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 sqlite3
import pandas as pd
import numpy as np
import scipy
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.preprocessing import normalize
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
import scikitplot.metrics as skplt


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


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

from tqdm import tqdm
import os
```

[1]. Reading Data

In [2]:

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')
#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data points
# you can change the number to any other number based on your computing power

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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 50000""", 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 0
    return 1

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

```
Number of data points in our data (50000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all

In [3]:

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

In [4]:

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

```
(80668, 7)
```

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [5]:

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

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	5

In [6]:

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

Out[6]:

```
393063
```

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 [7]:

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

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summ
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANIL WAFE
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANIL WAFE
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANIL WAFE
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANIL WAFE
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANIL WAFE

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 [8]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='qui
cksort', na_position='last')
```

In [9]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inpl
ace=False)
final.shape
```

Out[9]:

```
(46072, 10)
```

In [10]:

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

Out[10]:

```
92.144
```

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

In [11]:

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

display.head()
```

Out[11]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892800	Bought This for My Son at College
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside

In [12]:

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

In [13]:

```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
(46071, 10)
```

Out[13]:

```
1    38479
0     7592
Name: Score, dtype: int64
```

[3]. 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.

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

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

In [14]:

```
# https://stackoverflow.com/a/47091490/4084039
import re

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

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

In [15]:

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

In [16]:

```
# Combining all the above statements
from tqdm import tqdm
from bs4 import BeautifulSoup

ps=PorterStemmer()
preprocessed_reviews = []
```

```python
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)

    sentance = ' '.join(ps.stem(e.lower()) for e in sentance.split() if e.lower() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████████████████████████████| 46071/46071 [01:
10<00:00, 655.42it/s]
```

In [17]:

```python
#len(preprocessed_reviews)
preprocessed_reviews[1000]
```

Out[17]:

```
'yummi easi unusu make quick delic pie crisp cobbler home made better heck lot work great hand
last minut dessert need realli want impress wih creativ cook recommend'
```

In [18]:

```python
final['CleanedText']=preprocessed_reviews
final.columns
```

Out[18]:

```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'CleanedText'],
      dtype='object')
```

In [19]:

```python
final['Time'][0]
```

Out[19]:

```
1303862400
```

In [20]:

```python
#Sorting based on Time
final['Time'] = pd.to_datetime(final['Time'], origin='unix', unit='s')
final = final.sort_values('Time')
print(final.shape)
print(final['Time'].head(1000))
```

```
(46071, 11)
1146    2000-06-23
1145    2000-06-29
28086   2003-10-25
28087   2003-10-25
38740   2003-10-31
           ...
2873    2007-02-14
6560    2007-02-14
30910   2007-02-15
47172   2007-02-15
40986   2007-02-15
Name: Time, Length: 1000, dtype: datetime64[ns]
```

In [21]:

```python
#Splitting Data into Train CV and Test
```

```
%matplotlib inline
import warnings
from sklearn.model_selection import train_test_split

X_tr, X_test, Y_tr, Y_test = train_test_split(final['CleanedText'], final['Score'],
                                              test_size=.33, random_state=0)
X_train, X_cv, Y_train, Y_cv = train_test_split(X_tr, Y_tr, test_size=.33, random_state=0)
```

In [22]:

```
print([i.shape for i in [X_train,Y_train, X_cv, Y_cv, X_test, Y_test]])
```

```
[(20680,), (20680,), (10187,), (10187,), (15204,), (15204,)]
```

In [23]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score


def knn(X_train, Y_train, X_cv, Y_cv, X_test, Y_test, algorithm):
    pred_cv=[]
    pred_train=[]
    k=[]
    for i in tqdm(range (9, 70, 2)):
        knn=KNeighborsClassifier(n_neighbors=i, algorithm=algorithm, p=2, n_jobs=-1)
        # fitting the model on train
        knn.fit(X_train, Y_train)
        _prob_cv = knn.predict_proba(X_cv)[:,1]
        _prob_train = knn.predict_proba(X_train)[:,1]
        auc_score_cv = roc_auc_score(Y_cv,_prob_cv)
        auc_score_train = roc_auc_score(Y_train,_prob_train)
        pred_cv.append(auc_score_cv)
        pred_train.append(auc_score_train)
        k.append(i)


    best_hyperparameter=k[pred_cv.index(max(pred_cv))]
    print('Best Hyperparamer K is- ', best_hyperparameter)
    plt.plot(k, pred_cv,'r-', label = 'Validation AUC')
    plt.plot(k,pred_train,'g-', label ='Train AUC')
    plt.legend(loc='upper right')
    plt.title("Hyperparameter K v/s Auc Score")
    plt.ylabel('Auc Score')
    plt.xlabel('Hyper Paramer K')
    plt.show()

    return best_hyperparameter
```

In [24]:

```
def knn_test(X_train, Y_train, X_test, Y_test, algorithm, best_hyperparameter):
    pred_test=[]
    pred_train=[]
    knn= KNeighborsClassifier(n_neighbors=best_hyperparameter, algorithm=algorithm,p=2, n_jobs=-1)
    knn.fit(X_test, Y_test)
    prob_test=knn.predict_proba(X_test)[:,1]
    prob_train = knn.predict_proba(X_train)[:,1]
    test_fpr, test_tpr, _ = roc_curve(Y_test,prob_test )
    train_fpr, train_tpr, _ = roc_curve(Y_train,prob_train )
    print("AUC Score",roc_auc_score(Y_test,prob_test))

    # plot the roc curve
    plt.plot(test_fpr, test_tpr, linestyle='--', label='Test ROC')
    plt.plot(train_fpr, train_tpr, marker='.', label='Train ROC')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.legend()
    plt.show()
```

```python
    #plot confusion matrix
    skplt.plot_confusion_matrix(Y_test, knn.predict(X_test))
```

[4] Featurization using Brute Algorithm

[4.1] BAG OF WORDS

In [25]:

```python
#Compute BoW
countVector=CountVectorizer(min_df=5)
bow_train=countVector.fit_transform(X_train)

bow_cv=countVector.transform(X_cv)
bow_test=countVector.transform(X_test)

print(list(map(type, [bow_train,bow_cv,bow_test])))
print('Shape of bow_train is: ', bow_train.shape)
print('Shape of bow_cv is: ', bow_cv.shape)
print('Shape of bow_test is: ', bow_test.shape)
```

```
[<class 'scipy.sparse.csr.csr_matrix'>, <class 'scipy.sparse.csr.csr_matrix'>, <class
'scipy.sparse.csr.csr_matrix'>]
Shape of bow_train is:  (20680, 5911)
Shape of bow_cv is:  (10187, 5911)
Shape of bow_test is:  (15204, 5911)
```

In [26]:

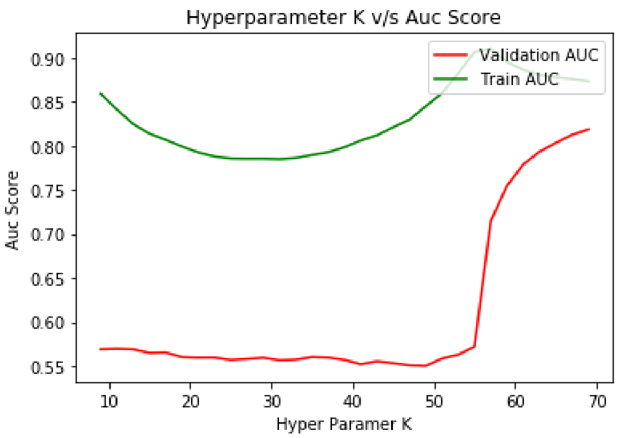
```python
#Normalise BoW Data
bow_train=normalize(X=bow_train, axis=1, norm='l2')
bow_cv=normalize(X=bow_cv, axis=1, norm='l2')
bow_test=normalize(X=bow_test,axis=1, norm='l2')
```

In [27]:

```python
#map(scipy.sparse.csr.csr_matrix.toarray, [bow_train, bow_cv, bow_test])
best_hyperparameter= knn(bow_train,Y_train, bow_cv,Y_cv, bow_test, Y_test,  'brute')
```

```
100%|████████████████████████████████████████| 31/31
[23:05<00:00, 44.68s/it]
```

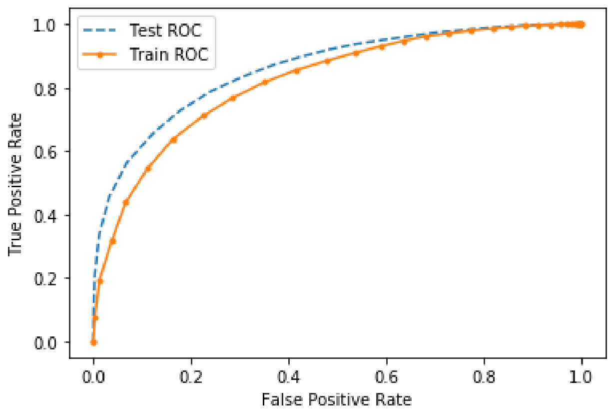
```
Best Hyperparamer K is-  69
```

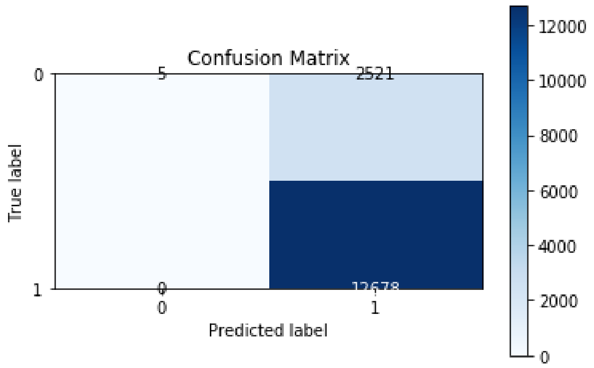


In [28]:

```python
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(bow_train,Y_train,  bow_test, Y_test,  'brute',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  69
AUC Score 0.8599941894719277
```





[4.2] TF-IDF

In [29]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=5)
tf_idf_train=tf_idf_vect.fit_transform(X_train)

tf_idf_cv = tf_idf_vect.transform(X_cv)
tf_idf_test=tf_idf_vect.transform(X_test)


print(list(map(type, [tf_idf_train,tf_idf_cv,tf_idf_test])))
print('Shape of bow_train is: ', tf_idf_train.shape)
print('Shape of bow_cv is: ', tf_idf_cv.shape)
print('Shape of bow_test is: ', tf_idf_test.shape)
```

```
[<class 'scipy.sparse.csr.csr_matrix'>, <class 'scipy.sparse.csr.csr_matrix'>, <class
'scipy.sparse.csr.csr_matrix'>]
Shape of bow_train is:  (20680, 28452)
Shape of bow_cv is:  (10187, 28452)
Shape of bow_test is:  (15204, 28452)
```

In [30]:

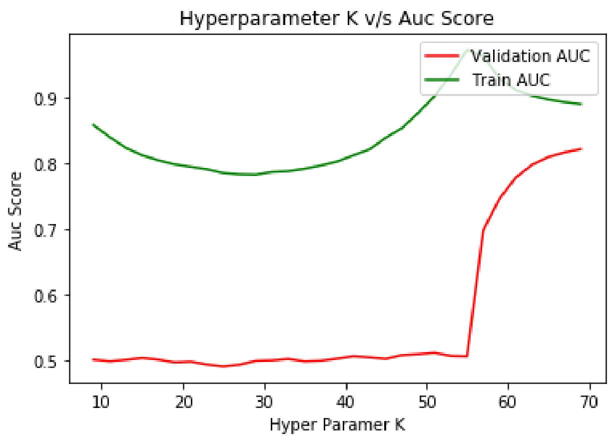
```
#normalize
tf_idf_train=normalize(tf_idf_train)
tf_idf_cv = normalize(tf_idf_cv)
tf_idf_test=normalize(tf_idf_test)
```

In [31]:

```
best_hyperparameter= knn(tf_idf_train,Y_train, tf_idf_cv,Y_cv, tf_idf_test, Y_test,  'brute')
```

```
100%|██████████████████████████████████████████████████| 31/31
[24:04<00:00, 46.60s/it]
```

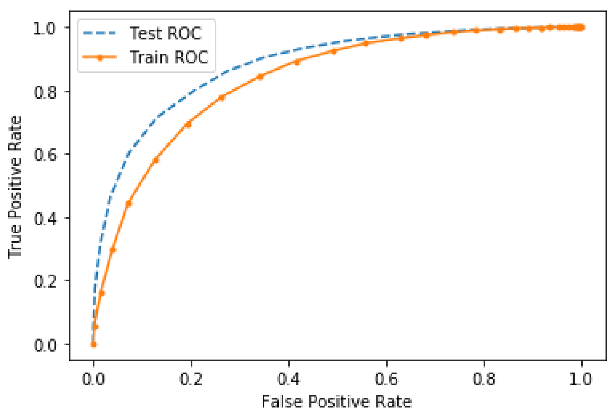
```
Best Hyperparamer K is-  69
```

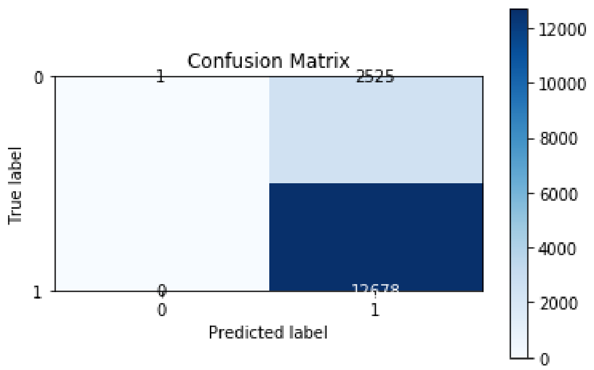


In [32]:

```python
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(tf_idf_train,Y_train,  tf_idf_test, Y_test,  'brute',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  69
AUC Score 0.8815858688506859
```





[4.3] Word2Vec

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

[4.3.1] Avg W2v

In [33]:

```python
# average Word2Vec for train, validation and test data
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)

#avgw2v for train data
sent_vectors_train = [];
for sent in tqdm(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_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))

#avgw2v for validation data
list_of_sentance_cv=[]
sent_vectors_cv = []
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())

for sent in tqdm(list_of_sentance_cv):
    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_cv.append(sent_vec)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))

#avgw2v for test data
sent_vectors_test = []
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
for sent in tqdm(list_of_sentance_test):
    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_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
100%|██████████████████████████████████████████████████████████████████████████| 20680/20680 [00:30<00:00, 674.25it/s]
```

```
20680
50
```

```
100%|██████████████████████████████████████████████████████████████████████████| 10187/10187 [00:15<00:00, 675.14it/s]
```

```
10187
50
```

```
100%|██████████████████████████████████████████████████| 15204/15204 [00:
22<00:00, 675.31it/s]
```

```
15204
50
```

In [34]:

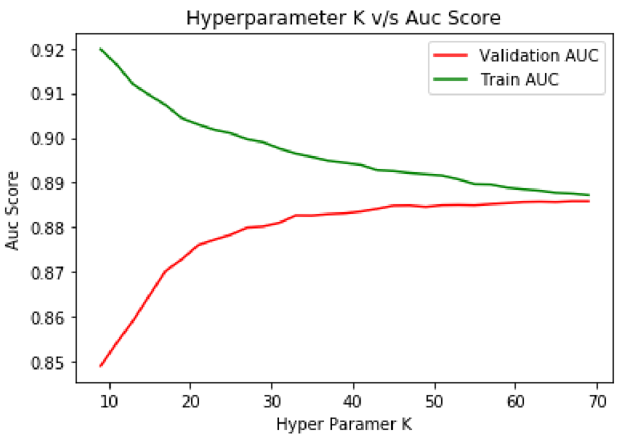
```python
#Normalizing
avgw2v_train=normalize(sent_vectors_train)
avgw2v_cv=normalize(sent_vectors_cv)
avgw2v_test=normalize(sent_vectors_test)
```

In [35]:

```python
best_hyperparameter= knn(avgw2v_train,Y_train, avgw2v_cv,Y_cv, avgw2v_test, Y_test,  'brute')
```

```
100%|████████████████████████████████████████████████████████| 31/31
[20:14<00:00, 39.18s/it]
```

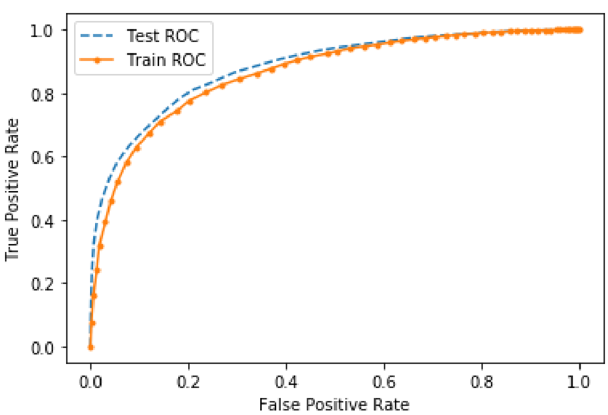
```
Best Hyperparamer K is-  67
```

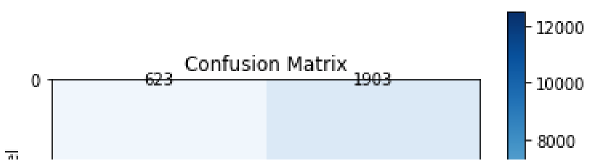


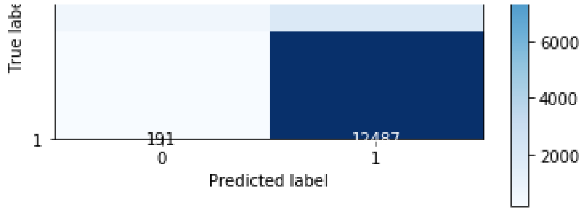
In [36]:

```python
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(avgw2v_train,Y_train,  avgw2v_test, Y_test,  'brute',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  67
AUC Score 0.8824298130801083
```







[4.3.2] TFIDF weighted W2V

In [37]:

```
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_)))

#TFIDF weighted W2V for train data
tfidf_sent_vectors_train = []
row=0;
for sent in tqdm(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

#TFIDF weighted W2V for validation data
list_of_sentance_cv=[]
tfidf_sent_vectors_cv = []

for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())

row=0;
for sent in tqdm(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
#TFIDF weighted W2V for test data

list_of_sentance_test=[]
tfidf_sent_vectors_test = []
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
row=0;
for sent in tqdm(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
```

```
100%|██████████████████████████████████████████████████████████████| 20680/20680 [00:43<00:00, 478.34it/s]
100%|██████████████████████████████████████████████████████████████| 10187/10187 [00:23<00:00, 437.68it/s]
100%|██████████████████████████████████████████████████████████████| 15204/15204 [00:32<00:00, 463.61it/s]
```

In [38]:

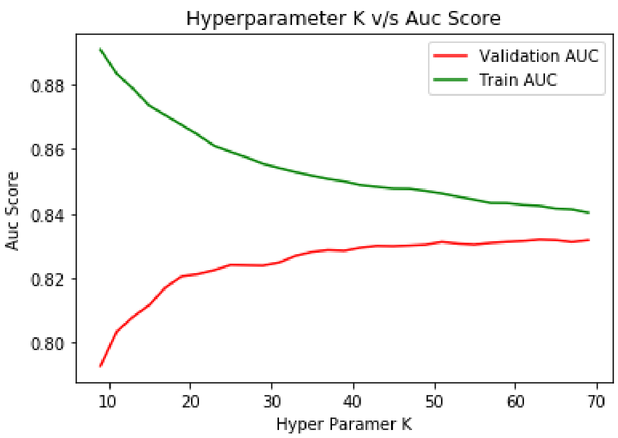
```
#normalize train, validation and test data
tfidf_w2v_train=normalize(tfidf_sent_vectors_train)
tfidf_w2v_cv=normalize(tfidf_sent_vectors_cv)
tfidf_w2v_test=normalize(tfidf_sent_vectors_test)
```

In [39]:

```
best_hyperparameter= knn(tfidf_w2v_train,Y_train, tfidf_w2v_cv,Y_cv, tfidf_w2v_test, Y_test,  'brute')
```

```
100%|██████████████████████████████████████████████████████████████████| 31/31 [20:10<00:00, 39.06s/it]
```

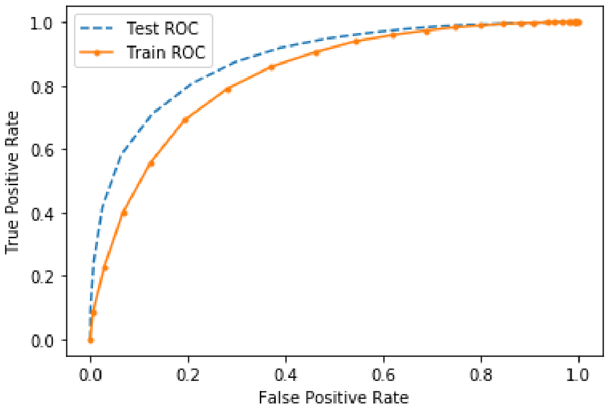
```
Best Hyperparamer K is-  63
```

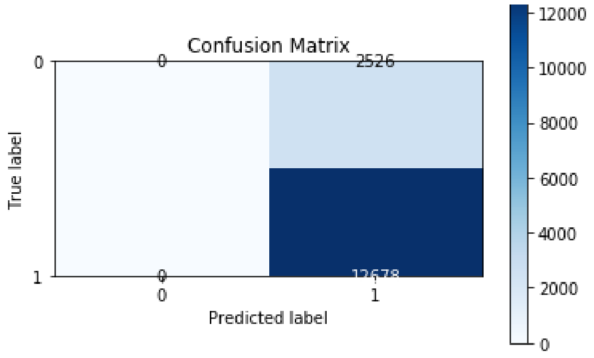


In [40]:

```
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(tf_idf_train,Y_train,  tf_idf_test, Y_test,  'brute',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  63
AUC Score 0.8825635538998298
```





[5] Featurization using kd-tree Algorithm

[5.1] Bag Of Words

In [41]:

```
#Compute BoW
countVector=CountVectorizer(min_df=5, max_features=500)
bow_train=countVector.fit_transform(X_train)

bow_cv=countVector.transform(X_cv)
bow_test=countVector.transform(X_test)

print(list(map(type, [bow_train,bow_cv,bow_test])))
print('Shape of bow_train is: ', bow_train.shape)
print('Shape of bow_cv is: ', bow_cv.shape)
print('Shape of bow_test is: ', bow_test.shape)
```

```
[<class 'scipy.sparse.csr.csr_matrix'>, <class 'scipy.sparse.csr.csr_matrix'>, <class
'scipy.sparse.csr.csr_matrix'>]
Shape of bow_train is:  (20680, 500)
Shape of bow_cv is:  (10187, 500)
Shape of bow_test is:  (15204, 500)
```

In [42]:

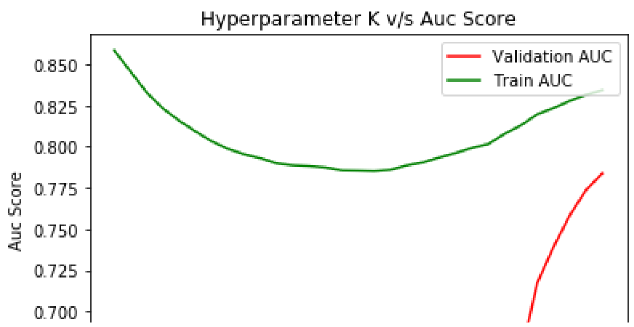
```
#Normalise BoW Data
bow_train=normalize(X=bow_train, axis=1, norm='l2')
bow_cv=normalize(X=bow_cv, axis=1, norm='l2')
bow_test=normalize(X=bow_test,axis=1, norm='l2')
```

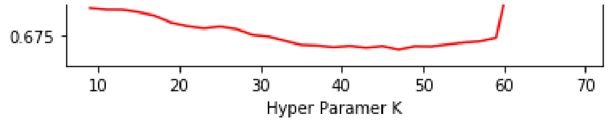
In [43]:

```
#convert sparse matrix to dense and find best k
map(scipy.sparse.csr.csr_matrix.toarray, [bow_train, bow_cv, bow_test])
best_hyperparameter= knn(bow_train,Y_train, bow_cv,Y_cv, bow_test, Y_test,  'kd_tree')
```

```
100%|████████████████████████████████████████████████████████████████| 31/31
[18:03<00:00, 34.95s/it]
```

```
Best Hyperparamer K is-  69
```

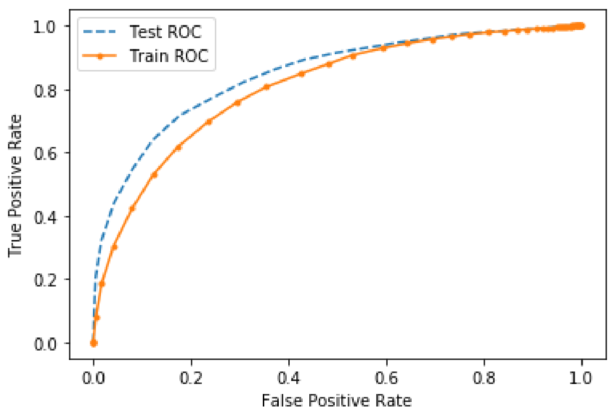


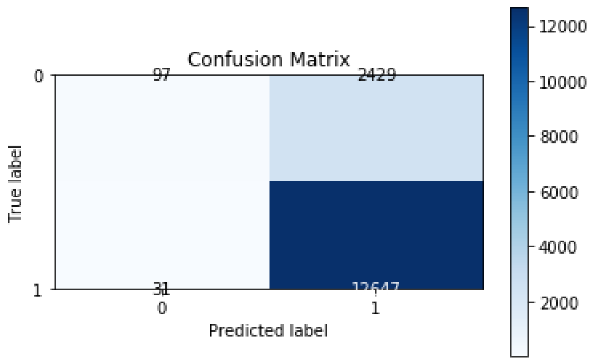


In [44]:

```
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(bow_train,Y_train,  bow_test, Y_test,  'kd_tree',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  69
AUC Score 0.8460979312546582
```





[5.2] TF_IDF

In [45]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=5, max_features=500)
tf_idf_train=tf_idf_vect.fit_transform(X_train)

tf_idf_cv = tf_idf_vect.transform(X_cv)
tf_idf_test=tf_idf_vect.transform(X_test)


print(list(map(type, [tf_idf_train,tf_idf_cv,tf_idf_test])))
print('Shape of bow_train is: ', tf_idf_train.shape)
print('Shape of bow_cv is: ', tf_idf_cv.shape)
print('Shape of bow_test is: ', tf_idf_test.shape)
```

```
[<class 'scipy.sparse.csr.csr_matrix'>, <class 'scipy.sparse.csr.csr_matrix'>, <class
'scipy.sparse.csr.csr_matrix'>]
Shape of bow_train is:  (20680, 500)
Shape of bow_cv is:  (10187, 500)
Shape of bow_test is:  (15204, 500)
```

In [46]:

```
tf_idf_train=normalize(tf_idf_train)
tf_idf_cv = normalize(tf_idf_cv)
```

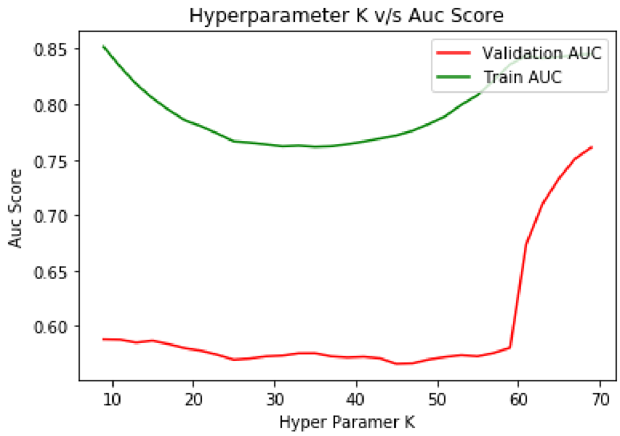
```
tf_idf_cv=normalize(tf_idf_cv)
tf_idf_test=normalize(tf_idf_test)
```

In [47]:

```
map(scipy.sparse.csr_matrix.toarray, [tf_idf_train, tf_idf_cv, tf_idf_test])
best_hyperparameter= knn(tf_idf_train,Y_train, tf_idf_cv,Y_cv, tf_idf_test, Y_test,  'kd_tree')
```

```
100%|██████████████████████████████████████████████████████████████████████| 31/31
[17:48<00:00, 34.47s/it]
```

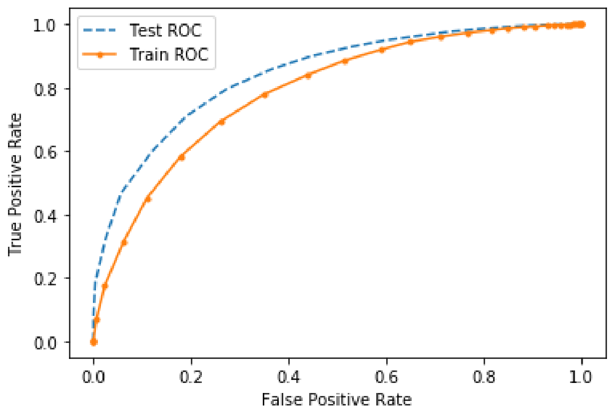
```
Best Hyperparamer K is-  69
```

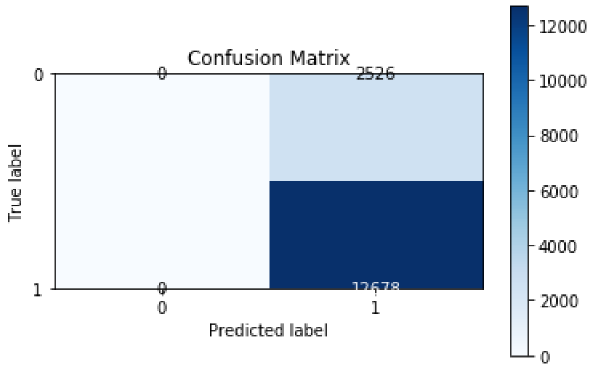


In [48]:

```
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(tf_idf_train,Y_train,  tf_idf_test, Y_test,  'kd_tree',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  69
AUC Score 0.8427393130062276
```





[5.3] Word2Vec

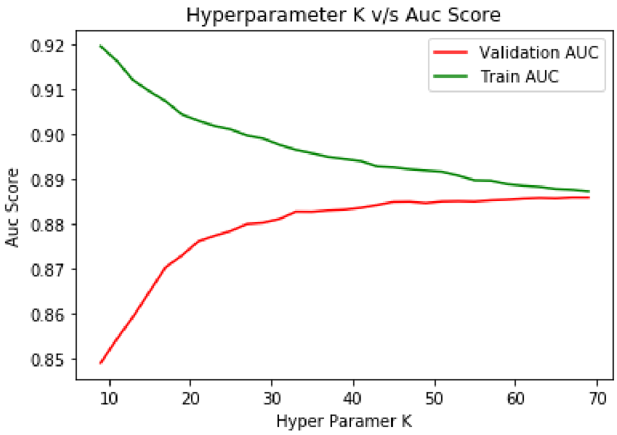
[5.3.1] Avg W2v

In [49]:

```
best_hyperparameter= knn(avgw2v_train,Y_train, avgw2v_cv,Y_cv, avgw2v_test, Y_test,  'kd_tree')
```

```
100%|██████████████████████████████████████████████████| 31/31
[19:12<00:00, 37.17s/it]
```

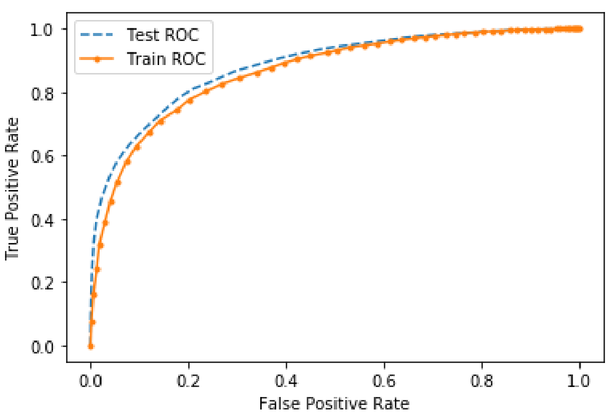
```
Best Hyperparamer K is-  67
```

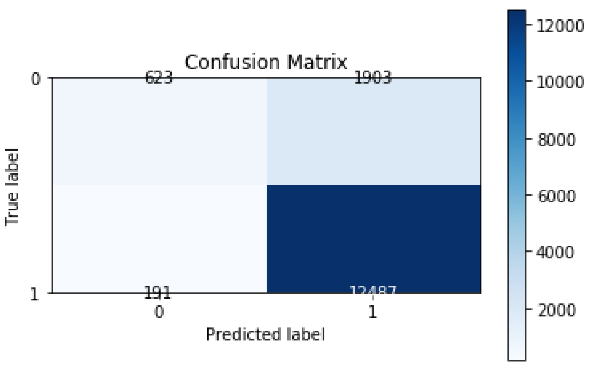


In [50]:

```
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(avgw2v_train,Y_train,  avgw2v_test, Y_test,  'kd_tree',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  67
AUC Score 0.8825657397175699
```



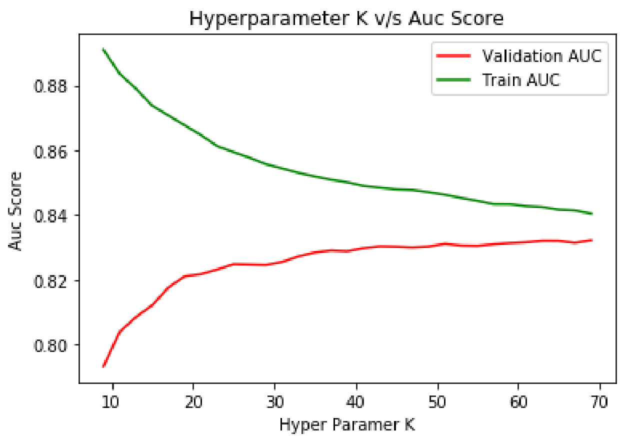


In [51]:

```
best_hyperparameter= knn(tfidf_w2v_train,Y_train, tfidf_w2v_cv,Y_cv, tfidf_w2v_test, Y_test,  'kd_t
ree')
```

```
100%|██████████████████████████████████████████████████████████████████████████████| 31/31
[18:54<00:00, 36.59s/it]
```

```
Best Hyperparamer K is-  69
```

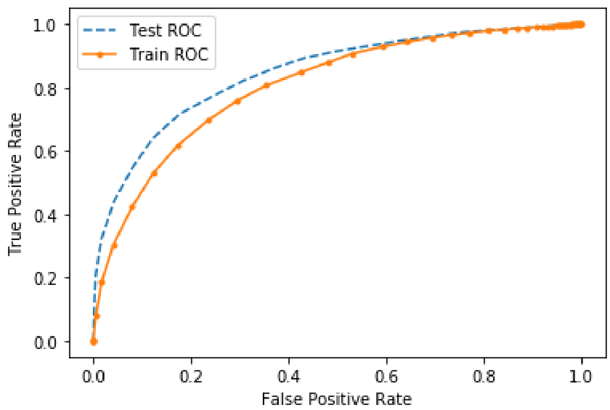


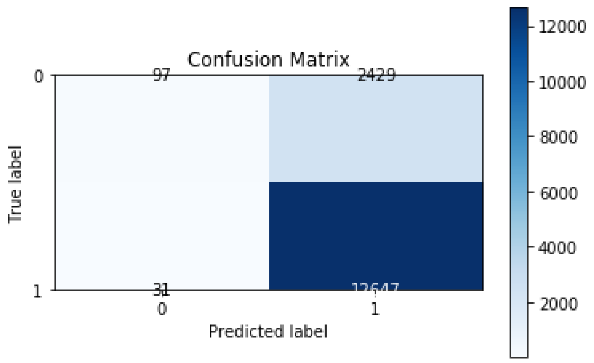
[5.3.2] TFIDF weighted W2V

In [53]:

```
print('\nROC Curve for Best Hyper parameter K: ', best_hyperparameter)
knn_test(bow_train,Y_train,  bow_test, Y_test,  'kd_tree',  best_hyperparameter)
```

```
ROC Curve for Best Hyper parameter K:  69
AUC Score 0.8460979312546582
```





In [55]:

```python
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "Best hyper parameter(K)","Test AUC Score"]

x.add_row(["BoW","Brute",69,0.859994])
x.add_row(["tf-idf","Brute",69,0.881585])
x.add_row(["avg Word2Vec","Brute",67,0.882429])
x.add_row(["tf-idf word2vec","Brute",63,0.882563])
x.add_row(["BoW","kd-Tree",69,0.846097])
x.add_row(["tf-idf","kd-Tree",69,0.842739])
x.add_row(["avg Word2Vec","kd-Tree",67,0.882565])
x.add_row(["tf-idf word2vec","kd-Tree",69,0.846097])

print(x)
```

```
+-----------------+---------+-------------------------+----------------+
|    Vectorizer   |  Model  | Best hyper parameter(K) | Test AUC Score |
+-----------------+---------+-------------------------+----------------+
|       BoW       |  Brute  |            69           |    0.859994    |
|      tf-idf     |  Brute  |            69           |    0.881585    |
|   avg Word2Vec  |  Brute  |            67           |    0.882429    |
| tf-idf word2vec |  Brute  |            63           |    0.882563    |
|       BoW       | kd-Tree |            69           |    0.846097    |
|      tf-idf     | kd-Tree |            69           |    0.842739    |
|   avg Word2Vec  | kd-Tree |            67           |    0.882565    |
| tf-idf word2vec | kd-Tree |            69           |    0.846097    |
+-----------------+---------+-------------------------+----------------+
```

Conclusion:

- We see that Brute alogorithm worked well on tf-idf, avg Word2Vec and tf-idf word2vec with AUC score of about 0.88
- Also, kd-tree version of vectorizers avg Word2Vec and tf-idf word2vec yield about 0.88 AUC score

In [ ]: