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

Objective :

Given a review, determine whether the review is positive or not

How to determine

we could use rating 4 or 5 as positive and 1 or 2 negative. A review of 3 is neutral and ignored

Let's import the library

In [1]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
import sqlite3
import nltk

import string
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer


from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve,auc
from nltk.stem.porter import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from sklearn.metrics import roc_auc_score
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
```

Let's Read the data

In [2]:

```
#use the SQLite Table to read data

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

filtered_data = pd.read_sql_query("""select * from reviews where score !=3 Limit 5000""",conn)
```

In [3]:

```
filtered_data.head()
```

Out[3]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
								Good

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy

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

We use score as rating

In [4]:

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

```
Number of data point in our data (5000, 10)
```

Out[4]:

	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
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	0	1307923200	Cough Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	1	1350777600	Great taffy

In [5]:

```
filtered_data['Score'].value_counts()
```

Out[5]:

```
1    4187
0     813
Name: Score, dtype: int64
```

In [6]:

```
filtered_data.columns
```

Out[6]:

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

We have to find the userid who gave review more than one time. So we will use groupby clause

In [ ]:

```

```

In [7]:

```
display = pd.read_sql_query("""select
UserId, ProductId, ProfileName,Score,Time,Text,Count(*)
from Reviews Group by userId
Having Count(*)>1""",conn)
```

In [8]:

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

```
(80668, 7)
```

Out[8]:

	UserId	ProductId	ProfileName	Score	Time	Text	Count(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	2	1331510400	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	5	1342396800	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1	1348531200	This coffee is horrible and unfortunately not ...	2

	UserId	ProductId	ProfileName	Score	Time	Text	Count(*)
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	5	1346889600	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1	1348617600	I didnt like this coffee. Instead of telling y...	2

In [9]:

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

Out[9]:

	UserId	ProductId	ProfileName	Score	Time	Text	Count(*)
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	5	1334707200	I was recommended to try green tea extract to ...	5

In [10]:

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

Out[10]:

```
393063
```

Exploratory Data Analysis

In [11]:

```
print(filtered_data['UserId'].value_counts())
```

```
A3PJZ8TU8FDQ1K     5
A31N6KB160O508     5
AY12DBB0U420B      5
A3OXHLG6DIBRW8     5
A2NLZ3M0OJV9NX     4
                  ..
A3O1I3KB7L1R9S     1
A3UCN2RGY7O6S1     1
A3PXSG75NMXNUF     1
AYMV2T86WIXVD      1
A2VDUVKIEMEBMF     1
Name: UserId, Length: 4824, dtype: int64
```

In [12]:

```
display_data = pd.read_sql_query("""select
* from Reviews where Score !=3 and
UserId = "A31N6KB160O508"
ORDER BY ProductId""",conn)
display_data.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
0	473869	B0005YW8C4	A31N6KB160O508	Fran W.	0	0	5	1323820800	Goo
1	491579	B0005YW8K6	A31N6KB160O508	Fran W.	0	0	5	1323820800	Goo

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
2	253563	B0005Z6ZK4	A31N6KB160O508	Fran W.	1	12	1	1309478400	Sea
3	508458	B00099XN7O	A31N6KB160O508	Fran W.	0	0	5	1216339200	Delicious,
4	13721	B000AY9U20	A31N6KB160O508	Fran W.	2	2	5	1204502400	Excellent

Observation : We found there are many duplicate entries with same UserId, ProfileName,Text

Sorted the dataset order by ProductId

In [13]:

```
sorted_data = filtered_data.sort_values("ProductId",axis=0,ascending = True,inplace =False,kind = "
quicksort",na_position = 'last')
```

In [14]:

```
#deduplication of entries
final = sorted_data.drop_duplicates(subset = {"UserId","ProductId","ProfileName","Text"},keep = 'fi
rst',inplace=False)
final.shape
```

Out[14]:

```
(4993, 10)
```

In [15]:

```
#checking to see how much % of data still remains

(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[15]:

```
99.86
```

Observation : We found there are two id for that helpfulnessNumerator is greater than helpfulnessDenominator which is not practically possible.Hence we remove these two rows for calculations

In [16]:

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

display.head()
```

Out[16]:

	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

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside

In [17]:

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

Let's take final data

In [18]:

```
final.shape
```

Out[18]:

```
(4993, 10)
```

In [19]:

```
final['Score'].value_counts()
```

Out[19]:

```
1    4183
0     810
Name: Score, dtype: int64
```

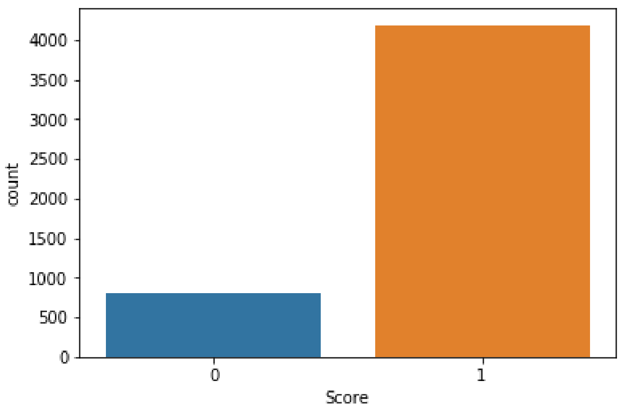
Observation : Total count for Positive Review : 4183 and Negative Review : 810

In [20]:

```
sns.countplot(x = 'Score',data = final)
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2532bb8d668>
```



Text Preprocessing

In [21]:

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

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

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

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

```
Why is this $[...] when the same product is available for $[...] here?<br
/>http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<br /><br />The Victor M380 and
M502 traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearby.
==================================================
These chips are quite tasty and the price is right.  Packaged very well, would buy again.
==================================================
After eating TANG's chocolate and double-chocolate cookies, all other cookies will taste like expi
red, tepid dogfood to you. Her cookies will enhance your life in ways you never dreamed possible.
Tim Horton's, Timothy's, Second Cup, Starbucks, Treats and those horrid packaged cookies at Zupas
are just pathetic imitators to the grandeur that is a TANG cookie. HER COOKIES ARE DA BOMB!!! A+++
++++ Hawt damn!
==================================================
My daughter, living and working in DC this summer, introduced me to this product while home for a
visit.  She encouraged me to give the plain version (just pure coconut water) a chance first, and
by the second container, I understood the amazing qualities of this drink.  I felt so refreshed, h
ydrated, and healthy!  I later tried the kind with pineapple, which is also delicious, but I think
the plain is more effective and purely refreshing when really hot, tired and thirsty, while the sw
eeter fruit infused version will be amazing as part of a cocktail.  Can't wait for 5:00!
==================================================
```

In [22]:

```python
#remove the URL from  text python
import re
sent_0 = re.sub(r"http\S+","",sent_0)
sent_1000 = re.sub(r"http\S+","",sent_1000)
sent_1500 = re.sub(r"http\S+","",sent_1500)
sent_4900 = re.sub(r"http\S+","",sent_4900)
print(sent_0)
print(sent_1000)
print(sent_1500)
print(sent_4900)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor M3
80 and M502 traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearb
y.
These chips are quite tasty and the price is right.  Packaged very well, would buy again.
After eating TANG's chocolate and double-chocolate cookies, all other cookies will taste like expi
red, tepid dogfood to you. Her cookies will enhance your life in ways you never dreamed possible.
Tim Horton's, Timothy's, Second Cup, Starbucks, Treats and those horrid packaged cookies at Zupas
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by the second container, I understood the amazing qualities of this drink.  I felt so refreshed, h
ydrated, and healthy!  I later tried the kind with pineapple, which is also delicious, but I think
the plain is more effective and purely refreshing when really hot, tired and thirsty, while the sw
eeter fruit infused version will be amazing as part of a cocktail.  Can't wait for 5:00!
```

In [23]:

```python
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0,"lxml")
text = soup.get_text()
print(text)
print("="*100)

soup = BeautifulSoup(sent_1000,"lxml")
text = soup.get_text()
print(text)
```

```
print("="*50)

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

soup = BeautifulSoup(sent_4900,"lxml")
text = soup.get_text()
print(text)
print("="*50)
```

```
Why is this $[...] when the same product is available for $[...] here? />The Victor M380 and M502
traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearby.
=====================================================================================================

These chips are quite tasty and the price is right.  Packaged very well, would buy again.
==================================================
After eating TANG's chocolate and double-chocolate cookies, all other cookies will taste like expi
red, tepid dogfood to you. Her cookies will enhance your life in ways you never dreamed possible.
Tim Horton's, Timothy's, Second Cup, Starbucks, Treats and those horrid packaged cookies at Zupas
are just pathetic imitators to the grandeur that is a TANG cookie. HER COOKIES ARE DA BOMB!!! A+++
++++ Hawt damn!
==================================================
My daughter, living and working in DC this summer, introduced me to this product while home for a
visit.  She encouraged me to give the plain version (just pure coconut water) a chance first, and
by the second container, I understood the amazing qualities of this drink.  I felt so refreshed, h
ydrated, and healthy!  I later tried the kind with pineapple, which is also delicious, but I think
the plain is more effective and purely refreshing when really hot, tired and thirsty, while the sw
eeter fruit infused version will be amazing as part of a cocktail.  Can't wait for 5:00!
==================================================
```

In [24]:

```
import re

def decontracted(phrase):
    phrase = re.sub(r"won't","will not",phrase)
    phrase = re.sub(r"can't","can not",phrase)
    phrase=  re.sub(r"\'s","is",phrase)
    phrase = re.sub(r"\'re","are",phrase)
    phrase= re.sub(r"\'not","not",phrase)
    phrase = re.sub(r"\'d","would",phrase)
    phrase = re.sub(r"\'ll","will",phrase)
    phrase = re.sub(r"\'ve","have",phrase)
    phrase = re.sub(r"\'m","am",phrase)
    return phrase
```

In [25]:

```
sent_0 = decontracted(sent_0)
print(sent_0)
print("="*50)

sent_1000 = decontracted(sent_1000)
print(sent_1000)
print("="*50)

sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)

sent_4900 = decontracted(sent_4900)
print(sent_4900)
print("="*50)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor M3
80 and M502 traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearb
y.
==================================================
These chips are quite tasty and the price is right.  Packaged very well, would buy again.
==================================================
After eating TANGis chocolate and double-chocolate cookies, all other cookies will taste like expi
red, tepid dogfood to you. Her cookies will enhance your life in ways you never dreamed possible.
```

```
Tim Hortonis, Timothyis, Second Cup, Starbucks, Treats and those horrid packaged cookies at Zupas
are just pathetic imitators to the grandeur that is a TANG cookie. HER COOKIES ARE DA BOMB!!! A+++
++++ Hawt damn!
==================================================
My daughter, living and working in DC this summer, introduced me to this product while home for a
visit.  She encouraged me to give the plain version (just pure coconut water) a chance first, and
by the second container, I understood the amazing qualities of this drink.  I felt so refreshed, h
ydrated, and healthy!  I later tried the kind with pineapple, which is also delicious, but I think
the plain is more effective and purely refreshing when really hot, tired and thirsty, while the sw
eeter fruit infused version will be amazing as part of a cocktail.  Can't wait for 5:00!
==================================================
```

In [26]:

```python
#remove words with numbers python
sent_0 = re.sub("\S*\d\S*","",sent_0).strip()
print(sent_0)

sent_1000 = re.sub("\S*\d\S*","",sent_1000).strip()
print(sent_1000)

sent_1500 = re.sub("\S*\d\S*","",sent_1500).strip()
print(sent_1500)

sent_4900 = re.sub("\S*\d\S*","",sent_4900).strip()
print(sent_4900)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor  a
nd  traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearby.
These chips are quite tasty and the price is right.  Packaged very well, would buy again.
After eating TANGis chocolate and double-chocolate cookies, all other cookies will taste like expi
red, tepid dogfood to you. Her cookies will enhance your life in ways you never dreamed possible.
Tim Hortonis, Timothyis, Second Cup, Starbucks, Treats and those horrid packaged cookies at Zupas
are just pathetic imitators to the grandeur that is a TANG cookie. HER COOKIES ARE DA BOMB!!! A+++
++++ Hawt damn!
My daughter, living and working in DC this summer, introduced me to this product while home for a
visit.  She encouraged me to give the plain version (just pure coconut water) a chance first, and
by the second container, I understood the amazing qualities of this drink.  I felt so refreshed, h
ydrated, and healthy!  I later tried the kind with pineapple, which is also delicious, but I think
the plain is more effective and purely refreshing when really hot, tired and thirsty, while the sw
eeter fruit infused version will be amazing as part of a cocktail.  Can't wait for
```

In [27]:

```python
#remove special character
sent_0 = re.sub('[^A-Za-z0-9]+',' ',sent_0)
print(sent_0)

sent_1000 = re.sub('[^A-Za-z0-9]+',' ',sent_1000)
print(sent_1000)

sent_1500 = re.sub('[^A-Za-z0-9]+',' ',sent_1500)
print(sent_1500)

sent_4900 = re.sub('[^A-Za-z0-9]+',' ',sent_4900)
print(sent_4900)
```

```
Why is this when the same product is available for here br br The Victor and traps are unreal of c
ourse total fly genocide Pretty stinky but only right nearby
These chips are quite tasty and the price is right Packaged very well would buy again
After eating TANGis chocolate and double chocolate cookies all other cookies will taste like expir
ed tepid dogfood to you Her cookies will enhance your life in ways you never dreamed possible Tim
Hortonis Timothyis Second Cup Starbucks Treats and those horrid packaged cookies at Zupas are just
pathetic imitators to the grandeur that is a TANG cookie HER COOKIES ARE DA BOMB A Hawt damn
My daughter living and working in DC this summer introduced me to this product while home for a vi
sit She encouraged me to give the plain version just pure coconut water a chance first and by the
second container I understood the amazing qualities of this drink I felt so refreshed hydrated and
healthy I later tried the kind with pineapple which is also delicious but I think the plain is mor
e effective and purely refreshing when really hot tired and thirsty while the sweeter fruit
infused version will be amazing as part of a cocktail Can t wait for
```

In [28]:

```
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"])
```

Combining all the above Stundents

In [29]:

```
from tqdm import tqdm
preprocessed_review = []
#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-z0-9]+',' ',sentence)
    sentence = ' '.join(e.lower() for e in sentence.split() if e.lower() not in stopwords)
    preprocessed_review.append(sentence.strip())
```

```
100%|████████████████████████████████████████████████████████████████████████████████| 4993/4993
[00:03<00:00, 1249.71it/s]
```

In [30]:

```
preprocessed_review[1500]
```

Out[30]:

```
'eating tangis chocolate double chocolate cookies cookies taste like expired tepid dogfood cookies
enhance life ways never dreamed possible tim hortonis timothyis second cup starbucks treats horrid
packaged cookies zupas pathetic imitators grandeur tang cookie cookies da bomb hawt damn'
```

Summary Text Preprocessing

In [31]:

```
#we will do later
```

Featurization

Bag Of Words

In [32]:

```
count_vect = CountVectorizer()
count_vect.fit(preprocessed_review)
print("Some feature names:",count_vect.get_feature_names()[:10])
print("="*50)

final_counts = count_vect.transform(preprocessed_review)
print("the type of count vectorizer",type(final))
print("The shape of count vectorizer:",final_counts.get_shape())
```

```
Some feature names: ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abbott', 'abby', 'abdominal',
'abiding', 'ability']
==================================================
the type of count vectorizer <class 'pandas.core.frame.DataFrame'>
The shape of count vectorizer: (4993, 13257)
```

Bi-gram and n-Grams

In [33]:

```
count_vect_bigram = CountVectorizer(ngram_range=(1,2),min_df=10,max_features=5000)
final_bigram_count = count_vect_bigram.fit_transform(preprocessed_review)
print("The type of Bi-gram vectorizer",type(final_bigram_count))
print("The shape of Bi-gram vectorizer",final_bigram_count.get_shape())
```

```
The type of Bi-gram vectorizer <class 'scipy.sparse.csr.csr_matrix'>
The shape of Bi-gram vectorizer (4993, 3127)
```

TF-IDF

In [34]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df=10)
tf_idf_vect.fit(preprocessed_review)
print("Sample Feature(Unique words in the corpus):",tf_idf_vect.get_feature_names()[0:10])
final_tf_idf_count = tf_idf_vect.transform(preprocessed_review)
print("the type of tf-idf vectorizer",type(final_tf_idf_count))
print("The shape of tf_idf vectorizer",final_tf_idf_count.get_shape())
```

```
Sample Feature(Unique words in the corpus): ['ability', 'able', 'able find', 'able get',
'absolute', 'absolutely', 'absolutely delicious', 'absolutely love', 'absolutely no', 'according']
the type of tf-idf vectorizer <class 'scipy.sparse.csr.csr_matrix'>
The shape of tf_idf vectorizer (4993, 3127)
```

Word2Vec

In [35]:

```
list_of_sentence = []
for sentence in preprocessed_review:
    list_of_sentence.append(sentence.split())
```

In [36]:

```
want_to_train_w2v = True

if want_to_train_w2v:
    w2v_model = Word2Vec(list_of_sentence,min_count=5,size=50,workers=4)
    print(w2v_model.wv.most_similar("great"))
    print("="*50)
    print(w2v_model.wv.most_similar('worst'))
```

```
[('bad', 0.9949325323104858), ('good', 0.9943092465400696), ('think', 0.9942871332168579),
('alternative', 0.9938706159591675), ('especially', 0.9937859773635864), ('snack',
0.9937231540679932), ('even', 0.9936879873275757), ('theyare', 0.9936805963516235), ('tasty', 0.99
36635494232178), ('easy', 0.9935598969459534)]
==================================================
[('varieties', 0.9992638230323792), ('popcorn', 0.9992542266845703), ('types',
0.9992510080337524), ('coffees', 0.9992208480834961), ('gotten', 0.9991645812988281), ('teas', 0.9
991454482078552), ('lover', 0.9990550875663757), ('hands', 0.9990262985229492), ('jerky',
0.9989897608757019), ('american', 0.9989853501319885)]
```

In [37]:

```
w2v_words = list(w2v_model.wv.vocab)
print("Number of word that occur minimum 5 times:",len(w2v_words))
print("sample words",w2v_words[0:50])
```

```
Number of word that occur minimum 5 times: 3855
sample words ['product', 'available', 'course', 'total', 'pretty', 'stinky', 'right', 'nearby', 'u
sed', 'beat', 'great', 'received', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', '
instead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use', 'car', 'windows',
'beautifully', 'shop', 'program', 'going', 'lot', 'fun', 'everywhere', 'like', 'tv', 'computer', '
really', 'good', 'idea', 'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'made',
'two', 'thumbs']
```

In [38]:

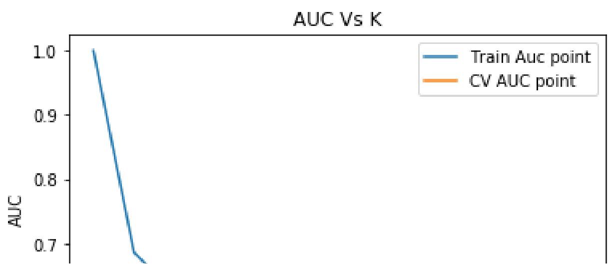
```
X = preprocessed_review
y = np.array(final['Score'])
X_1,x_test,Y_1,y_test = train_test_split(X,y,test_size=0.2,random_state=0)
x_train,x_cv,y_train,y_cv = train_test_split(X_1,Y_1,test_size=0.2)
```

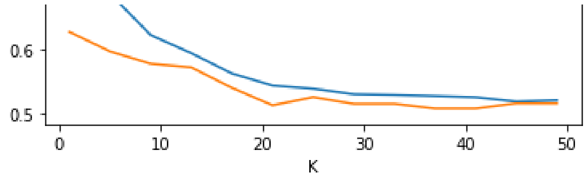
Apply KNN on BOW

In [39]:

```
final_xtr = count_vect.fit_transform(x_train)
final_xcv = count_vect.transform(x_cv)
final_xtest = count_vect.transform(x_test)
auc_cv = []
auc_train = []
k = list(range(1,50,4))
cv_scores = []
for i in k:
    knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',p=2,leaf_size=30,m
etric='cosine')
    knn.fit(final_xtr,y_train)
    pred = knn.predict(final_xcv)
    auc_cv.append(roc_auc_score(y_cv,pred))
    pred1 = knn.predict(final_xtr)

    auc_train.append(roc_auc_score(y_train,pred1))
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(k,auc_train,label="Train Auc point")
ax.plot(k,auc_cv,label = "CV AUC point")
plt.title("AUC Vs K")
plt.xlabel('K')
plt.ylabel('AUC')
ax.legend()
plt.show()
```





We found the best k = 49

In [40]:

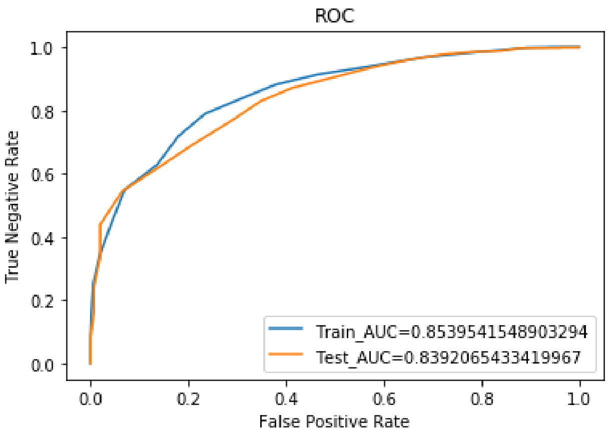
```
knn =
KNeighborsClassifier(n_neighbors=49,weights='uniform',algorithm='brute',leaf_size=30,p=2,metric='co
sine')
knn.fit(final_xtr,y_train)
pred1 = knn.predict_proba(final_xtr)[:,1]
fpr1,tpr1,threshold1 = metrics.roc_curve(y_train,pred1)

pred2 = knn.predict_proba(final_xtest)[:,1]

fpr2,tpr2,threshold2 = metrics.roc_curve(y_test,pred2)

plt.plot(fpr1,tpr1,label = "Train_AUC="+str(roc_auc_score(y_train,pred1)))
plt.plot(fpr2,tpr2,label = "Test_AUC="+str(roc_auc_score(y_test,pred2)))

plt.title("ROC")
plt.xlabel("False Positive Rate")
plt.ylabel("True Negative Rate")
plt.legend()
plt.show()
```



Confusion Matrix

In [41]:

```
knn =
KNeighborsClassifier(n_neighbors=49,weights='uniform',algorithm='brute',leaf_size=30,p=2,metric='co
sine')
knn.fit(final_xtr,y_train)
pred1 = knn.predict(final_xtest)
confusion_mat = confusion_matrix(y_test,pred1)
confusion_mat
```

Out[41]:

```
array([[  6, 149],
       [  2, 842]], dtype=int64)
```

Observation : We found the true negative 5,false negative 1 ,false positive 150 and true positive 843

Let's find f1_score

In [42]:

```
print("F1 score=",f1_score(y_test,pred1))
```

F1 score= 0.9177111716621252

In [43]:

```
print("accuracy=",accuracy_score(y_test,pred1))
```

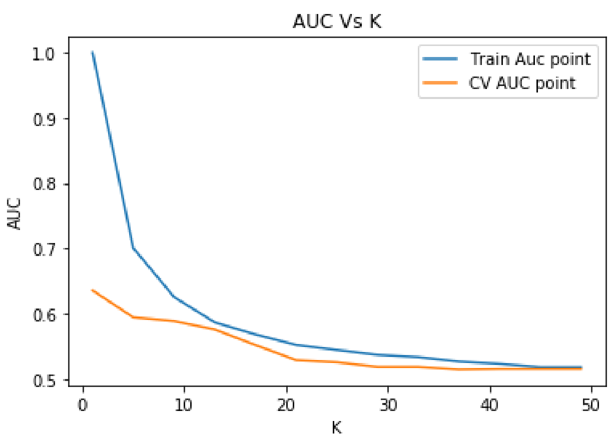
accuracy= 0.8488488488488488

Apply Knn on Bi-gram

In [44]:

```
final_xtr_bi_gram = count_vect_bigram.fit_transform(x_train)
final_xcv_bi_gram = count_vect_bigram.transform(x_cv)
final_xtest_bi_gram = count_vect_bigram.transform(x_test)
auc_cv = []
auc_train = []
k = list(range(1,50,4))
cv_scores = []
for i in k:
    knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',p=2,leaf_size=30,m
etric='cosine')
    knn.fit(final_xtr_bi_gram,y_train)
    pred = knn.predict(final_xcv_bi_gram)
    auc_cv.append(roc_auc_score(y_cv,pred))
    pred1 = knn.predict(final_xtr_bi_gram)

    auc_train.append(roc_auc_score(y_train,pred1))
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(k,auc_train,label="Train Auc point")
ax.plot(k,auc_cv,label = "CV AUC point")
plt.title("AUC Vs K")
plt.xlabel('K')
plt.ylabel('AUC')
ax.legend()
plt.show()
```



best k = 49

In [45]:

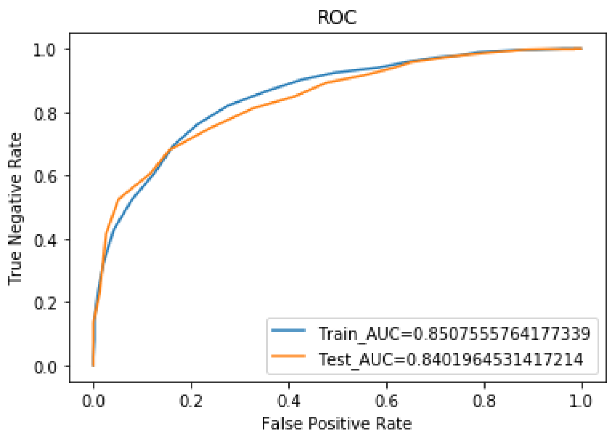
```
knn =
KNeighborsClassifier(n_neighbors=49,weights='uniform',algorithm='brute',leaf_size=30,p=2,metric='co
sine')
knn.fit(final_xtr_bi_gram,y_train)
pred1 = knn.predict_proba(final_xtr_bi_gram)[:,1]
fpr1,tpr1,threshold1 = metrics.roc_curve(y_train,pred1)
```

```
pred2 = knn.predict_proba(final_xtest_bi_gram)[:,1]

fpr2,tpr2,threshold2 = metrics.roc_curve(y_test,pred2)

plt.plot(fpr1,tpr1,label = "Train_AUC="+str(roc_auc_score(y_train,pred1)))
plt.plot(fpr2,tpr2,label = "Test_AUC="+str(roc_auc_score(y_test,pred2)))

plt.title("ROC")
plt.xlabel("False Positive Rate")
plt.ylabel("True Negative Rate")
plt.legend()
plt.show()
```



In [46]:

```
knn = 
KNeighborsClassifier(n_neighbors=49,weights='uniform',algorithm='brute',leaf_size=30,p=2,metric='co
sine')
knn.fit(final_xtr_bi_gram,y_train)
pred1 = knn.predict(final_xtest_bi_gram)
confusion_mat = confusion_matrix(y_test,pred1)
confusion_mat
```

Out[46]:

```
array([[  6, 149],
       [  1, 843]], dtype=int64)
```

Observation : We found the true negative 6,false negative : 1, false positive : 149 and true positive :843

In [47]:

```
print("f1_score",f1_score(y_test,pred1))
```

```
f1_score 0.9183006535947713
```

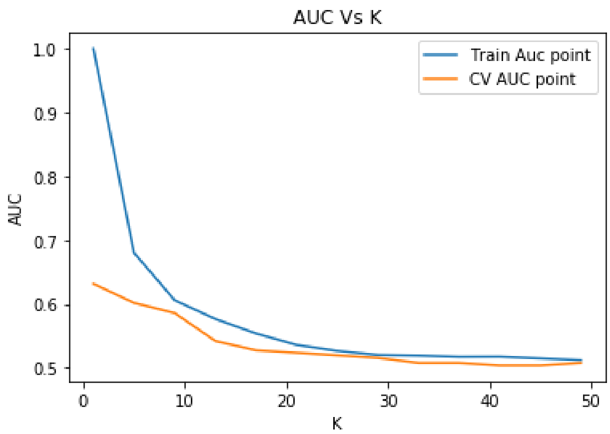
Apply KNN on TF-IDF

In [48]:

```
final_xtr_tf = tf_idf_vect.fit_transform(x_train)
final_xcv_tf = tf_idf_vect.transform(x_cv)
final_xtest_tf = tf_idf_vect.transform(x_test)
auc_cv = []
auc_train = []
k = list(range(1,50,4))
cv_scores = []
for i in k:
    knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',p=2,leaf_size=30,m
etric='cosine')
    knn.fit(final_xtr_tf,y_train)
    pred = knn.predict(final_xcv_tf)
    auc_cv.append(roc_auc_score(y_cv,pred))
```

```
    auc_cv.append(roc_auc_score(y_cv,pred))
    pred1 = knn.predict(final_xtr_tf)

    auc_train.append(roc_auc_score(y_train,pred1))
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(k,auc_train,label="Train Auc point")
ax.plot(k,auc_cv,label = "CV AUC point")
plt.title("AUC Vs K")
plt.xlabel('K')
plt.ylabel('AUC')
ax.legend()
plt.show()
```



Observation : We have observed the distance between train_curve and cross validation curve is very less on k =28, so this is our best K value

In [49]:

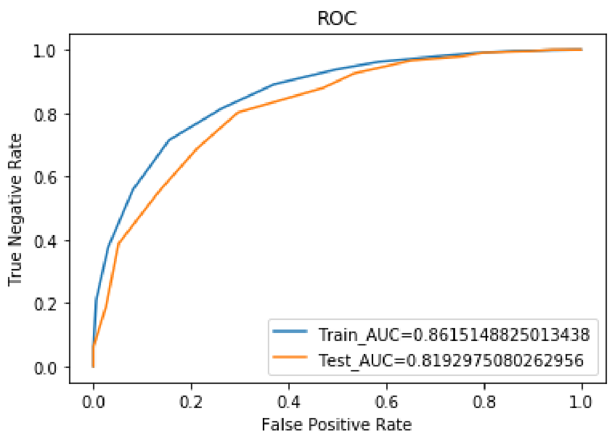
```
knn =
KNeighborsClassifier(n_neighbors=28,weights='uniform',algorithm='brute',leaf_size=30,p=2,metric='co
sine')
knn.fit(final_xtr_tf,y_train)
pred1 = knn.predict_proba(final_xtr_tf)[:,1]
fpr1,tpr1,threshold1 = metrics.roc_curve(y_train,pred1)

pred2 = knn.predict_proba(final_xtest_tf)[:,1]

fpr2,tpr2,threshold2 = metrics.roc_curve(y_test,pred2)

plt.plot(fpr1,tpr1,label = "Train_AUC="+str(roc_auc_score(y_train,pred1)))
plt.plot(fpr2,tpr2,label = "Test_AUC="+str(roc_auc_score(y_test,pred2)))

plt.title("ROC")
plt.xlabel("False Positive Rate")
plt.ylabel("True Negative Rate")
plt.legend()
plt.show()
```



Observation : We found the Train AUC = 0.861 and Test_AUC = 0.81

In [50]:

```
knn =
KNeighborsClassifier(n_neighbors=49,weights='uniform',algorithm='brute',leaf_size=30,p=2,metric='co
sine')
knn.fit(final_xtr_tf,y_train)
pred1 = knn.predict(final_xtest_tf)
confusion_mat = confusion_matrix(y_test,pred1)
confusion_mat
```

Out[50]:

```
array([[  5, 150],
       [  0, 844]], dtype=int64)
```

Observation : The total true negative 5 , false positive 150,false negative 0 and total true positive 844

In [51]:

```
print("F1_score",f1_score(y_test,pred1))
```

```
F1_score 0.9183895538628944
```

Observation : We found good f1 score for test data

In [52]:

```
print("accuracy:",accuracy_score(y_test,pred1))
```

```
accuracy: 0.8498498498498499
```

In [ ]: