'peanuts', 'ya', 'know',
'gluten', 'free', 'diet', 'treats', 'like', 'licorice', 'milk', 'realiz
ing', 'true', 'challenging', 'past', 'not', 'likely', 'ever', 'near',
'future', 'need', 'alter', 'expectations', 'treat', 'tried', 'company']
```

Converting Train data text

In [60]:
```
# Converting Reviews into Numerical Vectors using W2V vectors
## Algorithm: Avg W2V

# compute average word2vec for each review.
sent_vectors = []; #the average word2vec for each sentance/review will
 store in this list
# for sent in tqdm(list_of_sentance_train):
for sent in (list_of_sentance_train):

    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
```

```
            if word in w2v_words:
                vec =  w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0 :
            sent_vec /= cnt_words
        sent_vectors.append(sent_vec)
sent_vectors_train = np.array(sent_vectors)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
(9482, 50)
[-0.11904924  0.05156635 -0.60322445  0.03610602 -0.10563253 -0.2296690
9
  0.15978353  0.09175231  0.01748197  0.10083751 -0.08661146 -0.1210714
5
  0.50575272  1.01908121 -0.17595667 -0.42173152  0.18356361 -0.2371283
 -0.15513094 -0.85932106  0.14766067  0.05484553  0.42585287 -0.0499488
2
  0.05210002  0.50240977  0.27376763  0.12884795 -0.16541266 -0.0734285
9
  0.03009616  0.04021095 -0.35042987  0.15206765 -0.26183085  0.0471912
4
 -0.39578848 -0.4489209   0.23585904 -0.25438966 -0.55938988 -0.1785897
9
  0.0668553  -0.40438684 -0.23498576  0.53756303  0.16899143 -0.2392226
6
 -0.07088466 -0.03865883]
```

Converting CV data text

In [61]:

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

In [62]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; #the avg-w2v for each sentence/review is stored i
```

```
n this list
# for sent in tqdm(list_of_sentance_cv):
for sent in (list_of_sentance_cv):

    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent: #for each word in a review/sentance
        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])
```

```
(4065, 50)
[ 1.08675488e-01 -5.18561995e-02 -9.76259550e-01 -4.86533377e-01
 -4.99798699e-01 -3.63610545e-01  4.10777079e-01 -6.55350553e-02
  1.86135224e-01  1.06740478e-01  2.16978657e-04 -3.40001163e-01
  6.52732973e-01  9.21373936e-01  1.56128782e-01 -5.42078413e-01
  6.06317628e-01 -3.67312523e-01 -5.55941803e-01 -1.29280666e+00
 -3.69713756e-02  6.20774879e-02  5.93800420e-01  2.42623178e-01
  2.47707098e-01  9.81328165e-01  1.75006762e-01  4.84737765e-01
 -3.10388692e-01  1.58953508e-01 -6.40440612e-03 -2.63417226e-02
 -7.94731795e-01  1.68729715e-01 -2.65882980e-01  4.55308142e-01
 -5.24880229e-01 -1.44571070e-01  6.64029636e-01 -4.93892945e-03
 -9.28271315e-01 -4.21585944e-01 -4.34136733e-01  1.28186260e-01
 -6.61514573e-01  6.12255279e-01  1.79673382e-01 -4.70354701e-01
 -2.26046517e-01  3.45528575e-01]
```

Testing with Test data

In [63]:
```
list_of_sentance_test = []
for sentance in x_test:
    list_of_sentance_test.append(sentance.split())
```

In [64]:

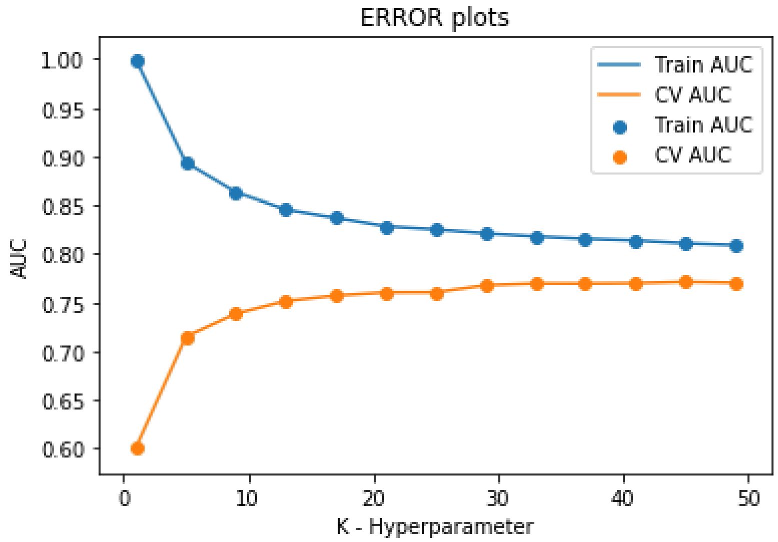
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; #the avg-w2v for each sentence/review is stored
 in this list
# for sent in tqdm(list_of_sentance_test):
for sent in (list_of_sentance_test):

    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent: #for each word in a review/sentance
        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])
```

```
(5807, 50)
[-0.12582644 -0.12281049 -0.88252326 -0.09540953 -0.29049125 -0.2226710
7
  0.15071908  0.16505331  0.06357586  0.35074272 -0.16103913 -0.2534373
2
  0.60182804  1.24713718 -0.22794516 -0.53399829  0.18482541  0.0309035
3
 -0.24134272 -0.90466988  0.29802347  0.12790198  0.57920605 -0.0568966
2
 -0.00320583  0.76965249  0.20169412  0.22055938 -0.19950745  0.1174691
6
  0.00544813 -0.04978439 -0.67059739  0.03233894 -0.28367862  0.0961676
3
 -0.32848275 -0.38669969  0.444644   -0.13702084 -0.6683806  -0.299794
  0.25817729 -0.64164366 -0.35535353  0.75326924  0.31471238 -0.3025509
5
 -0.18184619  0.09029683]
```

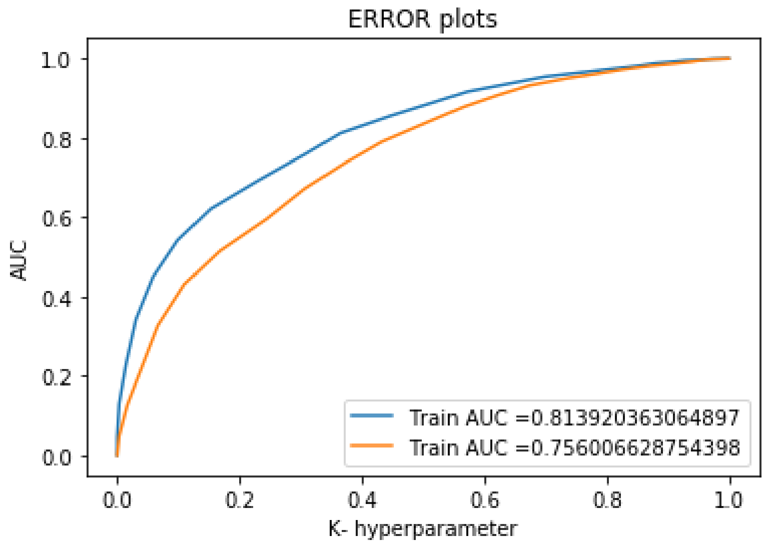
appliying KNN on avg W2V

In [65]:

```
train_auc = []
cv_auc = []
k = range(1,50,4)

for i in k:
    knn = KNeighborsClassifier(n_neighbors= i, algorithm='kd_tree')
    knn.fit(sent_vectors_train,y_train)
    y_train_pred = knn.predict_proba(sent_vectors_train)[:,1]
    y_cv_pred = knn.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(k, train_auc,label ='Train AUC')
plt.scatter(k, train_auc, label = 'Train AUC')
plt.plot(k, cv_auc , label = 'CV AUC')
plt.scatter(k, cv_auc ,label = 'CV AUC')
plt.legend()
plt.xlabel('K - Hyperparameter')
plt.ylabel('AUC')
plt.title('ERROR plots')
plt.show()
```



In [66]:
```
#from above statistics we take k=49 as our best hyperparameter
#ROC curve for k=41

knn = KNeighborsClassifier(n_neighbors= 41,algorithm= 'kd_tree')
knn.fit(sent_vectors_train,y_train)

train_fpr,train_tpr,tresholds = roc_curve(y_train, knn.predict_proba(se
nt_vectors_train)[:,1])
test_fpr,test_tpr,tresholds1 = roc_curve(y_test, knn.predict_proba(sent
_vectors_test)[:,1])

plt.plot(train_fpr, train_tpr, label = 'Train AUC ='+ str(auc(train_fpr
,train_tpr)))
plt.plot(test_fpr, test_tpr, label = 'Train AUC ='+ str(auc(test_fpr,te
st_tpr)))


plt.legend()
plt.xlabel('K- hyperparameter')
plt.ylabel('AUC')
plt.title('ERROR plots')
plt.show()
```

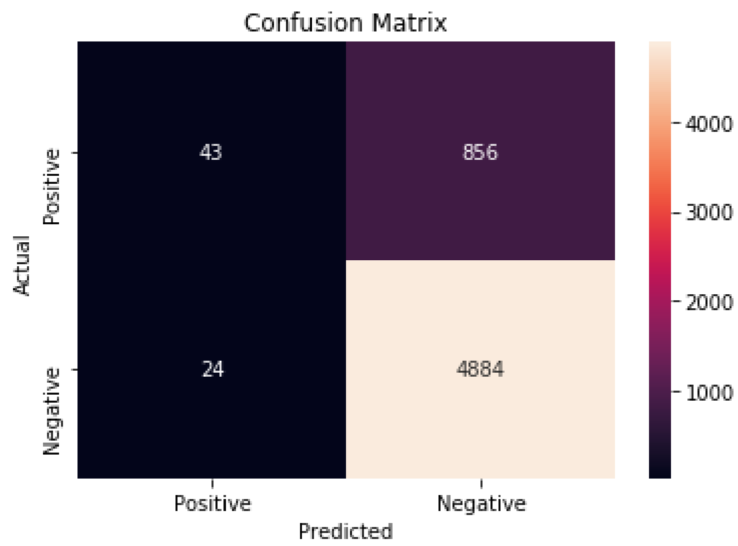


Confusion Matrix

In [67]:
```
#Confusion Matrix

print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(sent_vectors_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(sent_vectors_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(sent_vectors_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')


plt.title('Confusion Matrix')
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[ 105 1390]
 [  37 7950]]
Test confusion matrix
[[  43  856]
 [  24 4884]]
```



1.2.4 Applying KNN brute force on TFIDF W2V

Hyper parameter Tuning using Simple for loop

Training w2v model

In [68]:
```
# w2v for train
# Preparing Reviews for gensim model
```

```
list_of_sentance_train = []
for sentance in x_train:
    list_of_sentance_train.append(sentance.split())

w2v_model = Word2Vec(list_of_sentance_train , min_count = 5 ,size = 50,
 workers = 4)
w2v_words = list(w2v_model.wv.vocab)
```

In [69]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df= 10,max_features
= 500)

tf_idf_matrix = tf_idf_vect.fit_transform(x_train)
tfidf_feat = tf_idf_vect.get_feature_names()
dictionary = dict(zip(tf_idf_vect.get_feature_names(),list(tf_idf_vect.
idf_)))
```

Converting Train data text

In [70]:
```
tfidf_sent_vectors_train = []
row = 0

# for sent in tqdm(list_of_sentance_train):
for sent in (list_of_sentance_train):

    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum = tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

Converting CV data

In [71]:
```
list_of_sentance_cv = []
for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())

tfidf_sent_vectors_cv = []
row = 0

# for sent in tqdm(list_of_sentance_cv):
for sent in (list_of_sentance_cv):

    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum = tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1
```

Converting test data

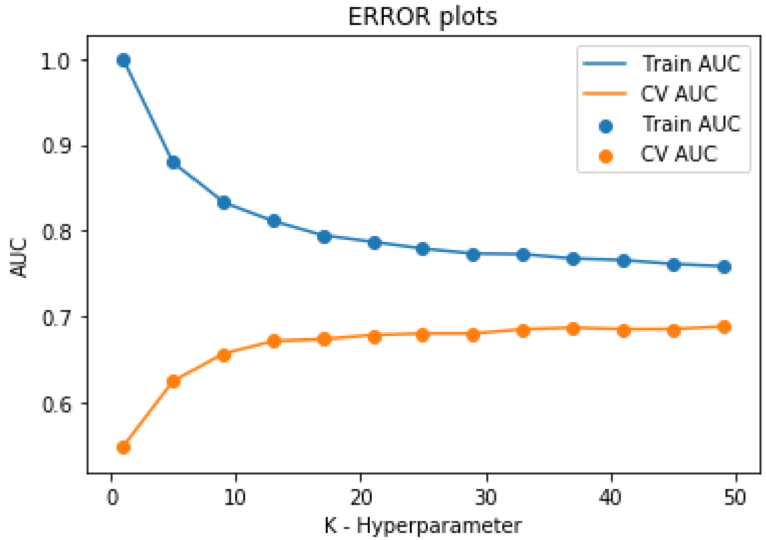
In [72]:
```
list_of_sentance_test = []
for sentance in x_test:
    list_of_sentance_test.append(sentance.split())

tfidf_sent_vectors_test = []
row = 0

# for sent in tqdm(list_of_sentance_test):
for sent in (list_of_sentance_test):
```

```
    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum = tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

appliying KNN on tfidf W2V

In [73]:

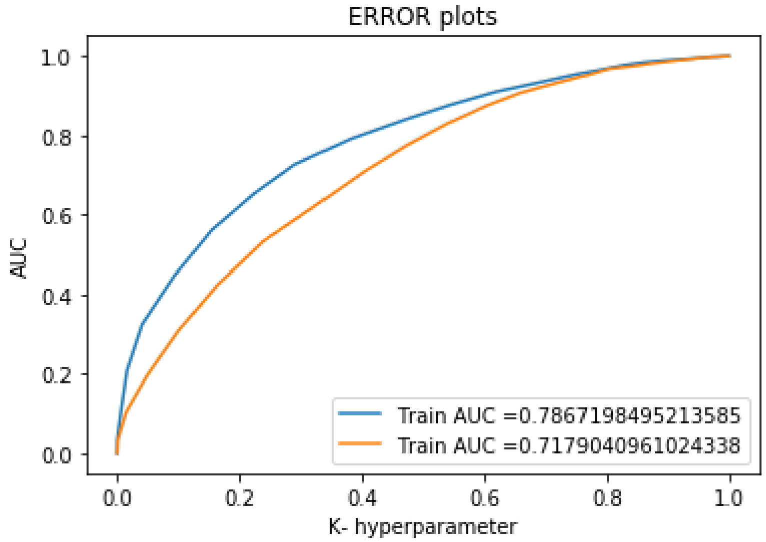
```
train_auc = []
cv_auc = []
k = range(1,50,4)

for i in k:
    knn = KNeighborsClassifier(n_neighbors= i,algorithm='kd_tree')
    knn.fit(tfidf_sent_vectors_train,y_train)
    y_train_pred = knn.predict_proba(tfidf_sent_vectors_train)[:,1]
    y_cv_pred = knn.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(k, train_auc,label ='Train AUC')
plt.scatter(k, train_auc, label = 'Train AUC')
plt.plot(k, cv_auc , label = 'CV AUC')
plt.scatter(k, cv_auc ,label = 'CV AUC')
plt.legend()
plt.xlabel('K - Hyperparameter')
plt.ylabel('AUC')
plt.title('ERROR plots')
plt.show()
```



In [74]:

```
#from above statistics we take k=49 as our best hyperparameter
#ROC curve for k=41

knn = KNeighborsClassifier(n_neighbors= 41, weights= 'uniform', algorit
hm= 'brute',leaf_size= 30, p=2, metric= 'cosine')
knn.fit(tfidf_sent_vectors_train,y_train)

train_fpr,train_tpr,tresholds = roc_curve(y_train, knn.predict_proba(tf
idf_sent_vectors_train)[:,1])
test_fpr,test_tpr,tresholds1 = roc_curve(y_test, knn.predict_proba(tfid
f_sent_vectors_test)[:,1])

plt.plot(train_fpr, train_tpr, label = 'Train AUC ='+ str(auc(train_fpr
,train_tpr)))
plt.plot(test_fpr, test_tpr, label = 'Train AUC ='+ str(auc(test_fpr,te
st_tpr)))


plt.legend()
plt.xlabel('K- hyperparameter')
plt.ylabel('AUC')
```

```
plt.title('ERROR plots')
plt.show()
```

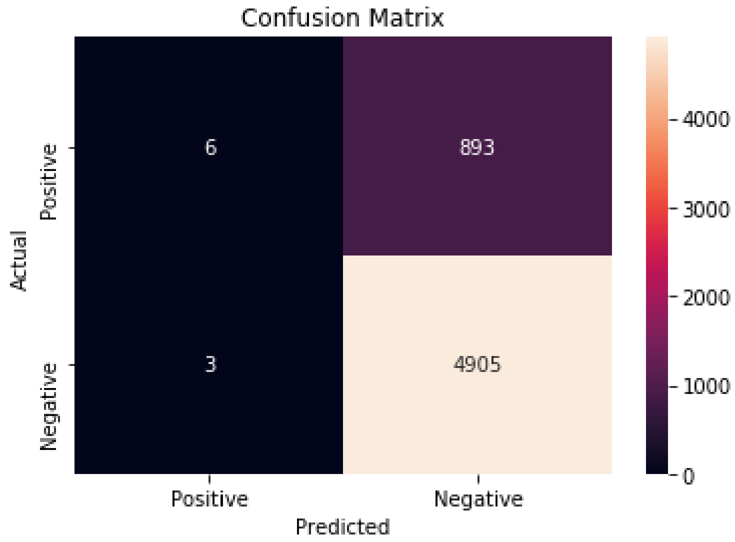


Confusion Matrix

In [75]:
```
#Confusion Matrix
knn = KNeighborsClassifier(n_neighbors= i,algorithm='kd_tree')
knn.fit(tfidf_sent_vectors_train,y_train)


print('Train confusion matrix')
print(confusion_matrix(y_train, knn.predict(tfidf_sent_vectors_train)))
print('Test confusion matrix')
print(confusion_matrix(y_test,knn.predict(tfidf_sent_vectors_test)))

cnf_mat = confusion_matrix(y_test,knn.predict(tfidf_sent_vectors_test))
class_labels = ['Positive','Negative']
df = pd.DataFrame(cnf_mat, index= class_labels , columns= class_labels)
sb.heatmap(df, annot= True, fmt= 'd')
```

```
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Train confusion matrix
[[  13 1482]
 [   3 7984]]
Test confusion matrix
[[   6  893]
 [   3 4905]]
```



[6] Conclusions

In [77]:

```
# compare all your models
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ['Vectorizer','Model','Hyperameter','AUC']
x.add_row(['BOW','Brute',49,0.81])
x.add_row(['TFIDF','Brute',49,0.85])
```

```
x.add_row(['AvgW2V','Brute',49,0.74])
x.add_row(['TFIDF W2V','Brute',41,0.72])
x.add_row(['BOW','Kd Tree',49,0.72])
x.add_row(['TFIDF','Kd Tree',49,0.77])
x.add_row(['AvgW2V','Kd Tree',49,0.75])
x.add_row(['TFIDF W2V','Kd Tree',41,0.71])
print(x)
```

```
+------------+---------+-------------+------+
| Vectorizer |  Model  | Hyperameter | AUC  |
+------------+---------+-------------+------+
|    BOW     |  Brute  |      49     | 0.81 |
|   TFIDF    |  Brute  |      49     | 0.85 |
|   AvgW2V   |  Brute  |      49     | 0.74 |
| TFIDF W2V  |  Brute  |      41     | 0.72 |
|    BOW     | Kd Tree |      49     | 0.72 |
|   TFIDF    | Kd Tree |      49     | 0.77 |
|   AvgW2V   | Kd Tree |      49     | 0.75 |
| TFIDF W2V  | Kd Tree |      41     | 0.71 |
+------------+---------+-------------+------+
```

In [ ]: