AmazonFineFoodReviewsAnalysisKNN

January 21, 2019

1 Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

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

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

2 [1]. Reading Data

2.1 [1.1] Loading the data

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

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

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

In [4]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os

from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV, RandomizedSearchCV
import pickle as pkl
from sklearn.decomposition import TruncatedSVD
from prettytable import PrettyTable
```

In [4]:
```
# Read the Amazon fine food review data from database using sqlite
con = sqlite3.connect('database.sqlite')
```

```
# Select all reviews where score is not 3 (neutral)
review_data = pd.read_sql_query("""SELECT * FROM Reviews WHERE Score != 3""", con)

# Assign positive class if score >=4 else assign negative class
score = review_data['Score']
PN_score = score.map(lambda x: "Positive" if x>=4 else "Negative")
review_data['Score'] = PN_score


print("Shape of review data is {}".format(review_data.shape))
review_data.head(3)
```

```
Shape of review data is (525814, 10)
```

Out[4]:

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

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  Positive  1303862400
1                     0                       0  Negative  1346976000
2                     1                       1  Positive  1219017600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
```

In [5]:

```
#Trying to visualize the duplicate data before removal
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [7]:

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

```
(80668, 7)
```

Out[7]:

```
               UserId   ProductId             ProfileName        Time  Score  \
0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
```

```
3  #oc-R11O5J5ZVQE25C  B005HG9ET0          Penguin Chick  1346889600      5
4  #oc-R12KPBODL2B5ZD  B0070SBE1U   Christopher P. Presta  1348617600      1

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

In [8]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[8]:
```
              UserId   ProductId                      ProfileName        Time  \
80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

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

In [9]:
```
display['COUNT(*)'].sum()
```

Out[9]: 393063

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [12]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[12]:
```
       Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2

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

```
3                          2       5  1199577600
4                          2       5  1199577600

                                 Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  LOACKER QUADRATINI VANILLA WAFERS
3  LOACKER QUADRATINI VANILLA WAFERS
4  LOACKER QUADRATINI VANILLA WAFERS

                                                 Text
0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

```
In [8]: #Sorting data according to ProductId in ascending order
        #sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fa

        #Deduplication of entries
        #final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep
        #final.shape
```

```
In [13]: #Remove the duplicate entries from the data


         sorted_data = review_data.sort_values('ProductId')
         final = sorted_data.drop_duplicates(subset=["UserId", "Time", "Summary"])
         print(final.shape)
```

```
(363186, 10)
```

```
In [15]: #Checking to see how much % of data still remains
         print((final['Id'].size*1.0)/(review_data['Id'].size*1.0)*100)
```

```
69.07119247490557
```

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

         display.head()

Out[16]:       Id   ProductId          UserId              ProfileName  \
         0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
         1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

            HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         0                     3                       1      5  1224892800
         1                     3                       2      4  1212883200

                                                 Summary  \
         0             Bought This for My Son at College
         1  Pure cocoa taste with crunchy almonds inside

                                                     Text
         0  My son loves spaghetti so I didn't hesitate or...
         1  It was almost a 'love at first bite' - the per...

In [18]: # Removing the reviews where HelpfullnessNumerator > HelpfulnessDenominator

         final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]

In [20]: #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?
         print(final['Score'].value_counts())

(363184, 10)
Positive    306173
Negative     57011
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

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

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

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

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

In [42]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
from bs4 import BeautifulSoup
```

In [47]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

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

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

In [43]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
```

In [116]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
```

```
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

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

In [55]:
```
from nltk.stem import SnowballStemmer

#Intializing SnowballStemmer
snow_stemmer = SnowballStemmer('english')

#Using Stemmer on a word
print(snow_stemmer.stem('Moves'))
```

```
move
```

In [48]:
```
# Combining all the above to clean reviews
from tqdm import tqdm
preprocessed_reviews = []

# tqdm is for printing the status bar
for sentence in tqdm(final['Text'].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 stopw
    preprocessed_reviews.append(sentence.strip())
```

```
100%|| 363184/363184 [04:45<00:00, 1270.29it/s]
```

In [64]:
```
# Storing the preprocessed reviews and stemmed preprocessed reviews seperately.
# We have performed the cleaning on the whole data so we can use it later on
```

```
# models other than KNN that can handle high dimensional data gracefully.

#############---- storing the data into .sqlite file ------########################
# Reviews are present in preprocessed_reviews

final['CleanedText'] = preprocessed_reviews

#Store the data into a sqlite database
if not os.path.isfile('final.sqlite'):
    conn = sqlite3.connect('final.sqlite')
    c = conn.cursor()
    conn.text_factory = str
    final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
                 index=True, index_label=None, chunksize=None, dtype=None)
    conn.close()
```

In [91]:
```
# Performing stemming on the preprocessed reviews
final['CleanedText'] = preprocessed_reviews
stemmed_reviews = []

for sentence in final['CleanedText'].values:
    sentence = b' '.join((snow_stemmer.stem(word)).encode('utf8') for word in sentence
    stemmed_reviews.append(sentence)
```

In [85]:
```
final['CleanedText'] = stemmed_reviews
final['CleanedText'] = final['CleanedText'].str.decode("utf-8")

if not os.path.isfile('final_stemmedreviews.sqlite'):
    conn = sqlite3.connect('final_stemmedreviews.sqlite')
    c = conn.cursor()
    conn.text_factory = str
    final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
                 index=True, index_label=None, chunksize=None, dtype=None)
    conn.close()
```

In [3]:
```
# Load the preprocessed dataset from the database final.sqlite
# Data is ordered by time stamps to facilitate time base splitting
# of data for cross validation

conn = sqlite3.connect('final.sqlite')
final = pd.read_sql_query("""SELECT * From Reviews ORDER BY Time""", conn)
conn.close()

conn = sqlite3.connect('final_stemmedreviews.sqlite')
final_stemmed = pd.read_sql_query("""SELECT * From Reviews ORDER BY Time""", conn)
conn.close()
```

In [4]:
```
# There is an extra index column in the data
final.head(1)
```

```
Out[4]:     index      Id   ProductId         UserId      ProfileName  \
        0  138706  150524  0006641040  ACITT7DI6IDDL  shari zychinski

           HelpfulnessNumerator  HelpfulnessDenominator     Score       Time  \
        0                     0                       0  Positive  939340800

                              Summary  \
        0  EVERY book is educational

                                                      Text  \
        0  this witty little book makes my son laugh at l...

                                               CleanedText
        0  witty little book makes son laugh loud recite ...
```

```
In [5]: #Removing the index column from data
        clean_data = final.drop(['index'], axis=1)

        #clean_data_stemmed = final_stemmed.drop(['index'], axis=1)

        # Map postive to 1 and negative to 0 in Score column
        score = clean_data['Score']
        bin_score = score.map(lambda x: 1 if x == "Positive" else 0)
        clean_data['Score'] = bin_score

        # Add stemmed reviews as an extra column in the data
        # This will be in addition to the preprocessed non stemmed
        # reviews which are stored in the CleanedText column.

        stemmed_reviews = final_stemmed['CleanedText']
        clean_data['StemmedText'] = stemmed_reviews
```

```
In [6]: clean_data.tail(1)
```

```
Out[6]:           Id   ProductId         UserId ProfileName  HelpfulnessNumerator  \
        363183  5703  B009WSNWC4  AMP7K1084DH1T        ESTY                     0

                HelpfulnessDenominator  Score        Time    Summary  \
        363183                       0      1  1351209600  DELICIOUS

                                                             Text  \
        363183  Purchased this product at a local store in NY ...

                                                      CleanedText  \
        363183  purchased product local store ny kids love qui...

                                                      StemmedText
        363183  purchas product local store ny kid love quick ...
```

In [7]:
```
# Split the dataset in training and test dataset
# We will use the training data for cross validation and training.
# Test data will not be known to model and will be used
# to calculate the accuracy.

# Data is split in 70-30 train-test split using slicing since
# data is sorted in ascending time order

# Instead of splitting the data and then sampling
# let's try to split the 100k samples directly and
# then just simple time split the data in 70-30k

data = clean_data.iloc[:,:]
subset_data = data.iloc[100000:200000,:]

train_cv_split = 70000

train = subset_data.iloc[:train_cv_split,:]
test = subset_data.iloc[train_cv_split:,:]

print(train.shape , '\n', test.shape)
```

```
(70000, 12)
 (30000, 12)
```

In [8]:
```
print(train[train['Score'] == 0].shape)
print(test[test['Score'] == 0].shape)
```

```
(11235, 12)
(4961, 12)
```

In [9]:
```
# Seperating the Score column from rest of the data
columns = list(clean_data.columns)
columns = [column for column in columns if column != 'Score']

X_train = train[columns]
y_train = train['Score']

X_test = test[columns]
y_test = test['Score']

print(X_train.shape , y_train.shape, '\n', X_test.shape, y_test.shape)
```

```
(70000, 11) (70000,)
 (30000, 11) (30000,)
```

```
In [10]: # Save the y_train and y_test so we
         # can directly use it later rather than rerunning
         # the splitting steps again

         pkl.dump(y_train, open("y_train.pkl", 'wb'))
         pkl.dump(y_test, open("y_test.pkl", 'wb'))
```

[3.2] Preprocessing Review Summary

```
In [6]: ## Similartly you can do preprocessing for review summary also.
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [ ]: # Obtanining a vectorizer on stemmed reviews
        # It was observed during Word2Vec transformation
        # that stemmed reviews give words which are close to
        # say good or bad otherwise we observe other words
        # which seem non-relevant. So we will use stemmed reviews.

        # Words in stemmed review that are most similar to great and worst
        #[('wonder', 0.7626501321792603), ('awesom', 0.7493463754653931), ('excel', 0.7475039
        #('fantast', 0.7294141054153442), ('good', 0.7276639938354492), ('terrif', 0.69687664
        #('nice', 0.6279305219650269), ('perfect', 0.6089357733726501), ('amaz', 0.5737729072
        #('decent', 0.5731742978096008)]
        #===================================================
        #[('horribl', 0.7659773826599121), ('disgust', 0.7506155967712402), ('terribl', 0.7292
        #('aw', 0.7216229438781738), ('nasti', 0.6849608421325684), ('foul', 0.66113215684890
        #('gag', 0.6592600345611572), ('weird', 0.6567815542221069), ('funni', 0.649346351623
        #('gross', 0.6418379545211792)]

        # Words in stemmed review that are most similar to great and worst
        # As we can see worst is similar to greatest and best in non-stemmed reviews.

        #[('awesome', 0.7547115087509155), ('fantastic', 0.7433849573135376), ('wonderful', 0.
        #('excellent', 0.7240736484527588), ('good', 0.7088381052017212), ('terrific', 0.6650
        #('amazing', 0.6410914659500122), ('perfect', 0.6294776201248169), ('fabulous', 0.624
        #('incredible', 0.5898726582527161)]
        #===================================================
        #[('greatest', 0.7661513090133667), ('best', 0.668804407119751), ('richest', 0.650985
        #('smoothest', 0.6451543569564819), ('nastiest', 0.639174222946167), ('tastiest', 0.61
        #('encountered', 0.6121875047683716), ('disgusting', 0.600991427898407), ('yummiest',
        #('nicest', 0.5876485705375671)]

In [100]: # Running count vectorizer on training data only
          # to avoid data leakage
          # we will use the uni-grams & bi-grams in BoW embedding
```

```
# count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
count_vec = CountVectorizer(ngram_range=(1,2), min_df=10)

X_train_bow = count_vec.fit_transform(X_train['StemmedText'].values)
X_test_bow = count_vec.transform(X_test['StemmedText'].values)

# Save the training and test BOW vectors in pickle files
# We can simply load this data later and use it

pkl.dump(X_train_bow, open("train_bow.pkl", 'wb'))
pkl.dump(X_test_bow, open("test_bow.pkl", 'wb'))

# Making another BoW representation for KD-Tree based KNN
count_vec = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)

X_train_bow_kd = count_vec.fit_transform(X_train['StemmedText'].values)
X_test_bow_kd = count_vec.transform(X_test['StemmedText'].values)

# Save the training and test BOW vectors in pickle files
# We can simply load this data later and use it

pkl.dump(X_train_bow_kd, open("train_bow_kd.pkl", 'wb'))
pkl.dump(X_test_bow_kd, open("test_bow_kd.pkl", 'wb'))
```

5.2 [4.2] TF-IDF

In [102]:
```
# Apply tfidf vectorizer to convert text to vectors

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

X_train_tfidf = tf_idf.fit_transform(X_train['StemmedText'].values)
X_test_tfidf = tf_idf.transform(X_test['StemmedText'].values)

# Save the training, CV and test TFIDF vectors in pickle files
# We can simply load this data later and use it

pkl.dump(X_train_tfidf, open("train_tfidf.pkl", 'wb'))
pkl.dump(X_test_tfidf, open("test_tfidf.pkl", 'wb'))

# Making another BoW representation for KD-Tree based KNN
tf_idf = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)

X_train_tfidf_kd = tf_idf.fit_transform(X_train['StemmedText'].values)
X_test_tfidf_kd = tf_idf.transform(X_test['StemmedText'].values)

# Save the training, CV and test TFIDF vectors in pickle files
# We can simply load this data later and use it
```

```
pkl.dump(X_train_tfidf_kd, open("train_tfidf_kd.pkl", 'wb'))
pkl.dump(X_test_tfidf_kd, open("test_tfidf_kd.pkl", 'wb'))
```

In [104]:
```
# Creating a dictionary with word as key and it's tfidf representation as value
dictionary = dict(zip(tf_idf.get_feature_names(), list(tf_idf.idf_)))

pkl.dump(dictionary, open("tfidf_dictionary.pkl", 'wb'))
```

5.3 [4.3] Word2Vec

In [11]:
```
# Train our own Word2Vec model using your own text corpus

list_of_sent_test = []
list_of_sent_train = []

for review in X_test['StemmedText'].values:
    list_of_sent_test.append(review.split())

for review in X_train['StemmedText'].values:
    list_of_sent_train.append(review.split())

w2v = Word2Vec(list_of_sent_train, min_count=5, size=100, workers=4)
w2v.save('w2v_model.bin')
w2v_words = list(w2v.wv.vocab)
```

In [12]:
```
print(w2v.wv.most_similar('great'))
print('='*50)
print(w2v.wv.most_similar('bad'))
```

```
[('fantast', 0.7587853670120239), ('excel', 0.7455682158470154), ('wonder', 0.7229946255683899)
==================================================
[('horribl', 0.706422746181488), ('terribl', 0.7024113535881042), ('aw', 0.674425482749939), (
```

In [13]:
```
w2v_words = list(w2v.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:100])
```

```
number of words that occured minimum 5 times  11131
sample words  ['hey', 'good', 'stuff', 'like', 'tasti', 'cold', 'hot', 'flavor', 'subtl', 'yet
```

5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [117]:
```
# Avg-W2V
from tqdm import tqdm
```

```
train_review_vectors = []
test_review_vectors = []

dataset = [(list_of_sent_train, train_review_vectors),
           (list_of_sent_test, test_review_vectors)]

for item in dataset:
    for review in tqdm(item[0]):
        nwords = 0
        rev_vec = np.zeros(100)
        for word in review:
            if word in w2v_words:
                vec = w2v.wv[word]
                rev_vec += vec
                nwords += 1
        if nwords != 0:
            rev_vec /= nwords
        item[1].append(rev_vec)
```

```
100%|| 70000/70000 [01:41<00:00, 686.62it/s]
100%|| 30000/30000 [00:43<00:00, 686.55it/s]
```

```
In [118]: # Save the review vectors so we can use later

          pkl.dump(train_review_vectors, open("train_avgw2v.pkl", 'wb'))
          pkl.dump(test_review_vectors, open("test_avgw2v.pkl", 'wb'))
```

[4.4.1.2] TFIDF weighted W2v

```
In [14]: tf_idf = TfidfVectorizer(ngram_range=(1,2), min_df=10)

         X_train_tfidf = tf_idf.fit_transform(X_train['StemmedText'].values)
         X_test_tfidf = tf_idf.transform(X_test['StemmedText'].values)

         dictionary_tfidf = dict(zip(tf_idf.get_feature_names(), list(tf_idf.idf_)))
         tfidf_features = tf_idf.get_feature_names()
```

```
In [15]: # review_vectors will store the tfidf-weighted W2V representation of the reviews in t

         # TFIDFWeighted-W2V
         from tqdm import tqdm

         train_review_vectors = []
         test_review_vectors = []

         list_of_sent_test = []
         list_of_sent_train = []
```

```
for review in X_test['CleanedText'].values:
    list_of_sent_test.append(review.split())

for review in X_train['CleanedText'].values:
    list_of_sent_train.append(review.split())

dataset = [(list_of_sent_train, train_review_vectors),
           (list_of_sent_test, test_review_vectors)]

w2v_model = Word2Vec.load('w2v_model.bin')
w2v_words = list(w2v_model.wv.vocab)


for item in dataset:
    row=0
    for review in tqdm(item[0]):
        rev_vec = np.zeros(100)
        weight_sum = 0
        for word in review:
            if word in w2v_words and word in tfidf_features:
                vec = w2v_model.wv[word]
                tf_idf = dictionary_tfidf[word]*(review.count(word)/len(review))
                rev_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            rev_vec /= weight_sum
        item[1].append(rev_vec)
        row += 1
```

```
100%|| 70000/70000 [40:56<00:00, 28.50it/s]
100%|| 30000/30000 [16:10<00:00, 30.92it/s]
```

In [16]:
```
# Save the review vectors so we can use later

pkl.dump(train_review_vectors, open("train_tfidfw2v.pkl", 'wb'))
pkl.dump(test_review_vectors, open("test_tfidfw2v.pkl", 'wb'))
```

5.5 Utility Functions used in KNN classification

In [47]:
```
# This function takes the vector representation of review data
# and returns the optimal k for KNN classification using 5-fold
# cross validation.

# Code below splits the TimeSeries data in linear fashion including
# another split of data progressively with each iteration.
```

```python
def get_optimal_k(X_train_data, y_train_data, algorithm, n_splits=5):
    auc_scores = []
    k_values = list(filter(lambda x : x % 2 != 0, range(1,30)))

    lot_size = int(X_train_data.shape[0] / n_splits)
    X_train_start = 0
    X_train_end = 0
    X_cv_start = 0
    X_cv_end = 0

    for k in k_values:
        avg_scores = []
        for i in range(1, n_splits):
            X_train_end = lot_size*i
            X_cv_start = X_train_end
            X_cv_end = X_cv_start + lot_size
            #print(X_train_start, X_train_end, X_cv_start, X_cv_end)
            X_train = X_train_data[X_train_start:X_train_end, :]
            X_cv = X_train_data[X_cv_start:X_cv_end, :]
            y_train = y_train_data[X_train_start:X_train_end]
            y_cv = y_train_data[X_cv_start:X_cv_end]
            #print(y_train.shape, y_cv.shape)
            knn = KNeighborsClassifier(n_neighbors=k, algorithm=algorithm)
            knn.fit(X_train, y_train)
            y_pred = knn.predict_proba(X_cv)[:,1]

            fpr, tpr, thresholds = roc_curve(y_cv, y_pred)
            avg_score = auc(fpr, tpr)

            avg_scores.append(avg_score)
        auc_score = round(sum(avg_scores) / float(len(avg_scores)), 2)
        auc_scores.append(auc_score)
        #print("Accuracy on CV data with k = {} is {}%".format(k, round(auc_score, 2)
    return k_values[auc_scores.index(max(auc_scores))], zip(k_values, auc_scores)
```

In [28]:
```python
# Running KNN with given K and algorithm specified
# returns a tuple indicating AUC obtained
# and the confusion matrix
# same function can be used on all vectorized data irrespective of vectorizer

def run_knn(X_train, y_train, X_test, y_test, k, algorithm):
    knn = KNeighborsClassifier(n_neighbors=k, algorithm=algorithm)
    knn.fit(X_train, y_train)
    y_pred = knn.predict_proba(X_test)
    y_pred_prob = y_pred[:,1]
    y_pred_label = np.argmax(y_pred, axis=1)
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
    auc_score = auc(fpr, tpr)
```

```
        conf_mat = confusion_matrix(y_test, y_pred_label)

        plt.figure()
        plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % au
        plt.plot([0, 1], [0, 1], color='navy', lw=1, linestyle='--')
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.0])
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('Receiver operating characteristic')
        plt.legend(loc="lower right")
        plt.show()

        return auc_score, conf_mat
```

```
In [40]: def plot_confusion_matrix(cm):
             labels = ['Negative', 'Positive']
             confmat = pd.DataFrame(cm, index = labels, columns = labels)
             sns.heatmap(confmat, annot = True, fmt = 'd', cmap="Greens")
             plt.title("Confusion Matrix")
             plt.xlabel("Predicted Label")
             plt.ylabel("True Label")
             plt.show()
```

6 [5] Assignment 3: KNN

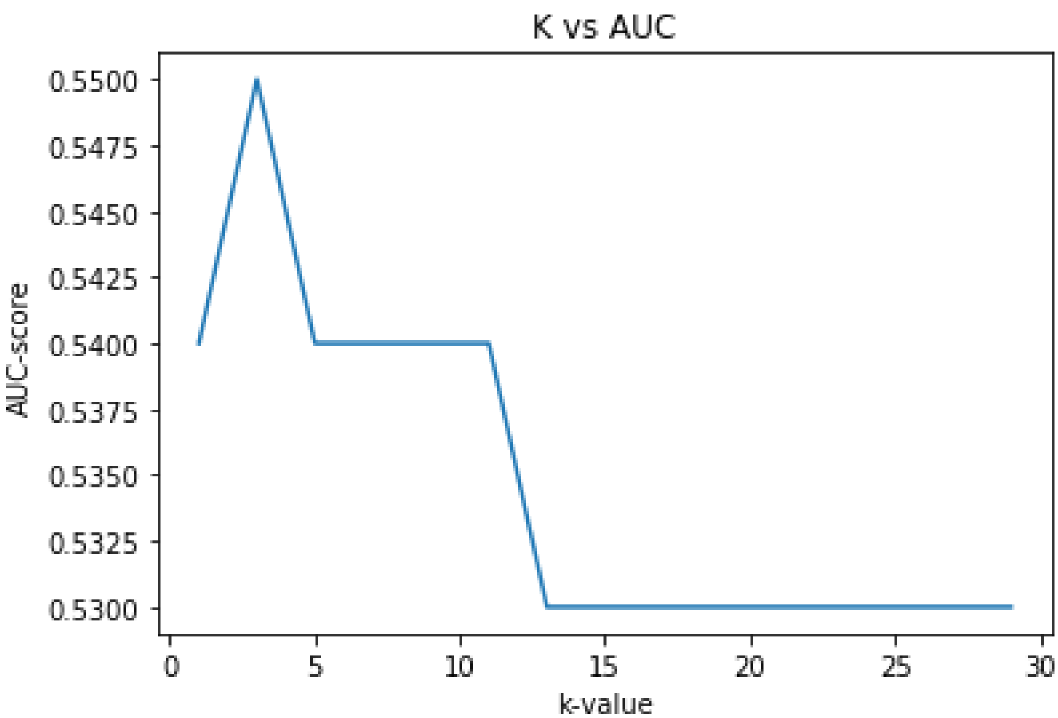
6.1 [5.1] Applying KNN brute force

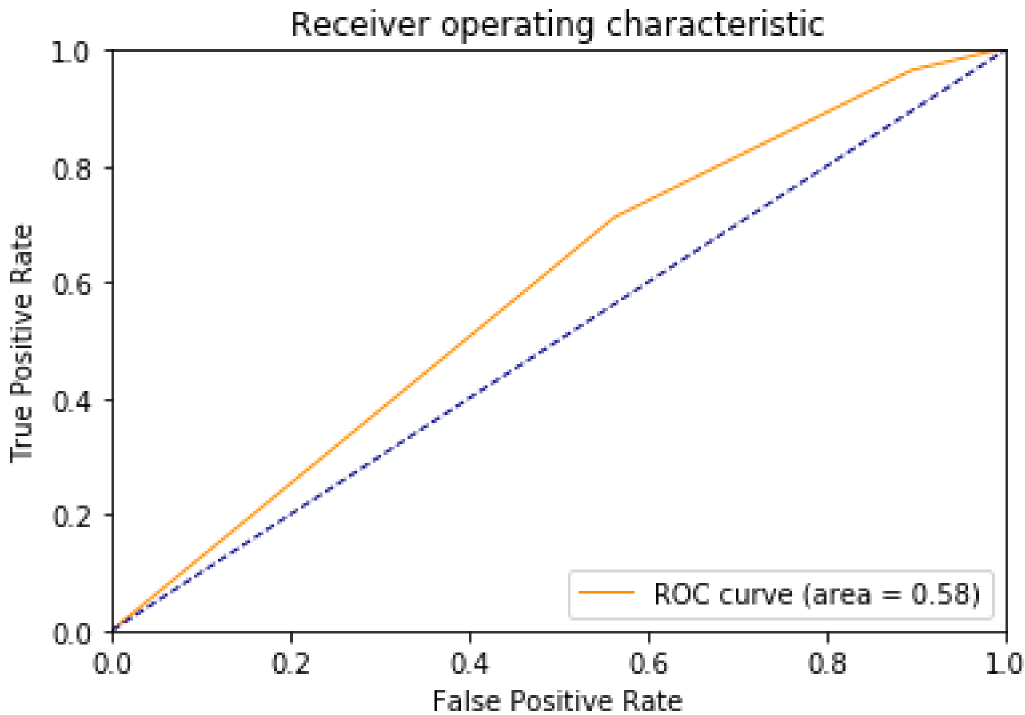
6.1.1 [5.1.1] Applying KNN brute force on BOW, SET 1

```
In [65]: # Load the saved vectorized data for train-test datapoints
         X_train_bow = pkl.load(open('train_bow.pkl', 'rb'))
         X_test_bow = pkl.load(open('test_bow.pkl', 'rb'))

         std = StandardScaler( with_mean=False)

         # Standardizing the vectors
         X_train_bow_std = std.fit_transform(X_train_bow)
         X_test_bow_std = std.transform(X_test_bow)

         # Getting an optimal value of hyperparameter K and AUC scores
         # This data is used to plot a graph of k-values vs AUC
         optimal_k, k_auc = get_optimal_k(X_train_bow_std, y_train, "brute")
         print("Optimal value of K : {}".format(optimal_k))

         auc_data = [(k, accuracy) for k, accuracy in k_auc]

         # Plotting K values vs AUC scores
```

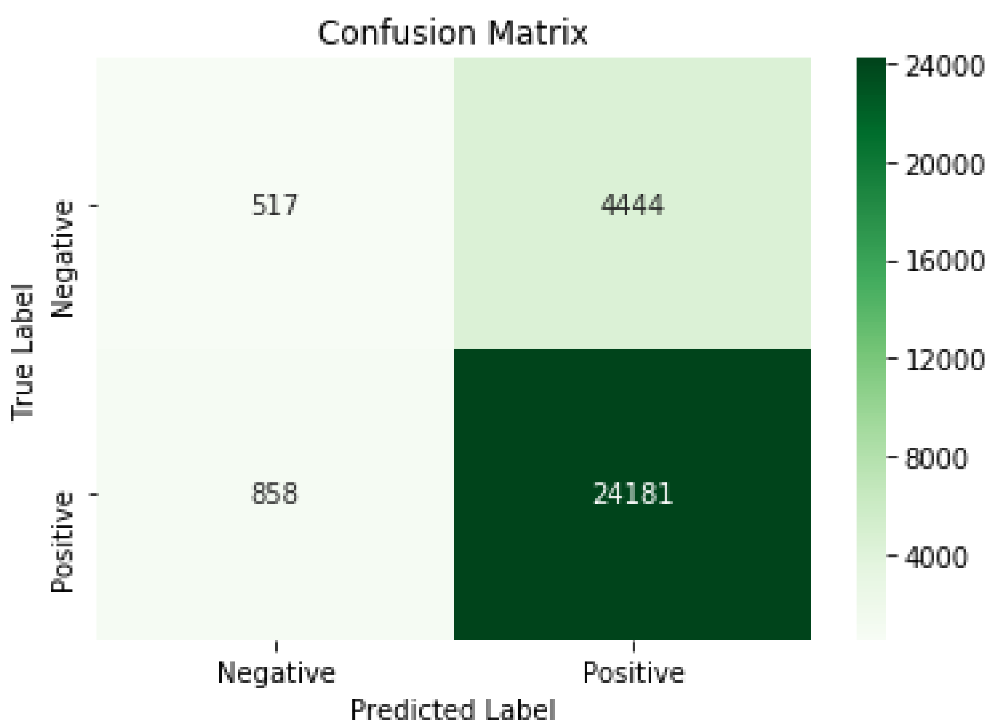
```
plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_bow_std, y_train,
                                      X_test_bow_std, y_test, optimal_k, 'brute')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 3
```





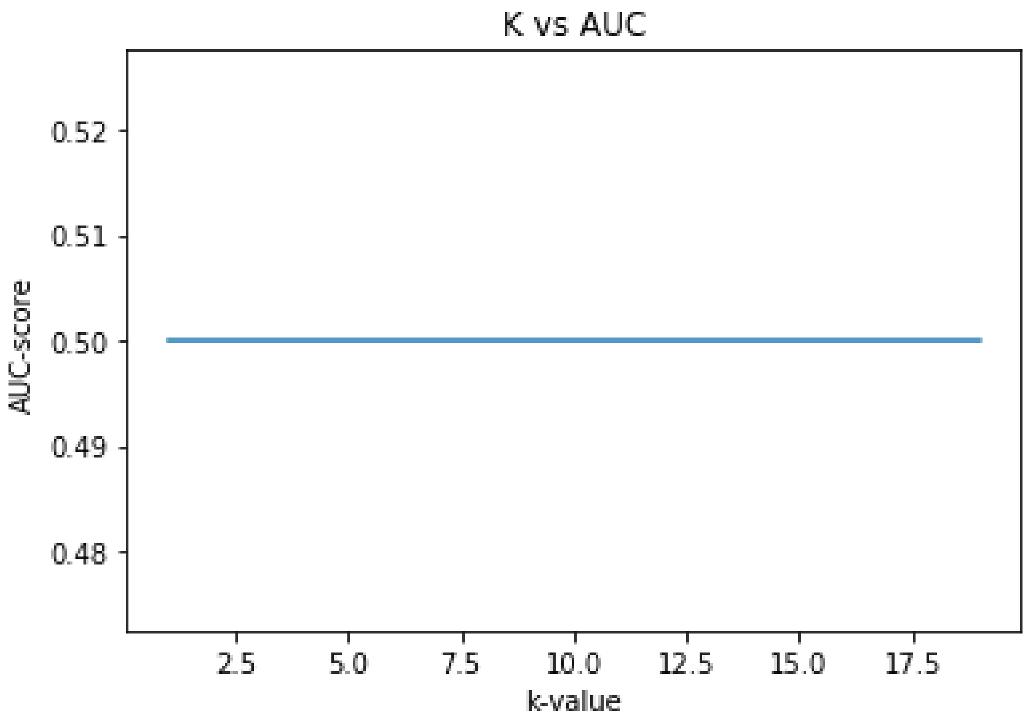

```
AUC score:
 0.58
```

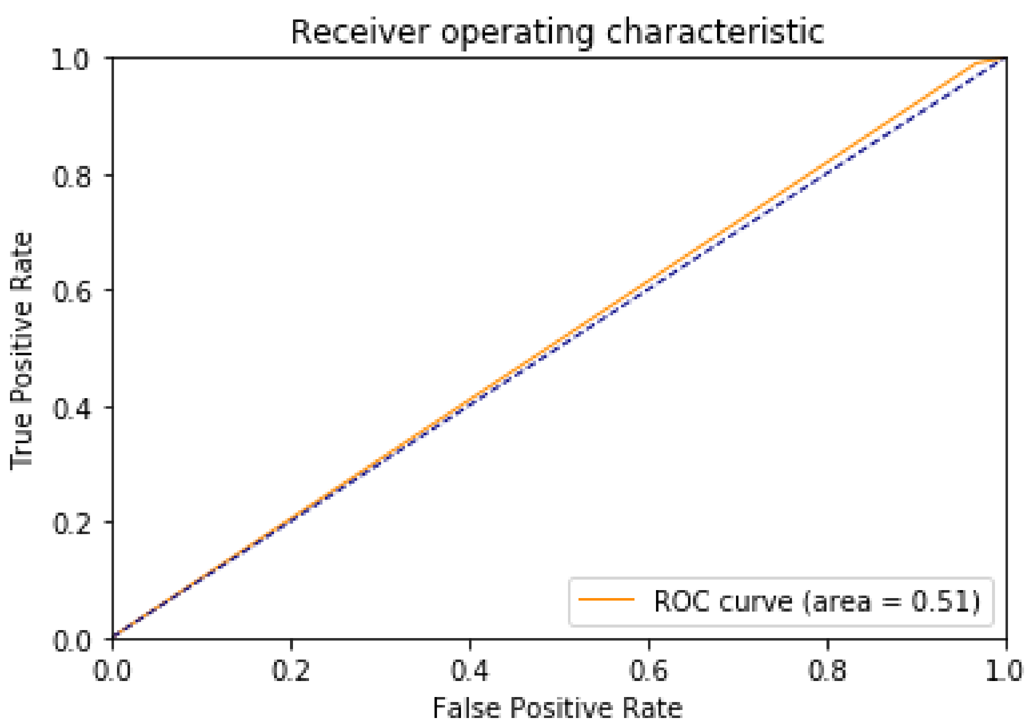


6.1.2 [5.1.2] Applying KNN brute force on TFIDF, SET 2

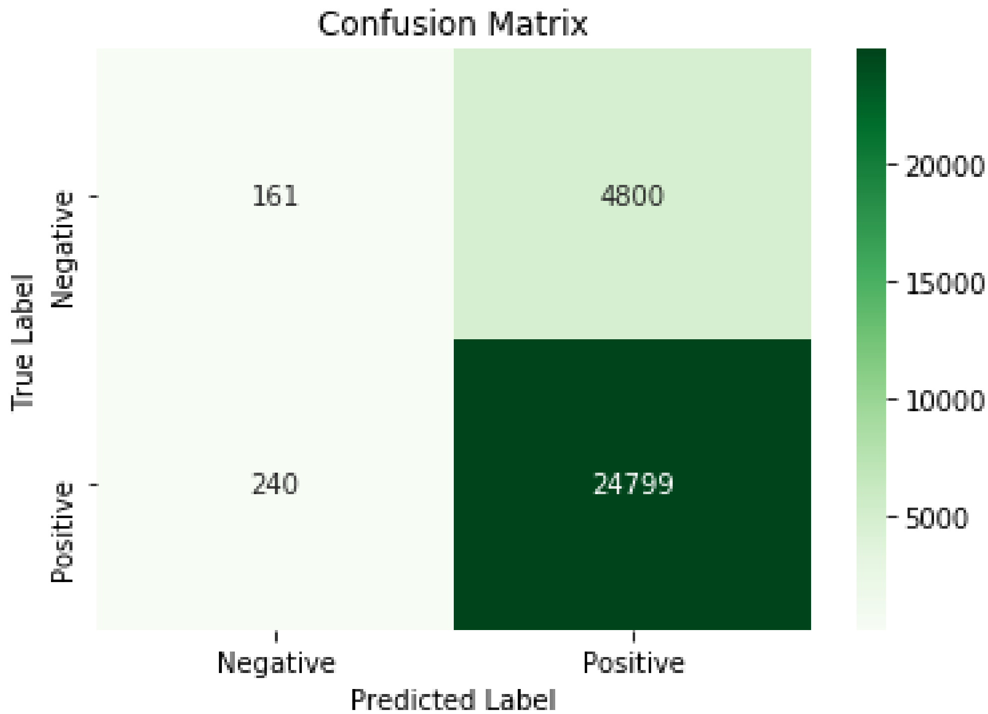
In [45]:
```
# Load the saved vectorized data for train-test datapoints
X_train_tfidf = pkl.load(open('train_tfidf.pkl', 'rb'))
X_test_tfidf = pkl.load(open('test_tfidf.pkl', 'rb'))

std = StandardScaler( with_mean=False)

# Standardizing the vectors
X_train_tfidf_std = std.fit_transform(X_train_tfidf)
X_test_tfidf_std = std.transform(X_test_tfidf)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC
optimal_k, k_auc = get_optimal_k(X_train_tfidf_std, y_train, "brute")
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]

# Plotting K values vs AUC scores

plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_tfidf_std, y_train,
                                      X_test_tfidf_std, y_test, optimal_k, 'brute')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 1
```


K vs AUC
0.52
0.51
0.50
0.49
0.48
AUC-score
2.5
5.0
7.5
10.0
12.5
15.0
17.5
k-value


Receiver operating characteristic
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.51)

```
AUC score:
 0.51
```

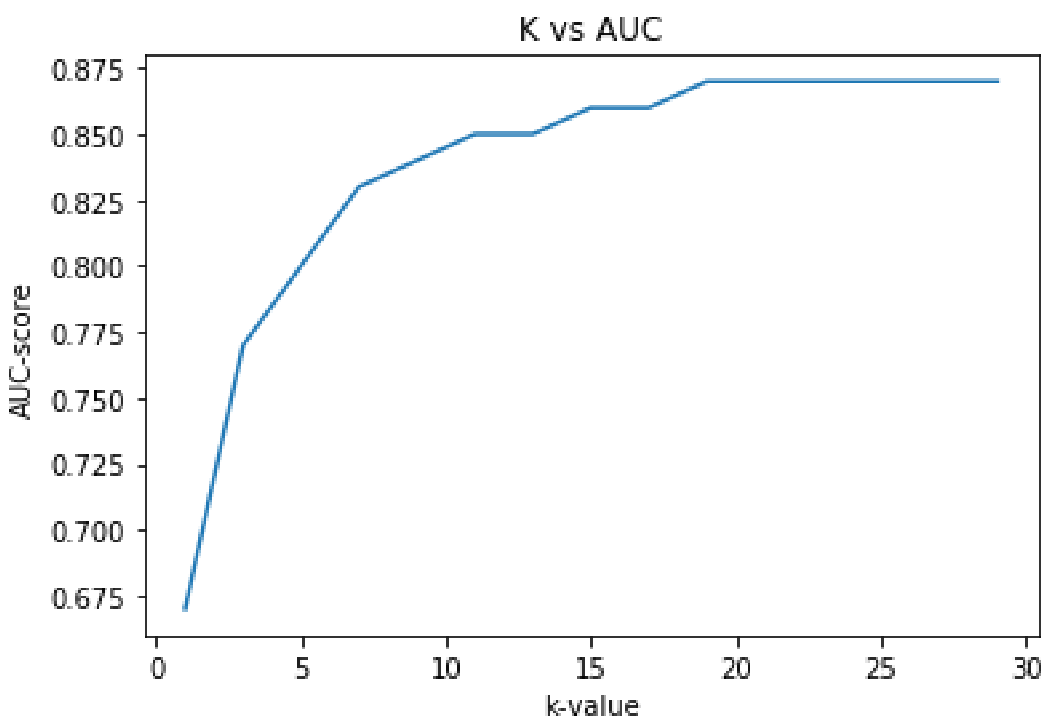


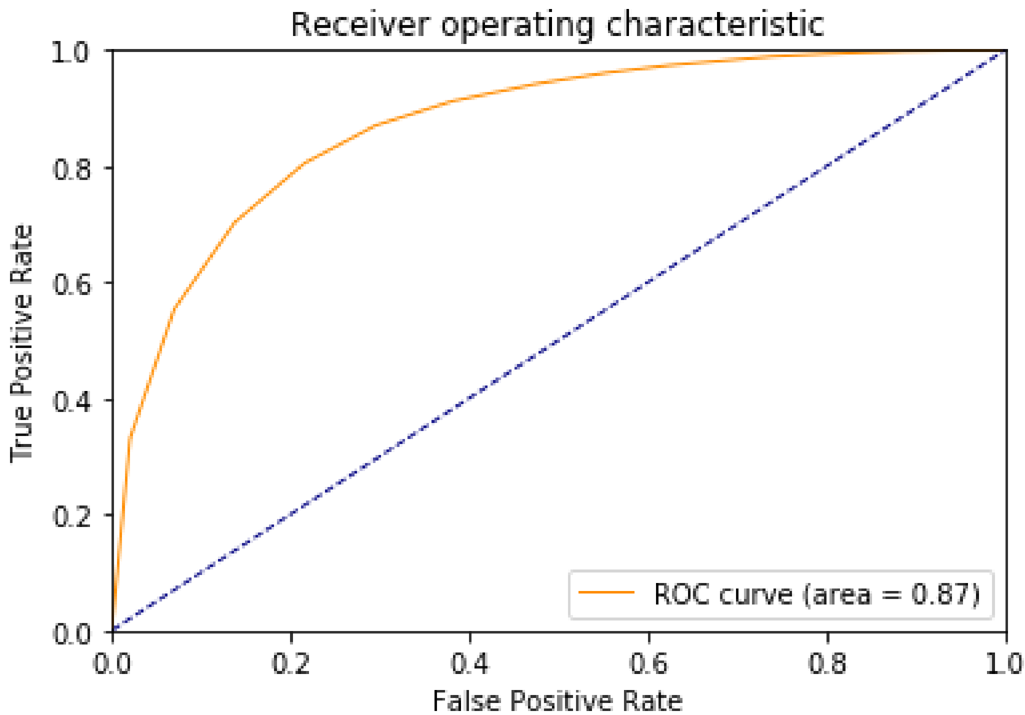
6.1.3 [5.1.3] Applying KNN brute force on AVG W2V, SET 3

In [48]:
```
# Load the saved vectorized data for train-test datapoints
X_train_avgw2v = pkl.load(open('train_avgw2v.pkl', 'rb'))
X_test_avgw2v = pkl.load(open('test_avgw2v.pkl', 'rb'))

std = StandardScaler()

# Standardizing the vectors
X_train_avgw2v_std = std.fit_transform(X_train_avgw2v)
X_test_avgw2v_std = std.transform(X_test_avgw2v)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC
optimal_k, k_auc = get_optimal_k(X_train_avgw2v_std, y_train, 'brute')
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]

# Plotting K values vs AUC scores
```

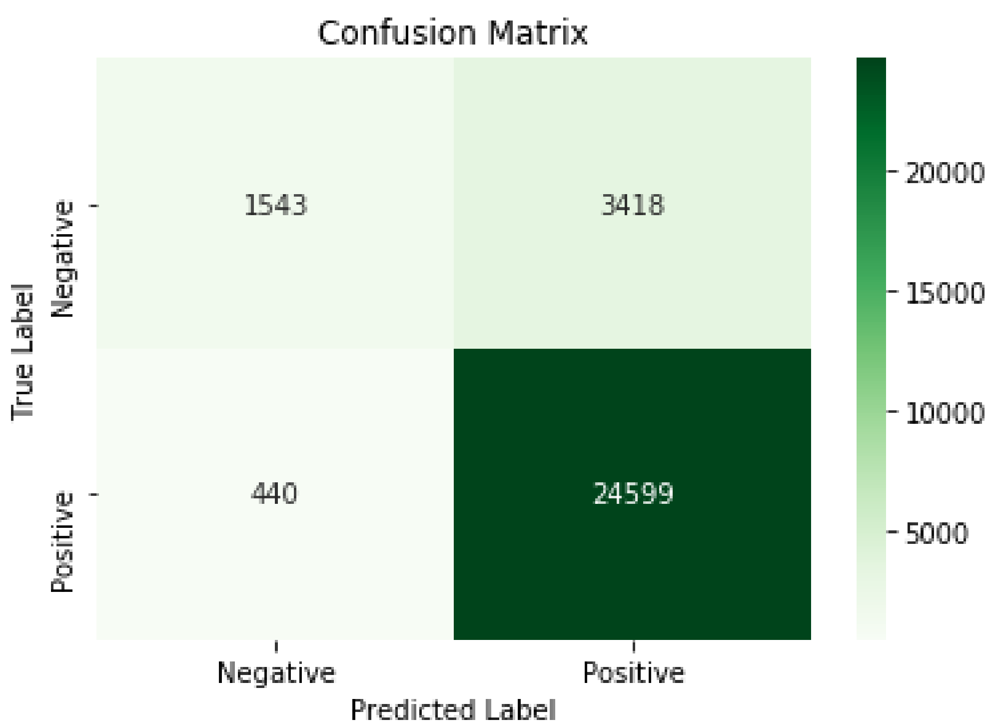
```
plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_avgw2v_std, y_train,
                              X_test_avgw2v_std, y_test, optimal_k, 'brute')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 19
```





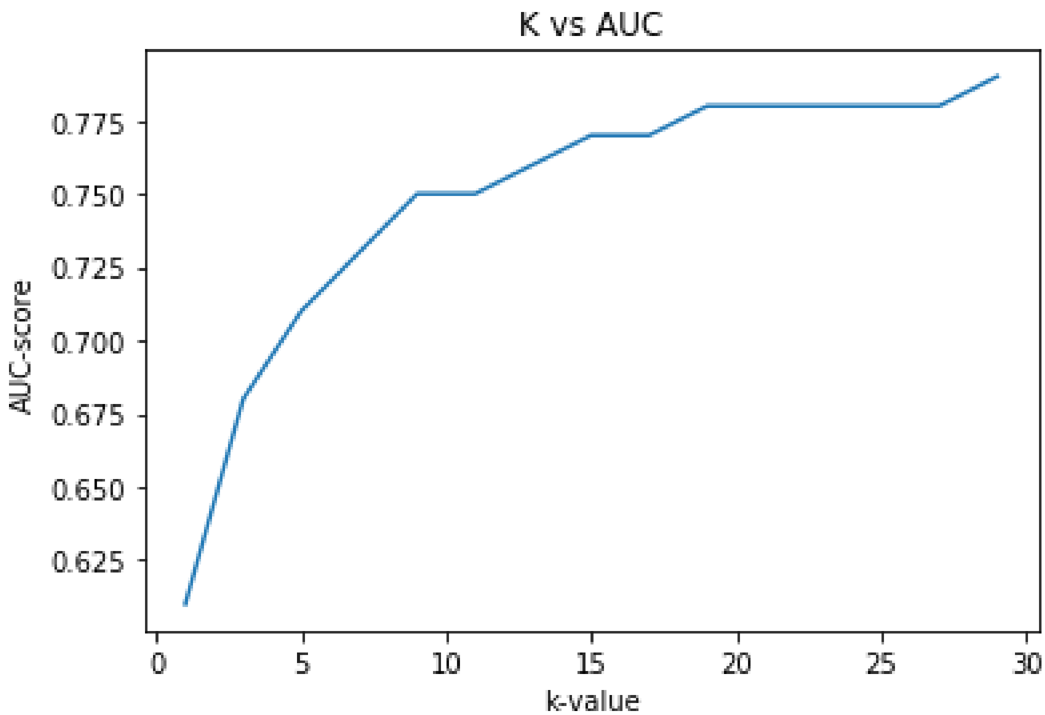

```
AUC score:
 0.87
```

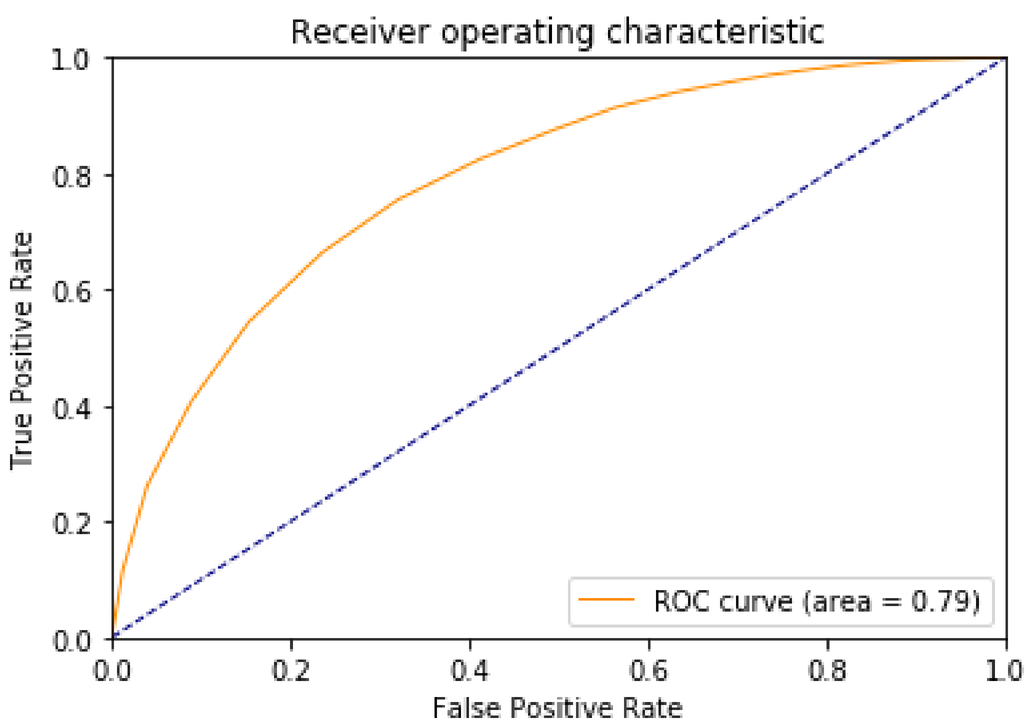


6.1.4 [5.1.4] Applying KNN brute force on TFIDF W2V, SET 4

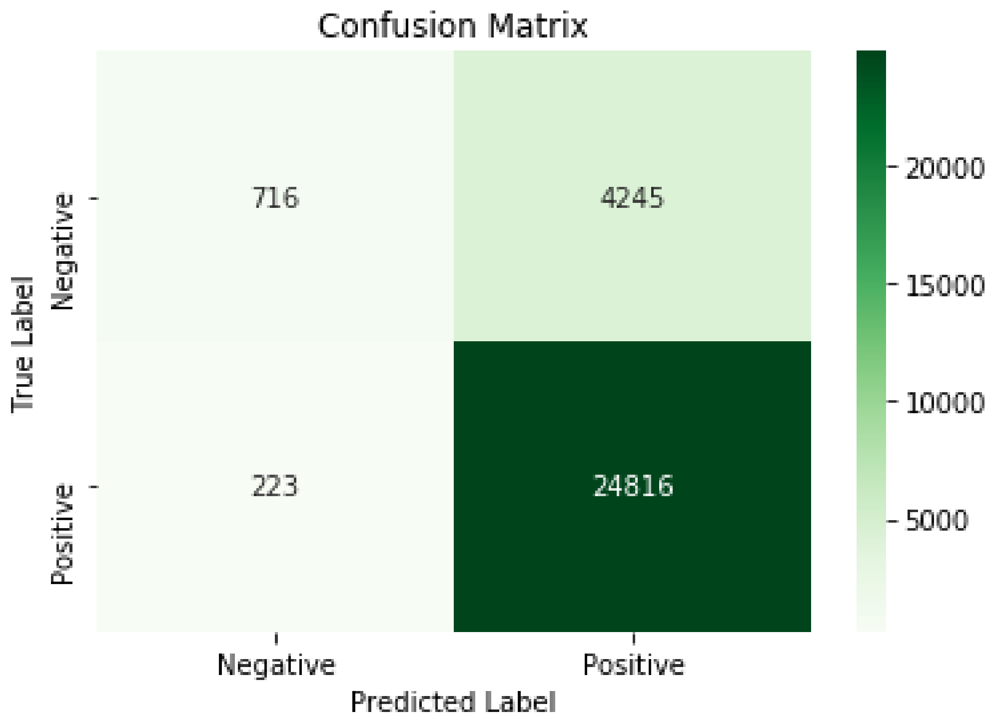
In [49]:
```
# Load the saved vectorized data for train-test datapoints
X_train_tfidfw2v = pkl.load(open('train_tfidfw2v.pkl', 'rb'))
X_test_tfidfw2v = pkl.load(open('test_tfidfw2v.pkl', 'rb'))

std = StandardScaler()

# Standardizing the vectors
X_train_tfidfw2v_std = std.fit_transform(X_train_tfidfw2v)
X_test_tfidfw2v_std = std.transform(X_test_tfidfw2v)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC

optimal_k, k_auc = get_optimal_k(X_train_tfidfw2v_std, y_train, 'brute')
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]

# Plotting K values vs AUC scores

plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_tfidfw2v_std, y_train,
                                      X_test_tfidfw2v_std, y_test, optimal_k, 'brute')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 29
```


K vs AUC
0.775
0.750
0.725
0.700
0.675
0.650
0.625
AUC-score
0
5
10
15
20
25
30
k-value


Receiver operating characteristic
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.79)

```
AUC score:
 0.79
```



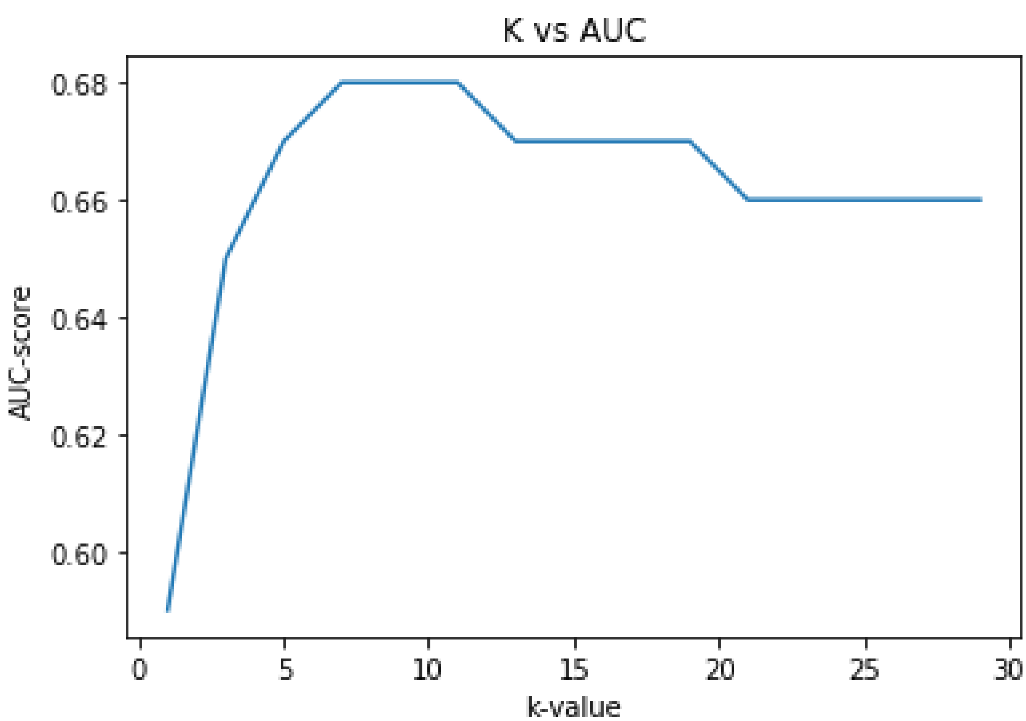
6.2 [5.2] Applying KNN kd-tree

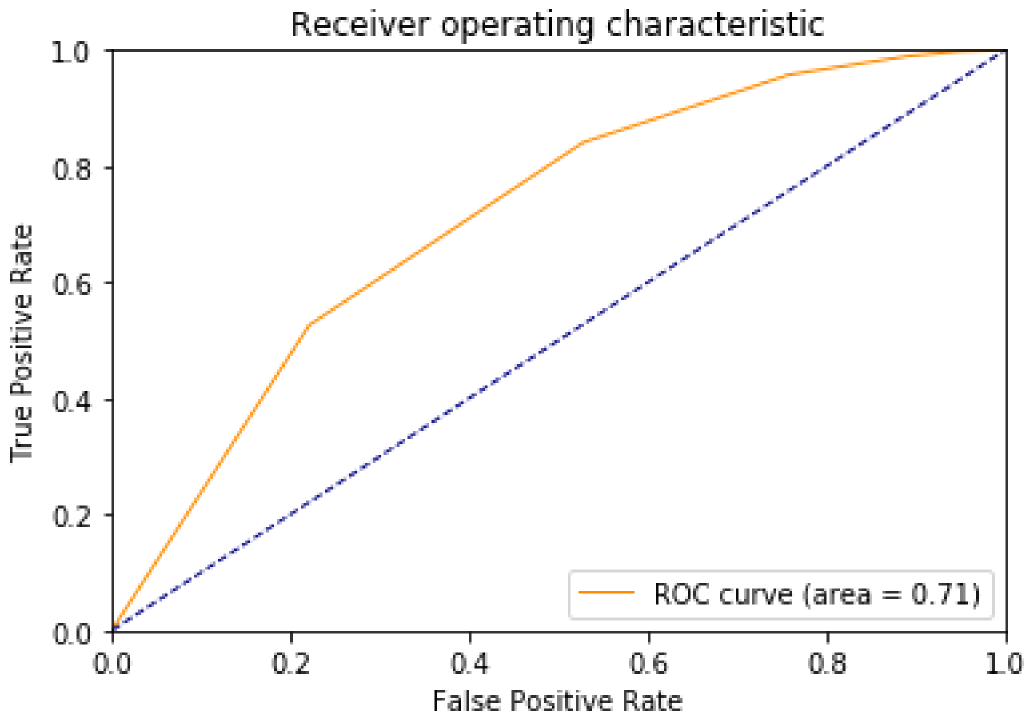
6.2.1 [5.2.1] Applying KNN kd-tree on BOW, SET 5

In [50]:
```
# Load the saved vectorized data for train-test datapoints
X_train_bow = pkl.load(open('train_bow_kd.pkl', 'rb'))
X_test_bow = pkl.load(open('test_bow_kd.pkl', 'rb'))

std = StandardScaler( with_mean=False)

# Standardizing the vectors
X_train_bow_std = std.fit_transform(X_train_bow)
X_test_bow_std = std.transform(X_test_bow)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC
optimal_k, k_auc = get_optimal_k(X_train_bow_std, y_train, "kd_tree")
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]
```

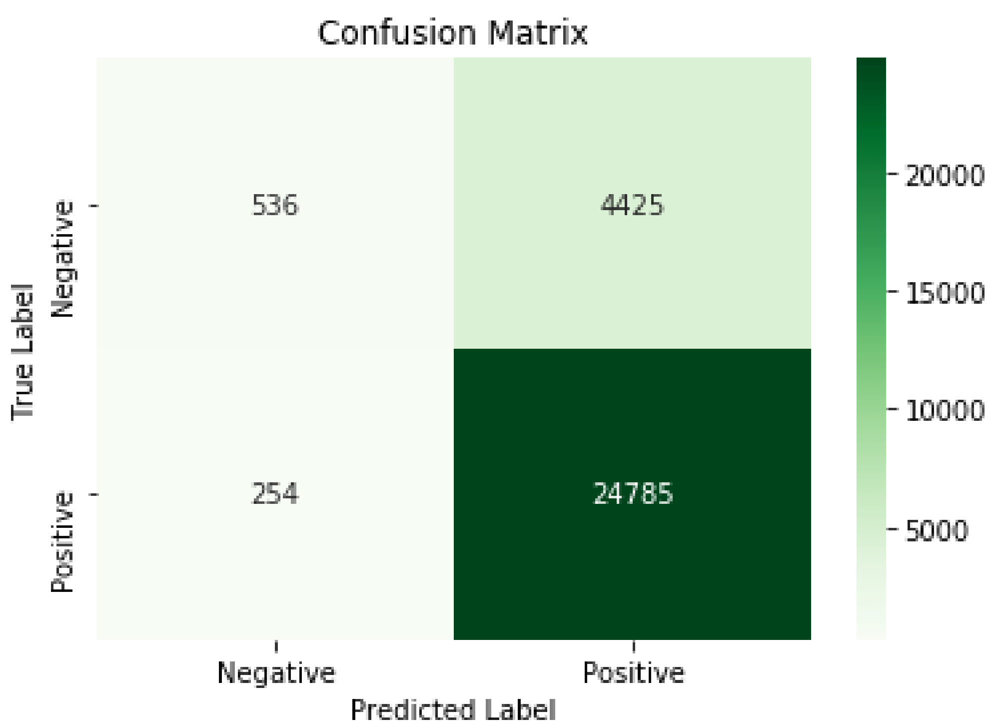
```python
# Plotting K values vs AUC scores
# These values are obtained during
# hyperparameter tuning and stored in
# auc_data

plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_bow_std, y_train,
                                      X_test_bow_std, y_test, optimal_k, 'kd_tree')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 7
```





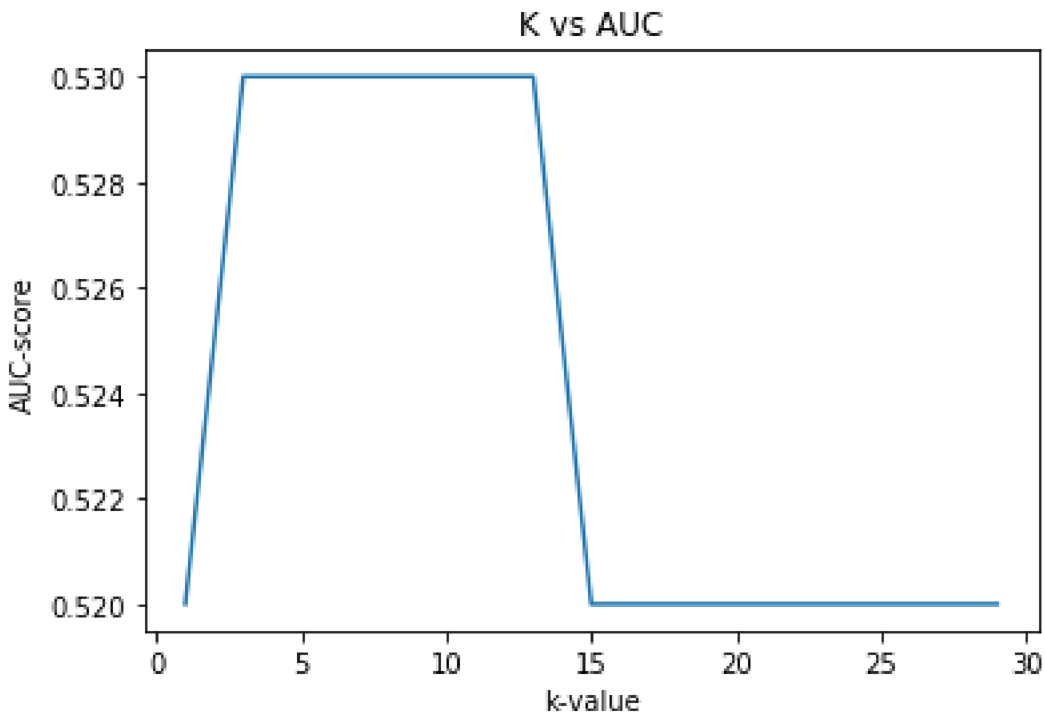

```
AUC score:
 0.71
```

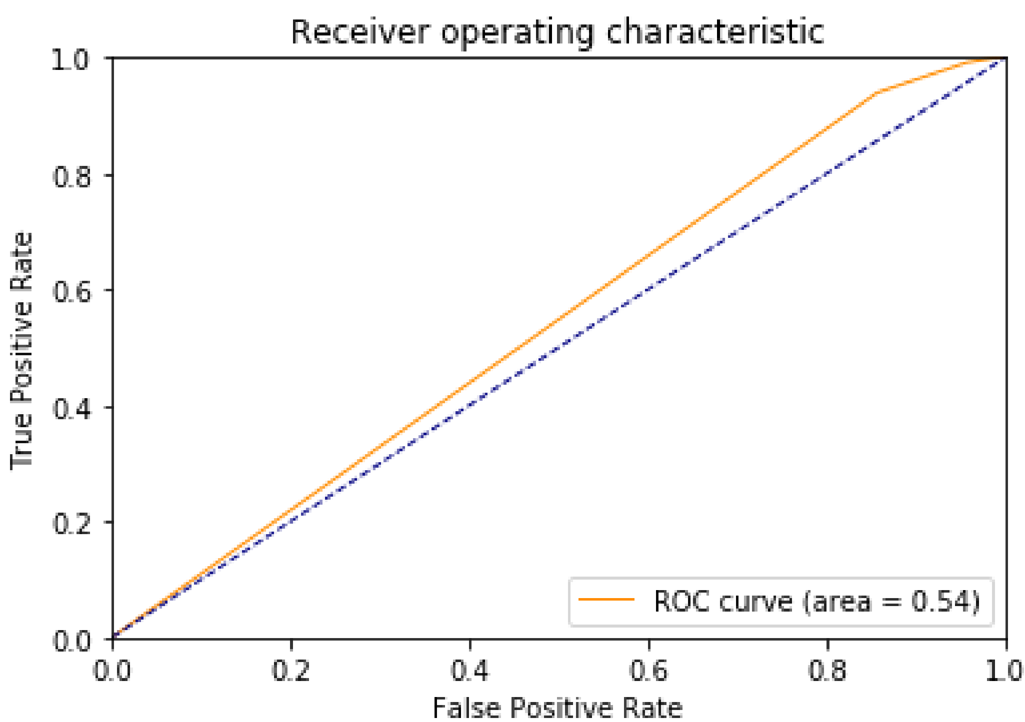


6.2.2 [5.2.2] Applying KNN kd-tree on TFIDF, SET 6

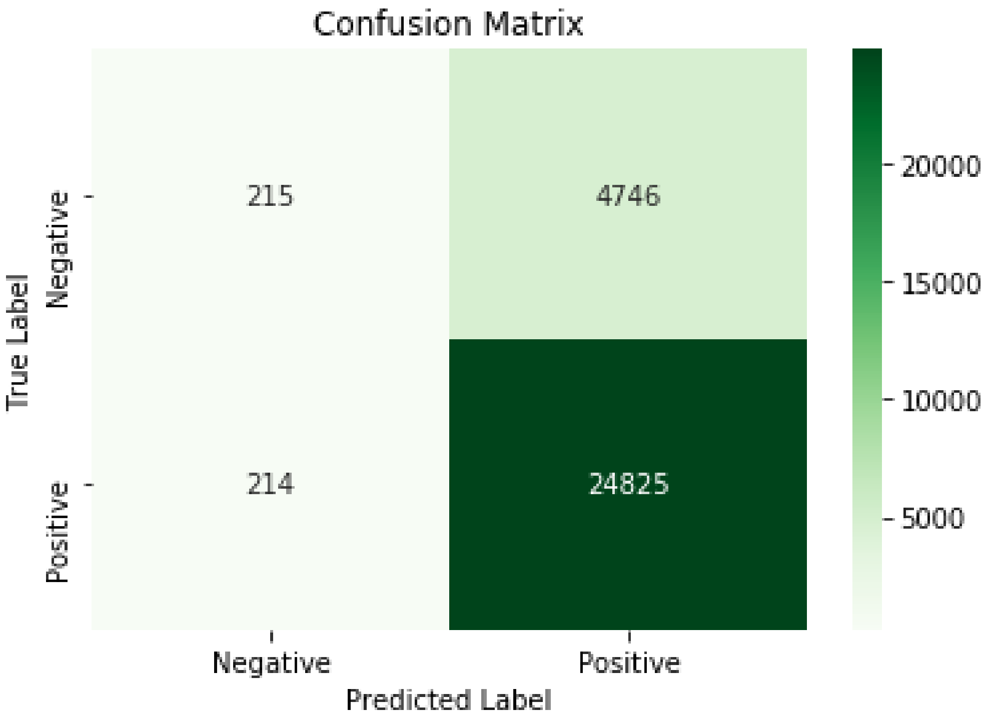
In [51]:
```
# Load the saved vectorized data for train-test datapoints
X_train_tfidf = pkl.load(open('train_tfidf_kd.pkl', 'rb'))
X_test_tfidf = pkl.load(open('test_tfidf_kd.pkl', 'rb'))

std = StandardScaler( with_mean=False)

# Standardizing the vectors
X_train_tfidf_std = std.fit_transform(X_train_tfidf)
X_test_tfidf_std = std.transform(X_test_tfidf)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC
optimal_k, k_auc = get_optimal_k(X_train_tfidf_std, y_train, "kd_tree")
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]

# Plotting K values vs AUC scores
# These values are obtained during
# hyperparameter tuning and stored in
# auc_data

plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_tfidf_std, y_train,
                                      X_test_tfidf_std, y_test, optimal_k, 'kd_tree')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 3
```


K vs AUC
0.530
0.528
0.526
0.524
0.522
0.520
AUC-score
0
5
10
15
20
25
30
k-value


Receiver operating characteristic
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.54)

```
AUC score:
 0.54
```

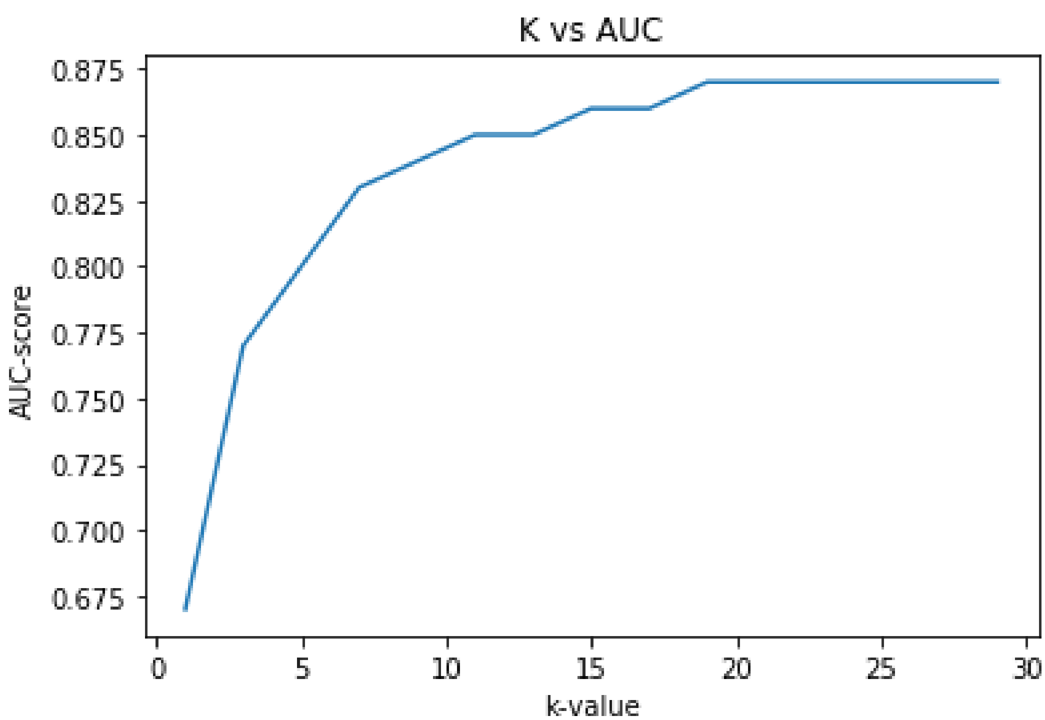


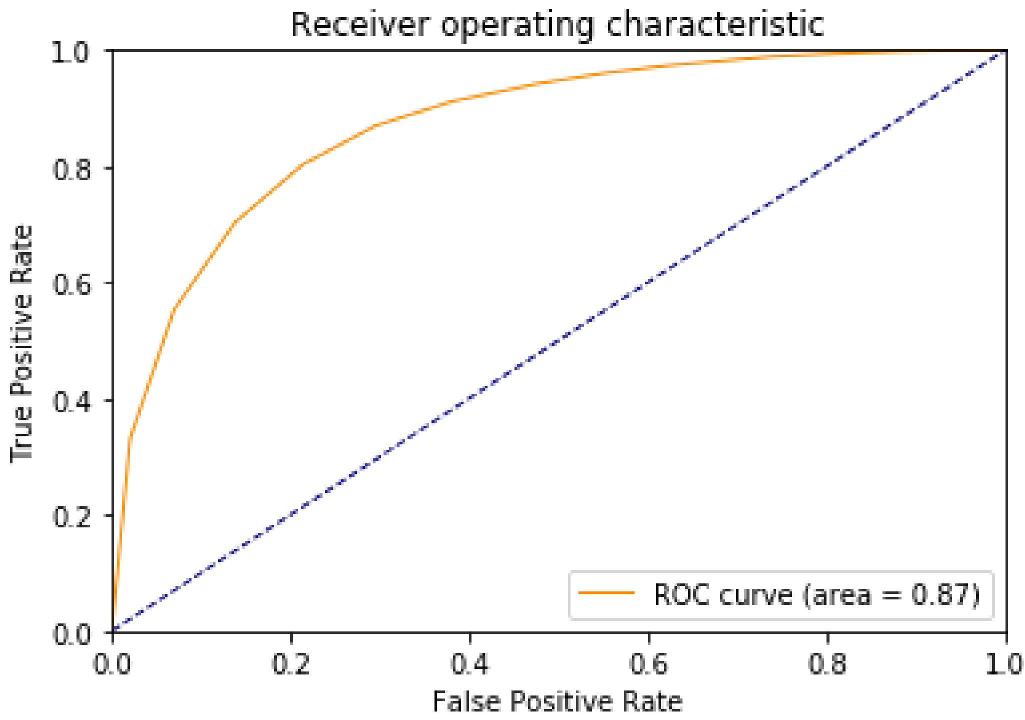
6.2.3 [5.2.3] Applying KNN kd-tree on AVG W2V, SET 3

In [52]:
```
# Load the saved vectorized data for train-test datapoints
X_train_avgw2v = pkl.load(open('train_avgw2v.pkl', 'rb'))
X_test_avgw2v = pkl.load(open('test_avgw2v.pkl', 'rb'))

std = StandardScaler()

# Standardizing the vectors
X_train_avgw2v_std = std.fit_transform(X_train_avgw2v)
X_test_avgw2v_std = std.transform(X_test_avgw2v)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC
optimal_k, k_auc = get_optimal_k(X_train_avgw2v_std, y_train, 'kd_tree')
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]

# Plotting K values vs AUC scores
```

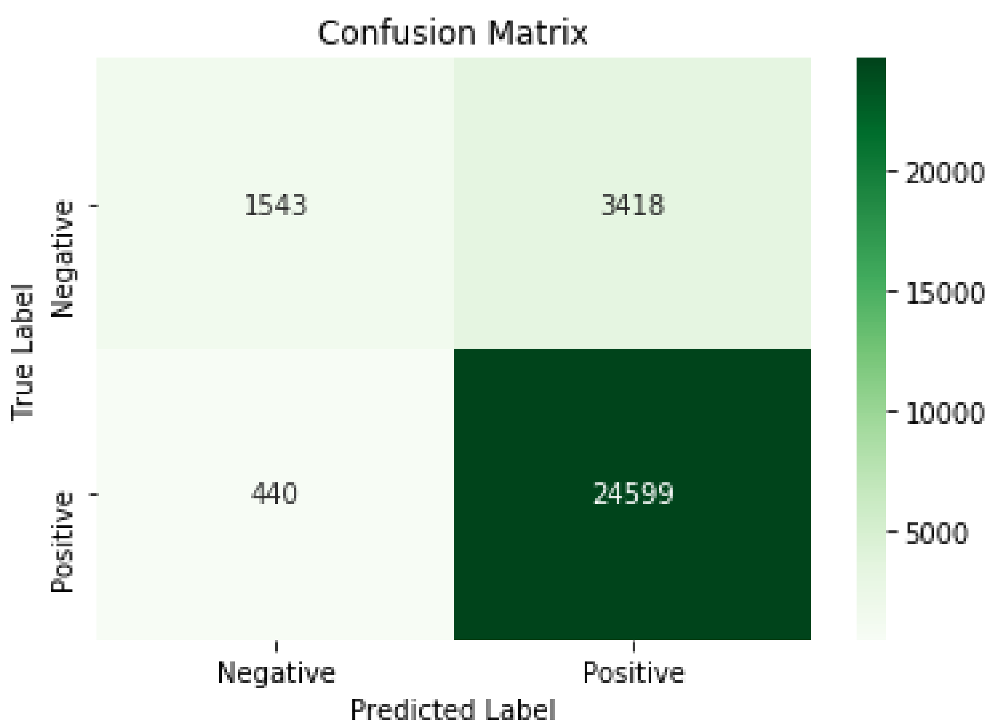
```
# These values are obtained during
# hyperparameter tuning and stored in
# auc_data

plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_avgw2v_std, y_train,
                                      X_test_avgw2v_std, y_test, optimal_k, 'kd_tree')

print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 19
```





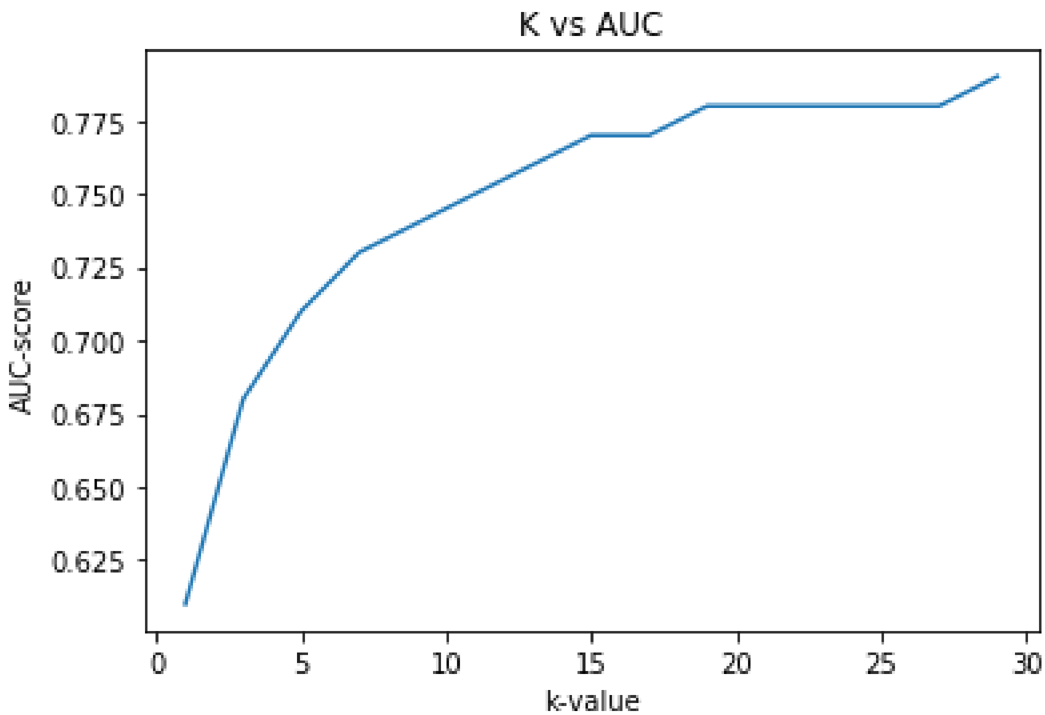

```
AUC score:
 0.87
```

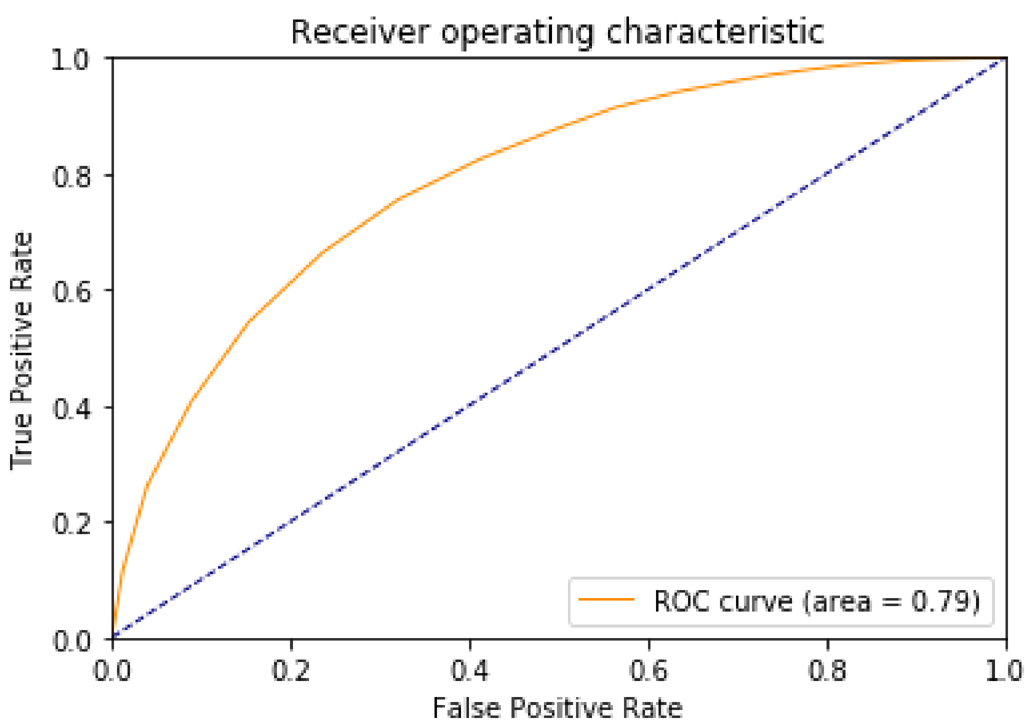


6.2.4 [5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 4

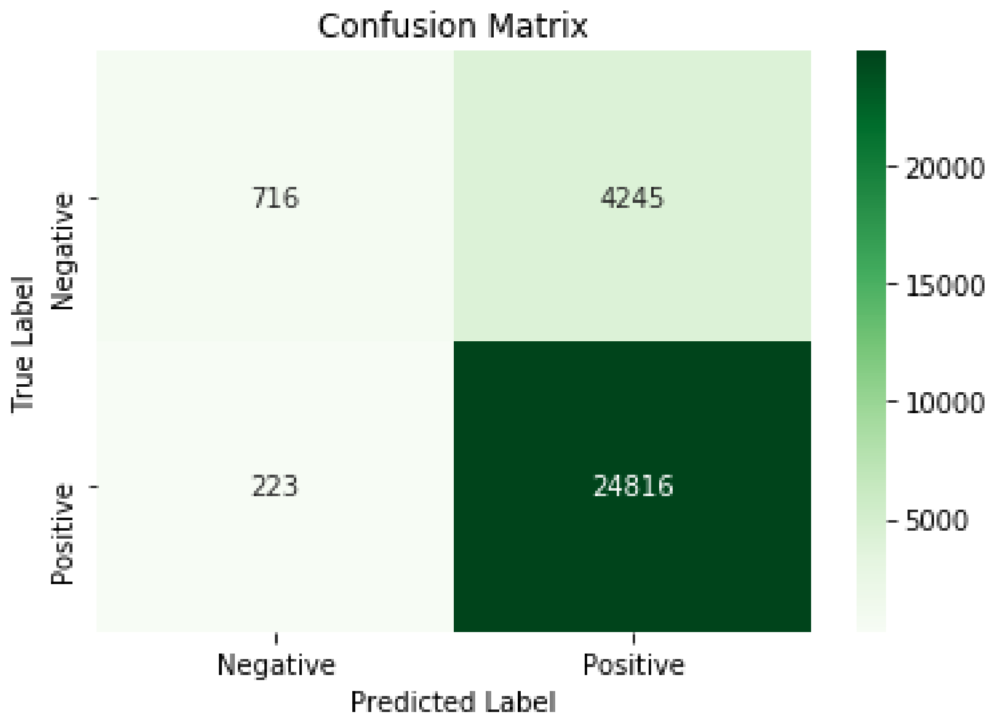
In [53]:
```
# Load the saved vectorized data for train-test datapoints
X_train_tfidfw2v = pkl.load(open('train_tfidfw2v.pkl', 'rb'))
X_test_tfidfw2v = pkl.load(open('test_tfidfw2v.pkl', 'rb'))

std = StandardScaler()

# Standardizing the vectors
X_train_tfidfw2v_std = std.fit_transform(X_train_tfidfw2v)
X_test_tfidfw2v_std = std.transform(X_test_tfidfw2v)

# Getting an optimal value of hyperparameter K and AUC scores
# This data is used to plot a graph of k-values vs AUC
optimal_k, k_auc = get_optimal_k(X_train_tfidfw2v_std, y_train, 'kd_tree')
print("Optimal value of K : {}".format(optimal_k))

auc_data = [(k, accuracy) for k, accuracy in k_auc]

# Plotting K values vs AUC scores
plt.title("K vs AUC")
plt.xlabel("k-value")
plt.ylabel("AUC-score")
plt.plot(*(zip(*auc_data)))
plt.show()

# Running KNN with optimal k value obtained
auc_score, conf_mat = run_knn(X_train_tfidfw2v_std, y_train,
                                      X_test_tfidfw2v_std, y_test, optimal_k, 'kd_tre
                                      
print("AUC score:\n {:.2f}".format(auc_score))

# Plotting confusion matrix
plot_confusion_matrix(conf_mat)
```

```
Optimal value of K : 29
```


K vs AUC
0.775
0.750
0.725
0.700
0.675
0.650
0.625
AUC-score
0
5
10
15
20
25
30
k-value


Receiver operating characteristic
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.79)

```
AUC score:
 0.79
```




```
In [1]: # Print the results obtained in a table format
        def print_results():
            headers = ['Vectorizer', 'Algorithm', 'K', 'AUC']
            result = PrettyTable(padding_width=5)
            result.field_names = headers

            #result.align["Vectorizer"] = "l"
            #result.align["K"] = "c"
            #result.align["AUC"] = "r"

            result.add_row(["BoW", 'Brute', 3, 0.58])
            result.add_row(["BoW", 'KD-Tree', 7, 0.71])
            result.add_row(["TFIDF", 'Brute', 1, 0.51])
            result.add_row(["TFIDF", 'KD-Tree', 3, 0.54])
            result.add_row(["AvgW2V", 'Brute', 19, 0.87])
            result.add_row(["AvgW2V", 'KD-Tree', 19, 0.87])
            result.add_row(["TfidfW2v", 'Brute', 29, 0.79])
            result.add_row(["TfidfW2v", 'KD-Tree', 29, 0.79])
            print(result)
```

7 [6] Conclusions

1. We tried BoW, TF-IDF, Average Word2Vec and Tfidf weighted Word2Vec vectorizers on KNN with Brute force and KD-Tree algorithms.
2. Average Word2Vec gives the best results with an AUC value of 0.87 with 19NN in both Brute force and KD-Tree algorithms.
3. TF-IDF performs the worst and AUC scores obtained were no better than a random model.

```
In [5]: print_results()
```

```
+--------------------+-------------------+------------+--------------+
|     Vectorizer     |     Algorithm     |     K      |     AUC      |
+--------------------+-------------------+------------+--------------+
|        BoW         |       Brute       |     3      |     0.58     |
|        BoW         |      KD-Tree      |     7      |     0.71     |
|       TFIDF        |       Brute       |     1      |     0.51     |
|       TFIDF        |      KD-Tree      |     3      |     0.54     |
|       AvgW2V       |       Brute       |     19     |     0.87     |
|       AvgW2V       |      KD-Tree      |     19     |     0.87     |
|      TfidfW2v      |       Brute       |     29     |     0.79     |
|      TfidfW2v      |      KD-Tree      |     29     |     0.79     |
+--------------------+-------------------+------------+--------------+
```