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. Userld 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. SOLite 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 will 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 nltk
         import string
         import matplotlib.pyplot as plt
         import seaborn as sns
         from nltk.stem.snowball import SnowballStemmer
         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
         from nltk.stem.porter import PorterStemmer
         import 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.model selection import train test split
         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 import model_selection
         from sklearn.metrics import roc auc score
```

[1]. Reading Data

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')
# filtering only positive and negative reviews

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 2

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

```
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 (20000, 10)
Out[2]:
            ld
                  ProductId
                                        UserId ProfileName HelpfulnessNumerator HelpfulnessDenominato
                B001E4KFG0 A3SGXH7AUHU8GW
                                                 delmartian
                                                                               1
             2 B00813GRG4
                                                                               0
                              A1D87F6ZCVE5NK
                                                     dll pa
                                                    Natalia
                                                     Corres
           3 B000LQOCH0
                               ABXLMWJIXXAIN
                                                    "Natalia
                                                    Corres"
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(*)
                                                                            Overall its just
                                                                                OK when
                        #oc-
                               B005ZBZLT4
                                                                                                 2
                                               Breyton 1331510400
             R115TNMSPFT9I7
                                                                           considering the
                                                                                  price...
                                                                              My wife has
                                               Louis E.
                        #oc-
                                                                                recurring
                              B005HG9ESG
                                                                                                 3
         1
                                                Emory 1342396800
              R11D9D7SHXIJB9
                                                                           extreme muscle
                                               "hoppy"
                                                                              spasms, u...
                                                                             This coffee is
                                                                             horrible and
                        #oc-
                                                       1348531200
                                                                                                 2
                               B005ZBZLT4
            R11DNU2NBKQ23Z
                                           Cieszykowski
                                                                             unfortunately
                                                                                   not ...
```

		UserId	ProductId	ProfileName	Time	Scor	e	Text	COUNT(*)
	3	#oc- R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600		5 I	This will be the pottle that you grab from the	3
	4	#oc- R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600			I didnt like this coffee. Instead of telling y	2
In [5]:	di	splay[display['l	JserId']=='A	ZY10LLTJ71N)	(']				
Out[5]:		UserId	Production	l ProfileN	ame 1	Гime	Scor	e Text	COUNT(*)
Out[5]:	806	UserId 538 AZY10LLTJ71NX		underthest	nrine 129669			I bought this 6 pack because for the price tha	COUNT(*) 5
Out[5]: In [6]:			B001ATMQK2	underthesl	nrine 129669			I bought this 6 pack 5 because for the	

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]:
                      ProductId
                                       UserId ProfileName HelpfulnessNumerator HelpfulnessDenomina
                                                   Geetha
            78445 B000HDL1RQ AR5J8UI46CURR
                                                  Krishnan
                                                   Geetha
         1 138317
                   B000HDOPYC AR5J8UI46CURR
                                                                             2
                                                  Krishnan
```

2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2

UserId ProfileName HelpfulnessNumerator HelpfulnessDenomina

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=F

In [9]: #Deduplication of entries
    final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, kee
    final.shape

Out[9]: (19354, 10)

In [10]: #Checking to see how much % of data still remains
    (final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

ld

ProductId

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()
                Id
                      ProductId
                                        UserId ProfileName HelpfulnessNumerator HelpfulnessDenomina
Out[11]:
                                               J. E. Stephens
          0 64422 B000MIDROQ A161DK06JJMCYF
                                                                              3
                                                                              3
          1 44737 B001EQ55RW A2V0I904FH7ABY
                                                      Ram
In [12]:
          final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]</pre>
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()
          (19354, 10)
         1
               16339
Out[13]:
               3015
```

[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

Name: Score, dtype: int64

- 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 observed to be better than Porter Stemming)

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

```
In [14]: # printing some random reviews
    sent_0 = final['Text'].values[0]
    print(sent_0)
    print("="*50)

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

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

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

We have used the Victor fly bait for 3 seasons. Can't beat it. Great product!

I received this box with great anticipation since they don't sell these on the west coast. I got the package, opened the box and was EXTREMELY disappointed. The cookies looked like a gorilla shook the box to death and left most of the box filled with cr umbs. AND THERE WAS A RODENT SIZED HOLE ON THE SIDE OF THE BOX!!!!!!!! So, needless to say I will not NOT be reordering these again.

I have two cats. My big boy has eaten these and never had a problem...as a matter of fact he has never vomited or had a hair ball since I adopted him at 2 months. My gir l cat throws up every time she eats this particular flavor. Since I treat them equal ly these are no longer purchased. I hate to see my girl sick so I just recommend you watch your cats after you give them these treats. If not a problem...carry on.

I was always a fan of Dave's, so I bought this at a local store to try Blair's and I'm glad I did. The jalepeno sause is very mild (for me) but one of the most delici ous condiments I've ever tasted. The Afterdeath is a bit painful, but still very ta sty on rice & beans, burritos, or any chicken dish I've tried it on. The Sudden Dea th kicked my ass when I underestimated it, but now a few drops in a dish or pot are just right if I want heat without changing flavor much.

```
-----
```

```
In [15]:
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
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)
```

We have used the Victor fly bait for 3 seasons. Can't beat it. Great product!

```
In [16]:
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-al
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
```

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

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

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

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

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```
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"\'d", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'t", " hor", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'t", " have", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'n", " am", phrase)
    return phrase
```

```
In [18]:
    sent_1500 = decontracted(sent_1500)
    print(sent_1500)
    print("="*50)
```

I have two cats. My big boy has eaten these and never had a problem...as a matter of fact he has never vomited or had a hair ball since I adopted him at 2 months. My gir l cat throws up every time she eats this particular flavor. Since I treat them equal

ly these are no longer purchased. I hate to see my girl sick so I just recommend you watch your cats after you give them these treats. If not a problem...carry on.

```
In [19]:
    #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
    sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
    print(sent_0)
```

We have used the Victor fly bait for seasons. Can't beat it. Great product!

```
In [20]:
    #remove spacial character: https://stackoverflow.com/a/5843547/4084039
    sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
    print(sent_1500)
```

I have two cats My big boy has eaten these and never had a problem as a matter of fact he has never vomited or had a hair ball since I adopted him at 2 months My girl cat throws up every time she eats this particular flavor Since I treat them equally these are no longer purchased I hate to see my girl sick so I just recommend you watch your cats after you give them these treats If not a problem carry on

```
In [22]:
#using snowball stemmer for stemming
snowball_stemmer = SnowballStemmer(language='english')

def performStemming(text):
    for word in text.split():
        text = text.replace(word, snowball_stemmer.stem(word))
    return text
```

[3.1] Preprocess Reviews

```
In [23]: # Combining all the above stundents
    from tqdm import tqdm
    preprocessed_reviews = []
    # tqdm is for printing the status bar
    for sentance in tqdm(final['Text'].values):
        sentance = re.sub(r"http\S+", "", sentance)
        sentance = BeautifulSoup(sentance, 'lxml').get_text()
        sentance = decontracted(sentance)
```

Out[24]: 'two cat big boy eaten never problem matter fact never vomit hair ball sinc adopt mo nth girl cat throw everi time eat particular flavor sinc treat equal no longer purch as hate see girl sick recommend watch cat give treat not problem carri'

[3.2] Preprocess Summary

```
In [25]:
           preprocessed_summaries = []
           # tqdm is for printing the status bar
           for sentance in tqdm(final['Summary'].values):
               sentance = re.sub(r"http\S+", "", sentance)
               sentance = BeautifulSoup(sentance, 'lxml').get_text()
               sentance = decontracted(sentance)
               sentance = re.sub("\S*\d\S*", "", sentance).strip()
sentance = re.sub('[^A-Za-z]+', ' ', sentance)
               # https://gist.github.com/sebleier/554280
               sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stop
               sentance = performStemming(sentance)
               preprocessed_summaries.append(sentance.strip())
          100%
          54/19354 [00:05<00:00, 3717.66it/s]
In [26]:
           preprocessed_summaries[1500]
Out[26]: 'temptat vomit'
```

[4] Featurization

[4.1] BAG OF WORDS

[4.2] Bi-Grams and n-Grams.

```
# bi-gram, tri-gram and n-gram

# removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/stable/mo
# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_bigra

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

[4.3] TF-IDF

[4.4] Word2Vec

```
In [30]:
         # Train your own Word2Vec model using your own text corpus
         i=0
         list of sentance=[]
         for sentance in preprocessed_reviews:
             list_of_sentance.append(sentance.split())
In [31]:
         w2v model=Word2Vec(list of sentance,min count=5, vector size=50, workers=4)
         print(w2v_model.wv.most_similar('great'))
         print('='*50)
         print(w2v_model.wv.most_similar('worst'))
         [('fantast', 0.7926201820373535), ('awesom', 0.7872790098190308), ('wonder', 0.76571
         72083854675), ('excel', 0.7590202689170837), ('amaz', 0.7559347748756409), ('good',
         0.7552913427352905), ('perfect', 0.7181152701377869), ('especi', 0.699252903461456
         3), ('nice', 0.6533973217010498), ('decent', 0.6212543845176697)]
         _____
         [('hate', 0.7069545388221741), ('heard', 0.7053143382072449), ('greatest', 0.7040787
         935256958), ('aw', 0.6983534693717957), ('disgust', 0.6910261511802673), ('complic',
```

```
0.6813580393791199), ('closest', 0.6794140338897705), ('experienc', 0.67745351791381 84), ('best', 0.6735631227493286), ('sad', 0.670515775680542)]
```

```
In [32]:
    w2v_words = list(w2v_model.wv.index_to_key)
    print("number of words that occured minimum 5 times ",len(w2v_words))
    print("sample words ", w2v_words[0:50])

number of words that occured minimum 5 times 6054
    sample words ['not', 'like', 'tast', 'good', 'flavor', 'love', 'one', 'product', 'g reat', 'use', 'coffe', 'tri', 'would', 'food', 'dog', 'get', 'make', 'tea', 'no', 'b uy', 'time', 'eat', 'realli', 'cup', 'price', 'order', 'much', 'treat', 'amazon', 'a lso', 'best', 'littl', 'bag', 'find', 'drink', 'even', 'well', 'store', 'mix', 'bett er', 'go', 'recommend', 'look', 'chocol', 'year', 'sugar', 'give', 'first', 'day', 'want']
```

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

[4.4.1.1] Avg W2v

```
In [33]:
          # average Word2Vec
          # compute average word2vec for each review.
          sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
          for sent in tqdm(list_of_sentance): # for each review/sentence
              sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need
              cnt_words =0; # num of words with a valid vector in the sentence/review
              for word in sent: # for each word in a review/sentence
                  if word in w2v_words:
                      vec = w2v_model.wv[word]
                      sent_vec += vec
                      cnt_words += 1
              if cnt_words != 0:
                  sent_vec /= cnt_words
              sent vectors.append(sent vec)
          print(len(sent_vectors))
          print(len(sent_vectors[0]))
         100%
                                                                                         193
         54/19354 [00:11<00:00, 1659.87it/s]
         19354
         50
```

```
[4.4.1.2] TFIDF weighted W2v

In [34]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
    model = TfidfVectorizer()
    model.fit(preprocessed_reviews)
    # we are converting a dictionary with word as a key, and the idf as a value dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

In [35]: # TF-IDF weighted Word2Vec
    tfidf_feat = model.get_feature_names() # tfidf words/col-names
    # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfid
    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this row=0;
```

for sent in tqdm(list_of_sentance[:10000]): # for each review/sentence
 sent_vec = np.zeros(50) # as word vectors are of zero length

for word in sent: # for each word in a review/sentence

weight_sum =0; # num of words with a valid vector in the sentence/review

```
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.append(sent_vec)
    row += 1
100%|
```

[5] KNN Model with reviews data

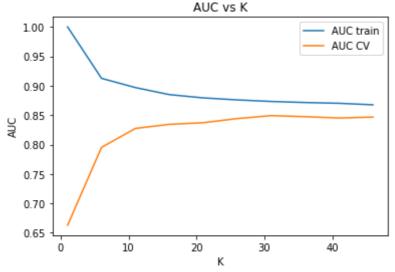
[5.1] Dividing data into train, test & CV

```
In [36]: X = preprocessed_reviews
Y = np.array(final['Score'])

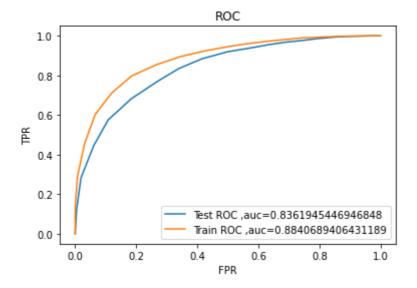
X_1, X_test, y_1, y_test = train_test_split(X, Y, test_size=0.3, random_state=0)
X_tr, X_cv, y_tr, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

[5.2] KNN Model with BOW

```
In [37]:
          count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=8000)
          final_bigram_counts = count_vect.fit(X_tr)
          x_train = count_vect.transform(X_tr)
          x_test = count_vect.transform(X_test)
          x_cv = count_vect.transform(X_cv)
          print("number of points in train data ", x_train.get_shape())
          print("number of points in test data ", x_test.get_shape())
          print("number of points in CV data ", x_cv.get_shape())
          auc_cv = []
          auc_train = []
          K = []
          for i in tqdm(range(1,50,5)):
              knn = KNeighborsClassifier(n_neighbors=i, weights='uniform', algorithm='brute', lea
              knn.fit(x_train, y_tr)
              pred = knn.predict_proba(x_cv)[:,1]
              pred1 = knn.predict_proba(x_train)[:,1]
              auc_cv.append(roc_auc_score(y_cv,pred))
              auc_train.append(roc_auc_score(y_tr,pred1))
              K.append(i)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(K, auc train, label='AUC train')
          ax.plot(K, auc_cv, label='AUC CV')
          plt.title('AUC vs K')
          plt.xlabel('K')
          plt.ylabel('AUC')
          ax.legend()
          plt.show()
```



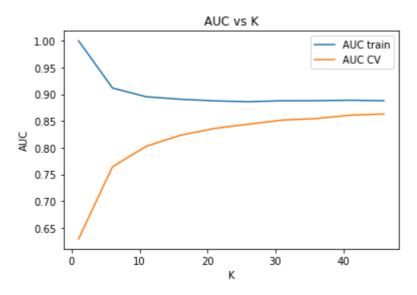
```
In [38]:
          # KNN with optimal parameters
          from sklearn.metrics import confusion_matrix
          final_counts = count_vect.fit(X_1)
          x_train = count_vect.transform(X_1)
          x_test = count_vect.transform(X_test)
          knn = KNeighborsClassifier(n_neighbors=26,weights='uniform',algorithm='brute',leaf_s
          knn.fit(x_train, y_1)
          predi = knn.predict_proba(x_test)[:,1]
          fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
          pred = knn.predict_proba(x_train)[:,1]
          fpr2,tpr2,thresholds2 = metrics.roc_curve(y_1,pred)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
          ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_1,pred)))
          plt.title('ROC')
          plt.xlabel('FPR')
          plt.ylabel('TPR')
          ax.legend()
          plt.show()
```



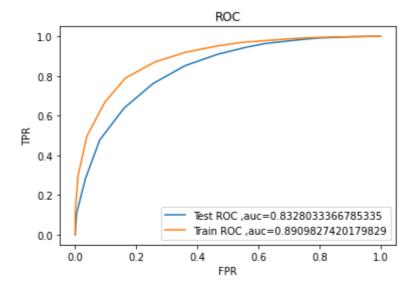
[5.3] KNN Model with TFIDF

| 10/10 [00:52<00:00, 5.22s/it]

```
In [39]:
          tfidf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=8000)
          final_bigram_counts = tfidf_vect.fit(X_tr)
          x_train = tfidf_vect.transform(X_tr)
          x_test = tfidf_vect.transform(X_test)
          x_cv = tfidf_vect.transform(X_cv)
          print("number of points in train data ", x_train.get_shape())
          print("number of points in test data ", x_test.get_shape())
          print("number of points in CV data ", x_cv.get_shape())
          auc_cv = []
          auc_train = []
          K = []
          for i in tqdm(range(1,50,5)):
              knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',lea
              knn.fit(x_train, y_tr)
              pred = knn.predict_proba(x_cv)[:,1]
              pred1 = knn.predict_proba(x_train)[:,1]
              auc_cv.append(roc_auc_score(y_cv,pred))
              auc train.append(roc auc score(y tr,pred1))
              K.append(i)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(K, auc_train, label='AUC train')
          ax.plot(K, auc_cv, label='AUC CV')
          plt.title('AUC vs K')
          plt.xlabel('K')
          plt.ylabel('AUC')
          ax.legend()
          plt.show()
           0%
         | 0/10 [00:00<?, ?it/s]
         number of points in train data (9482, 5862)
         number of points in test data (5807, 5862)
         number of points in CV data (4065, 5862)
         100%
```



```
In [40]:
          # KNN with optimal parameters
          from sklearn.metrics import confusion_matrix
          final_vect = tfidf_vect.fit(X_1)
          x_train = tfidf_vect.transform(X_1)
          x_test = tfidf_vect.transform(X_test)
          knn = KNeighborsClassifier(n_neighbors=26,weights='uniform',algorithm='brute',leaf_s
          knn.fit(x_train, y_1)
          predi = knn.predict_proba(x_test)[:,1]
          fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
          pred = knn.predict_proba(x_train)[:,1]
          fpr2,tpr2,thresholds2 = metrics.roc_curve(y_1,pred)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
          ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_1,pred)))
          plt.title('ROC')
          plt.xlabel('FPR')
          plt.ylabel('TPR')
          ax.legend()
          plt.show()
```



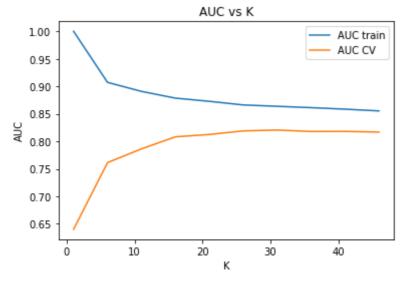
[5.4] KNN Model with TFIDF weighted W2V

```
In [41]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
          w2v_model=Word2Vec(list_of_sentance, min_count=5, vector_size=60, workers=4)
          model = TfidfVectorizer()
          model.fit(X_tr)
          # we are converting a dictionary with word as a key, and the idf as a value
          dictionary = dict(zip(model.get feature names(), list(model.idf )))
          def getTfidfWeightedVector(reviews):
              i=0
              list_of_sentance=[]
              for sentance in reviews:
                  list_of_sentance.append(sentance.split())
              tfidf_feat = model.get_feature_names()
              tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in t
              row=0;
              for sent in tqdm(list_of_sentance): # for each review/sentence
                  sent_vec = np.zeros(60) # as word vectors are of zero length
                  weight_sum =0; # num of words with a valid vector in the sentence/review
                  for word in sent: # for each word in a review/sentence
                      if word in w2v_words and word in tfidf_feat:
                          vec = w2v_model.wv[word]
                          tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                          sent_vec += (vec * tf_idf)
                          weight_sum += tf_idf
                  if weight_sum != 0:
                      sent_vec /= weight_sum
                  tfidf_sent_vectors.append(sent_vec)
                  row += 1
              return tfidf_sent_vectors
In [42]:
          print("Vectorizing train data")
          x train = getTfidfWeightedVector(X tr)
          print("Vectorizing test data")
          x_test = getTfidfWeightedVector(X_test)
          print("Vectorizing CV data")
          x_cv = getTfidfWeightedVector(X_cv)
           0%||
         21/9482 [00:00<00:45, 208.48it/s]
         Vectorizing train data
         100%
         9482/9482 [00:45<00:00, 208.07it/s]
         29/5807 [00:00<00:21, 271.83it/s]
         Vectorizing test data
         100%
         5807/5807 [00:28<00:00, 205.29it/s]
         | 40/4065 [00:00<00:21, 189.28it/s]
         Vectorizing CV data
         4065/4065 [00:19<00:00, 208.56it/s]
In [43]:
          print("number of points in train data ", len(x_train))
          print("number of points in test data ", len(x_test))
          print("number of points in CV data ", len(x_cv))
          auc_cv = []
          auc_train = []
          K = []
          for i in tqdm(range(1,50,5)):
```

```
knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',lea
    knn.fit(x_train, y_tr)
    pred = knn.predict_proba(x_cv)[:,1]
    pred1 = knn.predict_proba(x_train)[:,1]
    auc_cv.append(roc_auc_score(y_cv,pred))
    auc train.append(roc auc score(y tr,pred1))
    K.append(i)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(K, auc_train, label='AUC train')
ax.plot(K, auc_cv, label='AUC CV')
plt.title('AUC vs K')
plt.xlabel('K')
plt.ylabel('AUC')
ax.legend()
plt.show()
```

0%| | 0/10 [00:00<?, ?it/s] number of points in train data 9482 number of points in test data 5807 number of points in CV data 4065

100%| 10/10 [00:31<00:00, 3.11s/it]



```
In [44]:
          #KNN with optimal parameters
          w2v_model = Word2Vec(list_of_sentance, min_count=5, vector_size=60, workers=4)
          model = TfidfVectorizer()
          model.fit(X_1)
          # we are converting a dictionary with word as a key, and the idf as a value
          dictionary = dict(zip(model.get feature names(), list(model.idf )))
          print("Vectorizing train data")
          x train = getTfidfWeightedVector(X 1)
          print("Vectorizing test data")
          x_test = getTfidfWeightedVector(X_test)
          knn = KNeighborsClassifier(n_neighbors=26,weights='uniform',algorithm='brute',leaf_s
          knn.fit(x_train, y_1)
          predi = knn.predict_proba(x_test)[:,1]
          fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
          pred = knn.predict_proba(x_train)[:,1]
          fpr2,tpr2,thresholds2 = metrics.roc_curve(y_1,pred)
          fig = plt.figure()
          ax = plt.subplot(111)
```

```
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
 ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_1,pred)))
 plt.title('ROC')
 plt.xlabel('FPR')
 plt.ylabel('TPR')
 ax.legend()
 plt.show()
21/13547 [00:00<01:06, 202.40it/s]
Vectorizing train data
547/13547 [01:14<00:00, 181.66it/s]
| 50/5807 [00:00<00:29, 196.92it/s]
Vectorizing test data
5807/5807 [00:32<00:00, 180.97it/s]
                             ROC
  1.0
  0.8
  0.6
TR
  0.4
  0.2
                          Test ROC .auc=0.8281822689885439
                          Train ROC ,auc=0.8704440830898102
  0.0
                0.2
       0.0
                          0.4
                                   0.6
                                            0.8
                                                     1.0
                              FPR
```

[6] KNN Model with summary data

[6.1] Dividing data into train, test & CV

```
In [46]:
X = preprocessed_summaries
Y = np.array(final['Score'])

X_1, X_test, y_1, y_test = train_test_split(X, Y, test_size=0.3, random_state=0)
X_tr, X_cv, y_tr, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

[6.2] KNN Model with BOW

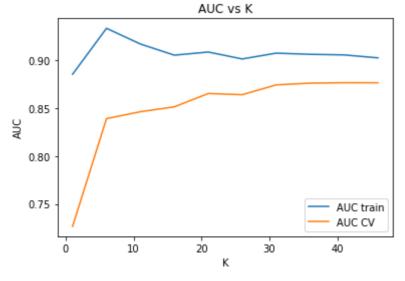
```
In [47]:
    count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=8000)
    final_bigram_counts = count_vect.fit(X_tr)

    x_train = count_vect.transform(X_tr)
    x_test = count_vect.transform(X_test)
    x_cv = count_vect.transform(X_cv)

    print("number of points in train data ", x_train.get_shape())
    print("number of points in test data ", x_test.get_shape())
    print("number of points in CV data ", x_cv.get_shape())

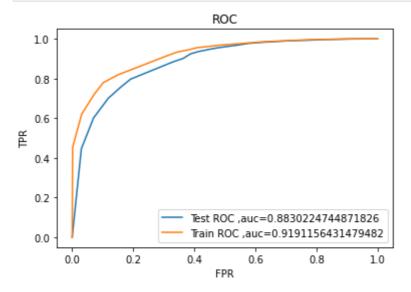
auc_cv = []
```

```
auc_train = []
K = []
for i in tqdm(range(1,50,5)):
    knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',lea
    knn.fit(x_train, y_tr)
    pred = knn.predict_proba(x_cv)[:,1]
    pred1 = knn.predict_proba(x_train)[:,1]
    auc_cv.append(roc_auc_score(y_cv,pred))
    auc_train.append(roc_auc_score(y_tr,pred1))
    K.append(i)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(K, auc_train, label='AUC train')
ax.plot(K, auc_cv, label='AUC CV')
plt.title('AUC vs K')
plt.xlabel('K')
plt.ylabel('AUC')
ax.legend()
plt.show()
 0%
| 0/10 [00:00<?, ?it/s]
number of points in train data (9482, 602)
number of points in test data (5807, 602)
number of points in CV data (4065, 602)
100%
 | 10/10 [00:35<00:00, 3.59s/it]
```



```
In [48]:
          # KNN with optimal parameters
          from sklearn.metrics import confusion matrix
          final counts = count vect.fit(X 1)
          x_train = count_vect.transform(X_1)
          x_test = count_vect.transform(X_test)
          knn = KNeighborsClassifier(n_neighbors=26,weights='uniform',algorithm='brute',leaf_s
          knn.fit(x_train, y_1)
          predi = knn.predict_proba(x_test)[:,1]
          fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
          pred = knn.predict_proba(x_train)[:,1]
          fpr2,tpr2,thresholds2 = metrics.roc_curve(y_1,pred)
          fig = plt.figure()
          ax = plt.subplot(111)
```

```
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_1,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```

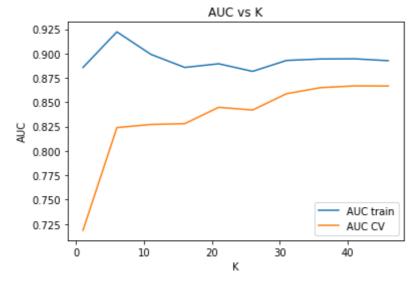


[6.3] KNN Model with TFIDF

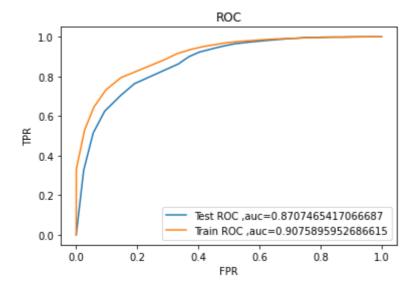
```
In [49]:
          tfidf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=8000)
          final_bigram_counts = tfidf_vect.fit(X_tr)
          x_train = tfidf_vect.transform(X_tr)
          x_test = tfidf_vect.transform(X_test)
          x_cv = tfidf_vect.transform(X_cv)
          print("number of points in train data ", x_train.get_shape())
          print("number of points in test data ", x_test.get_shape())
          print("number of points in CV data ", x_cv.get_shape())
          auc_cv = []
          auc_train = []
          K = []
          for i in tqdm(range(1,50,5)):
              knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',lea
              knn.fit(x train, y tr)
              pred = knn.predict_proba(x_cv)[:,1]
              pred1 = knn.predict_proba(x_train)[:,1]
              auc_cv.append(roc_auc_score(y_cv,pred))
              auc_train.append(roc_auc_score(y_tr,pred1))
              K.append(i)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(K, auc_train, label='AUC train')
          ax.plot(K, auc_cv, label='AUC CV')
          plt.title('AUC vs K')
          plt.xlabel('K')
          plt.ylabel('AUC')
          ax.legend()
          plt.show()
```

```
| 0/10 [00:00<?, ?it/s]
number of points in train data (9482, 602)
number of points in test data (5807, 602)
number of points in CV data (4065, 602)
```

100%| 10/10 [00:36<00:00, 3.65s/it]



```
In [50]:
          # KNN with optimal parameters
          from sklearn.metrics import confusion_matrix
          final_vect = tfidf_vect.fit(X_1)
          x_train = tfidf_vect.transform(X_1)
          x_test = tfidf_vect.transform(X_test)
          knn = KNeighborsClassifier(n_neighbors=26,weights='uniform',algorithm='brute',leaf_s
          knn.fit(x_train, y_1)
          predi = knn.predict_proba(x_test)[:,1]
          fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
          pred = knn.predict_proba(x_train)[:,1]
          fpr2,tpr2,thresholds2 = metrics.roc_curve(y_1,pred)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
          ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_1,pred)))
          plt.title('ROC')
          plt.xlabel('FPR')
          plt.ylabel('TPR')
          ax.legend()
          plt.show()
```



[6.4] KNN Model with TFIDF weighted W2V

11%

100%

997/9482 [00:00<00:01, 4964.19it/s]

Vectorizing train data

```
In [51]:
          # S = ["abc def pgr", "def def def abc", "pgr pgr def"]
          w2v_model=Word2Vec(list_of_sentance, min_count=5, vector_size=60, workers=4)
          model = TfidfVectorizer()
          model.fit(X_tr)
          # we are converting a dictionary with word as a key, and the idf as a value
          dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
          def getTfidfWeightedVector(reviews):
              i=0
              list_of_sentance=[]
              for sentance in reviews:
                  list_of_sentance.append(sentance.split())
              tfidf_feat = model.get_feature_names()
              tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in t
              for sent in tqdm(list_of_sentance): # for each review/sentence
                  sent_vec = np.zeros(60) # as word vectors are of zero length
                  weight_sum =0; # num of words with a valid vector in the sentence/review
                  for word in sent: # for each word in a review/sentence
                      if word in w2v_words and word in tfidf_feat:
                          vec = w2v model.wv[word]
                          tf idf = dictionary[word]*(sent.count(word)/len(sent))
                          sent_vec += (vec * tf_idf)
                          weight_sum += tf_idf
                  if weight_sum != 0:
                      sent_vec /= weight_sum
                  tfidf_sent_vectors.append(sent_vec)
                  row += 1
              return tfidf sent vectors
In [52]:
          print("Vectorizing train data")
          x_train = getTfidfWeightedVector(X_tr)
          print("Vectorizing test data")
          x test = getTfidfWeightedVector(X test)
          print("Vectorizing CV data")
          x_cv = getTfidfWeightedVector(X_cv)
```

```
482/9482 [00:01<00:00, 5212.95it/s]
                                                                                                        | 1
           17%
          000/5807 [00:00<00:00, 5001.24it/s]
           Vectorizing test data
           807/5807 [00:01<00:00, 5347.34it/s]
            28%
          151/4065 [00:00<00:00, 5307.40it/s]
           Vectorizing CV data
           100%
          065/4065 [00:00<00:00, 5131.27it/s]
In [53]:
           \label{eq:print}  \begin{array}{ll} \text{print}(\text{"number of points in train data ", len(x\_train))} \\ \text{print}(\text{"number of points in test data ", len(x\_test))} \end{array}
           print("number of points in CV data ", len(x_cv))
           auc_cv = []
           auc_train = []
           K = []
           for i in tqdm(range(1,50,5)):
                knn = KNeighborsClassifier(n_neighbors=i,weights='uniform',algorithm='brute',lea
                knn.fit(x_train, y_tr)
                pred = knn.predict_proba(x_cv)[:,1]
                pred1 = knn.predict_proba(x_train)[:,1]
                auc_cv.append(roc_auc_score(y_cv,pred))
                auc_train.append(roc_auc_score(y_tr,pred1))
                K.append(i)
           fig = plt.figure()
           ax = plt.subplot(111)
           ax.plot(K, auc_train, label='AUC train')
           ax.plot(K, auc_cv, label='AUC CV')
           plt.title('AUC vs K')
           plt.xlabel('K')
           plt.ylabel('AUC')
           ax.legend()
           plt.show()
             0%|
          | 0/10 [00:00<?, ?it/s]
          number of points in train data 9482
          number of points in test data 5807
          number of points in CV data 4065
          100%
           | | 10/10 [00:38<00:00, 3.84s/it]
                                        AUC vs K
                                                               AUC train
                                                               AUC CV
             0.95
             0.90
          을 0.85
             0.80
             0.75
                             10
                                        20
                                                              40
                                            Κ
```

```
#KNN with optimal parameters
In [54]:
          w2v_model = Word2Vec(list_of_sentance, min_count=5, vector_size=60, workers=4)
          model = TfidfVectorizer()
          model.fit(X 1)
          # we are converting a dictionary with word as a key, and the idf as a value
          dictionary = dict(zip(model.get feature names(), list(model.idf )))
          print("Vectorizing train data")
          x_train = getTfidfWeightedVector(X_1)
          print("Vectorizing test data")
          x_test = getTfidfWeightedVector(X_test)
          knn = KNeighborsClassifier(n_neighbors=26,weights='uniform',algorithm='brute',leaf_s
          knn.fit(x_train, y_1)
          predi = knn.predict_proba(x_test)[:,1]
          fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
          pred = knn.predict_proba(x_train)[:,1]
          fpr2,tpr2,thresholds2 = metrics.roc_curve(y_1,pred)
          fig = plt.figure()
          ax = plt.subplot(111)
          ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
          ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_1,pred)))
          plt.title('ROC')
          plt.xlabel('FPR')
          plt.ylabel('TPR')
          ax.legend()
          plt.show()
                                                                                              | 1
         020/13547 [00:00<00:02, 4473.56it/s]
         Vectorizing train data
                                                                                             135
         47/13547 [00:02<00:00, 4674.06it/s]
           9%|
         512/5807 [00:00<00:01, 5075.04it/s]
         Vectorizing test data
         807/5807 [00:01<00:00, 3936.21it/s]
            1.0
            0.8
            0.6
            0.4
            0.2
                                   Test ROC ,auc=0.8654778514205315
                                  Train ROC, auc=0.9101574805949199
            0.0
                0.0
                         0.2
                                           0.6
                                                    0.8
                                                            1.0
                                      FPR
```

[7.0] Overall Results (AUC Score)

KNN on Reviews

Vectorizer Train Test

BOW	0.88	0.83
TFIDF	0.89	0.83
TFIDF weighted W2V	0.87	0.82

KNN on Summary

Vectorizer	Train	Test
BOW	0.91	0.88
TFIDF	0.90	0.87
TFIDF weighted W2V	0.91	0.86