Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

Objective:

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

[Q] How to determine if a review is positive or negative?

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

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

In [65]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os

# ============================== loading libraries =========================================
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
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
# =============================================================================================
```

In [89]:

```
# using 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""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 100000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative rating(0).
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 (100000, 10)
```

Out[89]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Ti

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Ti
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017

In [90]:

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

In [91]:

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

```
(80668, 7)
```

Out[91]:

	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 [92]:

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

Out[92]:

	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 [93]:

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

Out[93]:

```
393063
```

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

In [94]:

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

Out[94]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	11995
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	11995
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	11995
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	11995
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	11995

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

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

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

In [95]:

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

Out[95]:

```
<function sorted(iterable, /, *, key=None, reverse=False)>
```

In [96]:

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

Out[96]:

```
(87773, 11)
```

In [97]:

```
#Sorting data according to Time in ascending order
final=temp_final.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na_positi
on='last')
sorted
```

Out[97]:

```
<function sorted(iterable, /, *, key=None, reverse=False)>
```

In [98]:

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

Out[98]:

```
87.775
```

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 [99]:

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

display.head()
```

Out[99]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	12248
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	12128

In [101]:

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

In [116]:

```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)
#print(final.head)
#How many positive and negative reviews are present in our dataset?
print(final['Score'].value_counts())
y=final['Score']
```

```
(87773, 11)
1    73592
0    14181
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

In [105]:

```
# 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)
```

```
I bought a few of these after my apartment was infested with fruit flies. After only a few hours, the t
rap had &quot;attracted&quot; many flies and within a few days they were practically gone. This may not
be a long term  solution, but if flies are driving you crazy, consider buying this. One  caution- the s
urface is very sticky, so try to avoid touching it.
==================================================
I have made these brownies for family and for a den of cub scouts and no one would have known they were
gluten free and everyone asked for seconds!  These brownies have a fudgy texture and have bits of choco
late chips in them which are delicious.  I would say the mix is very thick and a little difficult to wo
rk with.  The cooked brownies are slightly difficult to cut into very neat edges as the edges tend to c
rumble a little and I would also say that they make a slightly thinner layer of brownies than most of t
he store brand gluten containing but they taste just as good, if not better.  Highly recommended!<br />
<br />(For those wondering, this mix requires 2 eggs OR 4 egg whites and 7 tbs melted butter to prepare
.  They do have suggestions for lactose free and low fat preparations)
==================================================
This gum is my absolute favorite. By purchasing on amazon I can get the savings of large quanities at a
very good price. I highly recommend to all gum chewers. Plus as you enjoy the peppermint flavor and fre
shing of breath you are whitening your teeth all at the same time.
==================================================
This is an excellent product, both tastey and priced right. It's difficult to find this product in regu
lar local grocery stores, so I was thrilled to find it.
==================================================
```

In [106]:

```
# 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_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
I bought a few of these after my apartment was infested with fruit flies. After only a few hours, the t
rap had &quot;attracted&quot; many flies and within a few days they were practically gone. This may not
be a long term  solution, but if flies are driving you crazy, consider buying this. One  caution- the s
urface is very sticky, so try to avoid touching it.
```

In [107]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-tags-from-an-elem
ent
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(text)
```

```
I bought a few of these after my apartment was infested with fruit flies. After only a few hours, the t
rap had "attracted" many flies and within a few days they were practically gone. This may not be a long
term  solution, but if flies are driving you crazy, consider buying this. One  caution- the surface is
very sticky, so try to avoid touching it.
==================================================
I have made these brownies for family and for a den of cub scouts and no one would have known they were
gluten free and everyone asked for seconds!  These brownies have a fudgy texture and have bits of choco
late chips in them which are delicious.  I would say the mix is very thick and a little difficult to wo
```

```
rk with.  The cooked brownies are slightly difficult to cut into very neat edges as the edges tend to c
rumble a little and I would also say that they make a slightly thinner layer of brownies than most of t
he store brand gluten containing but they taste just as good, if not better.  Highly recommended!(For t
hose wondering, this mix requires 2 eggs OR 4 egg whites and 7 tbs melted butter to prepare.  They do h
ave suggestions for lactose free and low fat preparations)
==================================================
This gum is my absolute favorite. By purchasing on amazon I can get the savings of large quanities at a
very good price. I highly recommend to all gum chewers. Plus as you enjoy the peppermint flavor and fre
shing of breath you are whitening your teeth all at the same time.
==================================================
This is an excellent product, both tastey and priced right. It's difficult to find this product in regu
lar local grocery stores, so I was thrilled to find it.
```

In [108]:

```python
# 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 [109]:

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

```
This gum is my absolute favorite. By purchasing on amazon I can get the savings of large quanities at a
very good price. I highly recommend to all gum chewers. Plus as you enjoy the peppermint flavor and fre
shing of breath you are whitening your teeth all at the same time.
==================================================
```

In [110]:

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

```
I bought a few of these after my apartment was infested with fruit flies. After only a few hours, the t
rap had &quot;attracted&quot; many flies and within a few days they were practically gone. This may not
be a long term  solution, but if flies are driving you crazy, consider buying this. One  caution- the s
urface is very sticky, so try to avoid touching it.
```

In [111]:

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

```
This gum is my absolute favorite By purchasing on amazon I can get the savings of large quanities at a
very good price I highly recommend to all gum chewers Plus as you enjoy the peppermint flavor and fresh
ing of breath you are whitening your teeth all at the same time
```

In [112]:

```python
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# 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', "you'r
e", "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', 't
heir',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these',
'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'd
o', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'whil
e', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'bef
ore', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'a
gain', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each
', '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', "doesn
'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 [113]:

```
# 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)
    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 stopwords)
    preprocessed_reviews.append(sentance.strip())
final['CleanedText'] = preprocessed_reviews
#final['CleanedText']=final['CleanedText'].str.decode("utf-8")
#final['CleanedText'].shape
```

```
100%|██████████| 87773/87773 [00:37<00:00, 2311.03it/s]
```

In [87]:

```
#print(final.columns.values)
#preprocessed_reviews[1:4]
#print(final['Text'].head)
#print(final['CleanedText'].head)
print(final.columns.values)
```

```
['Id' 'ProductId' 'UserId' 'ProfileName' 'HelpfulnessNumerator'
 'HelpfulnessDenominator' 'Score' 'Time' 'Summary' 'Text' 'CleanedText']
```

[3.2] Preprocessing Review Summary

In [142]:

```
## Similartly you can do preprocessing for review summary also.
```

[4] Featurization

[5] Assignment 4: Apply Naive Bayes

1. **Apply Multinomial NaiveBayes on these feature sets**

    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

2. **The hyper paramter tuning(find best Alpha)**

    - Find the best hyper parameter which will give the maximum AUC value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Feature importance**

    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using absolute values of `coef_` parameter of MultinomialNB and print their corresponding feature names

4. **Feature engineering**

    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

5. **Representation of results**

    - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure. Here on X-axis you will have alpha values, since they have a wide range, just to represent those alpha values on the graph, apply log function on those alpha values.
    - Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
    - Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

6. **Conclusion**

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

Splitting into train and test data based on time

In [129]:

```
#Splitting 70% data into train set and 30 % as test set
train_set_temp,test_set= np.split(final, [int(.70 *len(final))])
#X_train, X_test, y_train, y_test = train_test_split(final, y, test_size=0.2)
print(train_set_temp.shape, test_set.shape)
#Splitting train set into train and cv set
train_set,cv_set = np.split(train_set_temp, [int(.50 *len(final))])
print(train_set.shape, cv_set.shape)
#Splitting train data into train and cv(60:20)
#X_tr, X_cv, y_tr, y_cv = train_test_split(X_train, y_train, test_size=0.2)
#print(X_tr.shape, y_tr.shape)
#print(X_cv.shape, y_cv.shape)
y_tr=train_set['Score']
print(y_tr.shape)
y_cv=cv_set['Score']
print(y_cv.shape)
y_test=test_set['Score']
```

```
print(y_test.shape)
```

```
(61441, 11) (26332, 11)
(43886, 11) (17555, 11)
(43886,)
(17555,)
(26332,)
```

In [130]:

```
#Applying BoW
model = CountVectorizer()
model.fit(train_set['CleanedText'])
train_bow = model.transform(train_set['CleanedText'])
cv_bow = model.transform(cv_set['CleanedText'])
test_bow = model.transform(test_set['CleanedText'])
print(test_bow.shape)
print(cv_bow.shape)
print(train_bow.shape)
```

```
(26332, 39252)
(17555, 39252)
(43886, 39252)
```

Note: Data Leakage

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

Applying Multinomial Naive Bayes

[5.1] Applying Naive Bayes on BOW, SET 1

In [131]:

```
#Applying GridSearch to find the best hyperparameter alpha

alphas = np.array([0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000])
# create and fit a NB model, testing each alpha
#model = Ridge()
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB(class_prior=[0.5,0.5])
scoring = {'AUC': 'roc_auc'}
grid = GridSearchCV(estimator=clf, param_grid=dict(alpha=alphas),scoring = scoring, refit = 'AUC')
grid.fit(train_bow, y_tr)
print(grid)
# summarize the results of the grid search
(grid.best_score_)
print(grid.best_estimator_.alpha)
results_tr_bow = grid.cv_results_
#print(results_tr_bow)
#print(grid.confusion_matrix)
```

```
GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=MultinomialNB(alpha=1.0, class_prior=[0.5, 0.5],
                                     fit_prior=True),
             iid='warn', n_jobs=None,
             param_grid={'alpha': array([1.e-05, 1.e-04, 1.e-03, 1.e-02, 1.e+00, 1.e+01, 1.e+02, 1.e+03
])},
             pre_dispatch='2*n_jobs', refit='AUC', return_train_score=False,
             scoring={'AUC': 'roc_auc'}, verbose=0)
1.0
```

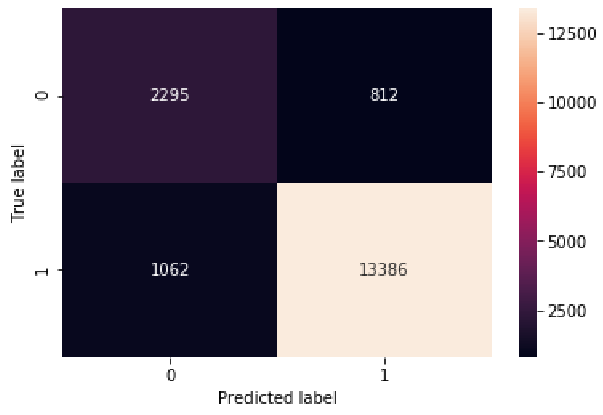
In [132]:

```
# After finding the best hyperparameter value for BOW which is 1, applying naive bayes on train dataset
and predicting
# accuracy/AUC score for cv dataset
from sklearn.naive_bayes import MultinomialNB
#alphas = np.array([0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000]
clf = MultinomialNB(alpha = 1, class_prior=[0.5,0.5])
#clf.fit(train_bow,y_tr)
cclf=clf.fit(train_bow, y_tr).predict(cv_bow)
pred_cv = clf.predict_proba(cv_bow)[:,1]
print('alpha value = ',1)
fpr, tpr, thresholds = roc_curve(y_cv,pred_cv)
roc_auc_cv = auc(fpr, tpr)
print('Area under the ROC curve : %f', + roc_auc_cv)

#Plotting confusion matrix
import seaborn as sns
conf_mat = confusion_matrix(y_cv, cclf)
print(conf_mat)
#conf_normalized = conf_mat.astype('int') / conf_mat.sum(axis=1)[:, np.newaxis]
sns.heatmap(conf_mat, annot=True, fmt ='g')
plt.ylabel('True label')
plt.xlabel('Predicted label')
```

```
alpha value =  1
Area under the ROC curve : %f 0.90867665750292
[[ 2295   812]
 [ 1062 13386]]
```

Out[132]:

```
Text(0.5, 15.0, 'Predicted label')
```



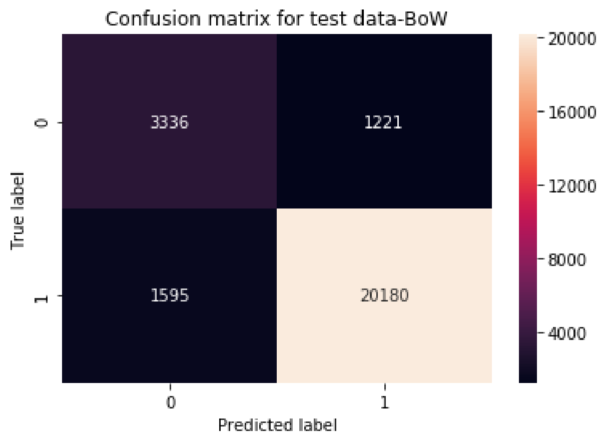
In [133]:

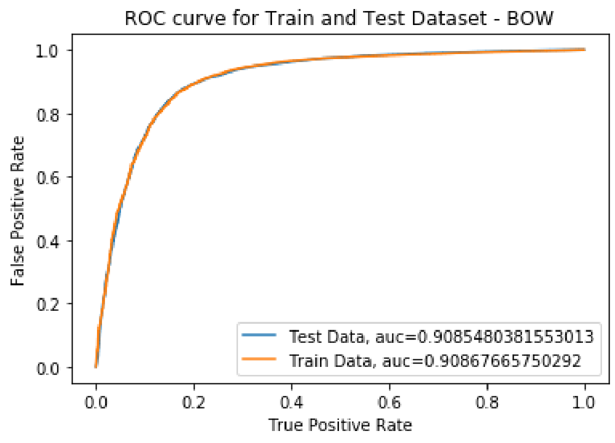
```
# After finding the best hyperparameter value for BOW which is 1, applying naive bayes on train dataset
and predicting
# accuracy/AUC score for cv dataset
from sklearn.naive_bayes import MultinomialNB
#alphas = np.array([0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000]
clf = MultinomialNB(alpha = 1, class_prior=[0.5,0.5])
#clf.fit(train_bow,y_tr)
cclf=clf.fit(train_bow, y_tr).predict(test_bow)
pred_test = clf.predict_proba(test_bow)[:,1]
print('alpha value = ',1)
fpr, tpr, thresholds = roc_curve(y_test,pred_test)
roc_auc_test = auc(fpr, tpr)
print('Area under the ROC curve : %f', + roc_auc_test)

#Plotting confusion matrix
import seaborn as sns
conf_mat = confusion_matrix(y_test, cclf)
print(conf_mat)
#conf_normalized = conf_mat.astype('int') / conf_mat.sum(axis=1)[:, np.newaxis]
sns.heatmap(conf_mat, annot=True, fmt ='g')
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.title('Confusion matrix for test data-BoW')

#Plot ROC Curve
plt.figure(0).clf()
fpr, tpr, thresholds = roc_curve(y_test,pred_test)
roc_auc_test = auc(fpr, tpr)
plt.plot(fpr,tpr,label="Test Data, auc="+str(roc_auc_test))

fpr, tpr, thresh = roc_curve(y_cv, pred_cv)
roc_auc_cv = auc(fpr, tpr)
plt.plot(fpr,tpr,label="Train Data, auc="+str(roc_auc_cv))
plt.title('ROC curve for Train and Test Dataset - BOW')
plt.xlabel('True Positive Rate')
plt.ylabel('False Positive Rate')
plt.legend(loc=0)
```

```
alpha value =  1
Area under the ROC curve : %f 0.9085480381553013
[[ 3336  1221]
 [ 1595 20180]]
```

Out[133]:

```
<matplotlib.legend.Legend at 0x25e63f60>
```





[5.1.1] Top 10 important features of positive/negative class from SET 1

In [134]:

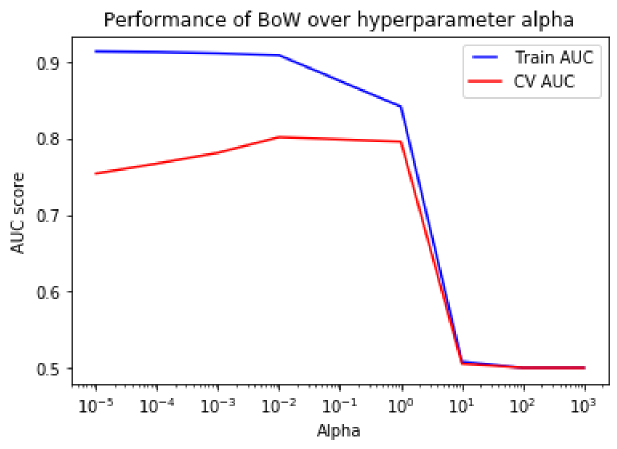
```
#Finding the top 20 features in BOW:
import matplotlib.pyplot as plt

def plot_coefficients(classifier, feature_names, top_features=20):
    coef = classifier.coef_.ravel()
    top_positive_coefficients = np.argsort(coef)[-top_features:]
    top_negative_coefficients = np.argsort(coef)[:top_features]
    top_coefficients = np.hstack([top_negative_coefficients, top_positive_coefficients])
    feature_names = np.array(feature_names)
    print("Positive coefficients:",feature_names[top_positive_coefficients])
    print("Negative coefficients:",feature_names[top_negative_coefficients])
```

```
plot_coefficients(clf, model.get_feature_names(), top_features=20)
```

```
Positive coefficients: ['was' 'as' 'they' 'but' 'with' 'you' 'are' 'that' 'have' 'my' 'not' 'in'
 'for' 'this' 'of' 'to' 'it' 'is' 'and' 'the']
Negative coefficients: ['contaminating' 'waaaaay' 'believers' 'hausbrandt' 'believewhat'
 'popovers' 'poplite' 'chessie' 'poper' 'havedoes' 'havegetarian'
 'havenot' 'poorely' 'muchhh' 'chery' 'darjeelings' 'pooing' 'cherryheads'
 'haveto' 'snadwich']
```

In [135]:

```
#Performance of BoW over hyperparameter alpha
alpha = [0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000]
train_results = []
test_results = []
for i in alpha:
    clf = MultinomialNB(alpha=i)
    clf.fit(train_bow, y_tr)
    train_pred = clf.predict(train_bow)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_tr, train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = clf.predict(cv_bow)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_cv, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)
from matplotlib.legend_handler import HandlerLine2D
ax = plt.gca()
ax.set_xscale('log')
line1, = ax.plot(alpha, train_results, 'b', label="Train AUC")
line2, = ax.plot(alpha, test_results, 'r', label="CV AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.title("Performance of BoW over hyperparameter alpha")
plt.ylabel('AUC score')
plt.xlabel('Alpha')
plt.show()
```



Observation:

```
The graph shows that for best alpha value of 1, the AUC score for train and test data is 0.84 an
d 0.8 respectively.
As alpha increases, AUC score decreases to 0.5.
```

[5.2] Applying Naive Bayes on TFIDF, SET 2

In [137]:

```
#Applying tf_idf vectorization
tf_idf_vec = TfidfVectorizer(ngram_range=(1,2))
tf_idf_vec.fit(train_set['Text'])
train_tf_idf = tf_idf_vec.transform(train_set['Text'])
test_tf_idf = tf_idf_vec.transform(test_set['Text'])
```

```
cv_tf_idf = tf_idf_vec.transform(cv_set['Text'])

print(test_tf_idf.shape)
print(train_tf_idf.shape)
print(cv_tf_idf.shape)
```

```
(26332, 717931)
(43886, 717931)
(17555, 717931)
```

In [134]:

```
## [5.2] Applying Gridsearch to find best hyperparameter value on TFIDF,<font color='red'> SET 2</font>
```

In [138]:

```
alphas = np.array([0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000])
# create and fit a NB model, testing each alpha
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
clsf = MultinomialNB(class_prior=[0.5,0.5])
scoring = {'AUC': 'roc_auc'}
grid = GridSearchCV(estimator=clsf, param_grid=dict(alpha=alphas),scoring = scoring, refit = 'AUC')
grid.fit(train_tf_idf, y_tr)
print(grid)
# summarize the results of the grid search
print(grid.best_score_)
print(grid.best_estimator_.alpha)
results_tfidf = grid.cv_results_
#print(results_tfidf)
```

```
GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=MultinomialNB(alpha=1.0, class_prior=[0.5, 0.5],
                                     fit_prior=True),
             iid='warn', n_jobs=None,
             param_grid={'alpha': array([1.e-05, 1.e-04, 1.e-03, 1.e-02, 1.e+00, 1.e+01, 1.e+02, 1.e+03
])},
             pre_dispatch='2*n_jobs', refit='AUC', return_train_score=False,
             scoring={'AUC': 'roc_auc'}, verbose=0)
0.9223090948575503
0.01
```

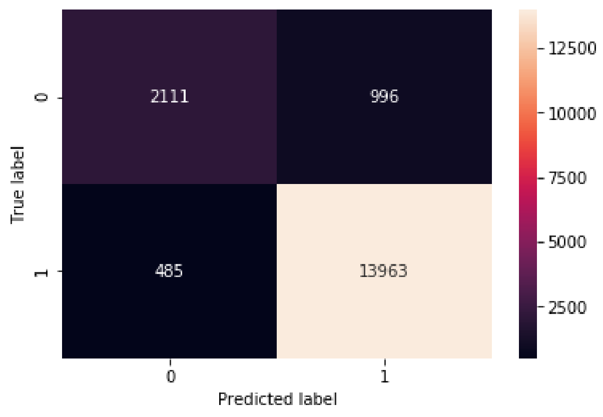
In [139]:

```
# After finding the best hyperparameter value for tfidf which is 0.01, applying naive bayes on train da
taset and predicting
# accuracy/AUC score for cv dataset
from sklearn.naive_bayes import MultinomialNB
#alphas = np.array([0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000]
clf = MultinomialNB(alpha = 0.01, class_prior=[0.5,0.5])
#clf.fit(train_bow,y_tr)
cclf=clf.fit(train_tf_idf, y_tr).predict(cv_tf_idf)
pred_cv = clf.predict_proba(cv_tf_idf)[:,1]
print('alpha value = ',0.01)
fpr, tpr, thresholds = roc_curve(y_cv,pred_cv)
roc_auc_cv = auc(fpr, tpr)
print('Area under the ROC curve : %f', + roc_auc_cv)

#Plotting confusion matrix
import seaborn as sns
conf_mat = confusion_matrix(y_cv, cclf)
print(conf_mat)
#conf_normalized = conf_mat.astype('int') / conf_mat.sum(axis=1)[:, np.newaxis]
sns.heatmap(conf_mat, annot=True, fmt ='g')
plt.ylabel('True label')
plt.xlabel('Predicted label')
```

```
alpha value =  0.01
Area under the ROC curve : %f 0.9446221197553055
[[ 2111   996]
 [  485 13963]]
```

Out[139]:

```
Text(0.5, 15.0, 'Predicted label')
```



In [140]:

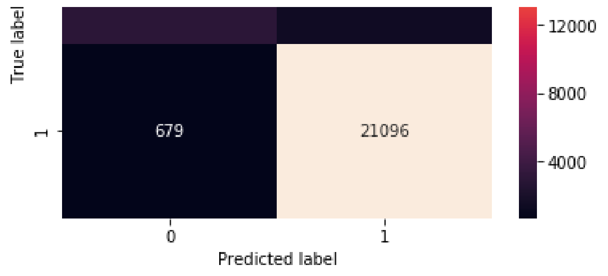
```
# After finding the best hyperparameter value for Tfidf which is 0.01, applying naive bayes on train da
taset and predicting
# accuracy/AUC score for test dataset
from sklearn.naive_bayes import MultinomialNB
#alphas = np.array([0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000]
clf = MultinomialNB(alpha = 0.01, class_prior=[0.5,0.5])
#clf.fit(train_bow,y_tr)
cclf=clf.fit(train_tf_idf, y_tr).predict(test_tf_idf)
pred_test = clf.predict_proba(test_tf_idf)[:,1]
print('alpha value = ',0.01)
fpr, tpr, thresholds = roc_curve(y_test,pred_test)
roc_auc_test = auc(fpr, tpr)
print('Area under the ROC curve : %f', + roc_auc_test)

#Plotting confusion matrix
import seaborn as sns
conf_mat = confusion_matrix(y_test, cclf)
print(conf_mat)
#conf_normalized = conf_mat.astype('int') / conf_mat.sum(axis=1)[:, np.newaxis]
sns.heatmap(conf_mat, annot=True, fmt ='g')
plt.ylabel('True label')
plt.xlabel('Predicted label')

#Plot ROC Curve
plt.figure(0).clf()
fpr, tpr, thresholds = roc_curve(y_test,pred_test)
roc_auc_test = auc(fpr, tpr)
plt.plot(fpr,tpr,label="Test Data, auc="+str(roc_auc_test))

fpr, tpr, thresh = roc_curve(y_cv, pred_cv)
roc_auc_cv = auc(fpr, tpr)
plt.plot(fpr,tpr,label="Train Data, auc="+str(roc_auc_cv))
plt.title('ROC curve for Train and Test Dataset - Tfidf')
plt.xlabel('True Positive Rate')
plt.ylabel('False Positive Rate')
plt.legend(loc=0)
```

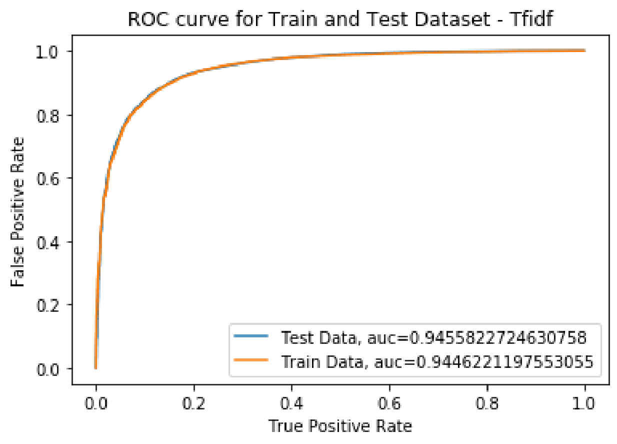
```
alpha value =  0.01
Area under the ROC curve : %f 0.9455822724630758
[[ 3019  1538]
 [  679 21096]]
```

Out[140]:

```
<matplotlib.legend.Legend at 0x32ec0e80>
```

3019
1538
0
20000
16000





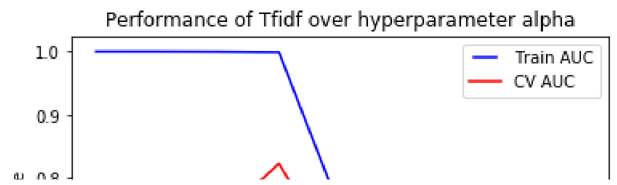
In [141]:

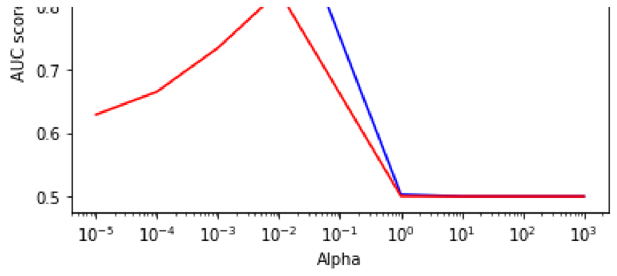
```
plot_coefficients(clf, tf_idf_vec.get_feature_names(), top_features=20)
```

```
Positive coefficients: ['them' 'but' 'these' 'with' 'have' 'they' 'that' 'are' 'you' 'my' 'in'
 'for' 'this' 'of' 'br' 'is' 'to' 'it' 'and' 'the']
Negative coefficients: ['rate as' 'no direct' 'bad facsimile' 'bad expired' 'pick kona'
 'seller buyer' 'bad experiance' 'seller cares' 'bad everything' 'no dirt'
 'demonstrated how' 'bad ethoxyquin' 'seller checked' 'seller claims'
 'demonstrates failure' 'demonstrates the' 'no did' 'to orville'
 'denied however' 'bad even']
```

In [142]:

```
#Performance of BoW over hyperparameter alpha
alpha = [0.00001, 0.0001, 0.001, 0.01, 1, 10, 100, 1000]
train_results = []
test_results = []
for i in alpha:
    clf = MultinomialNB(alpha=i,class_prior=[0.5,0.5])
    clf.fit(train_tf_idf, y_tr)
    train_pred = clf.predict(train_tf_idf)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_tr, train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = clf.predict(cv_tf_idf)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_cv, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)
from matplotlib.legend_handler import HandlerLine2D
ax = plt.gca()
ax.set_xscale('log')
line1, = ax.plot(alpha, train_results, 'b', label="Train AUC")
line2, = ax.plot(alpha, test_results, 'r', label="CV AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.title("Performance of Tfidf over hyperparameter alpha")
plt.ylabel('AUC score')
plt.xlabel('Alpha')
plt.show()
```





Observation:

```
The graph shows that for best alpha value of 0.01, the AUC score for train and test data is 0.98
and 0.74 respectively.
As alpha increases, AUC score decreases to 0.5
```

[6] Conclusions

In [143]:

```
# Please compare all your models using Prettytable library

print("Performance results for random splitted data")

from prettytable import PrettyTable
table = PrettyTable(["model","alpha value","Train AUC","Test AUC"])
table.add_row(["Naive Bayes using BoW", "1",0.9169,0.9171])
table.add_row(["Naives Bayes using TFIDF","0.01",0.954,0.954])
print(table)

print("Performance results for time based splitted data")

table = PrettyTable(["model","alpha value","Train AUC","Test AUC"])
table.add_row(["Naive Bayes using BoW", "1",0.908,0.908])
table.add_row(["Naives Bayes using TFIDF","0.01",0.945,0.945])
print(table)
```

```
Performance results for random splitted data
+--------------------------+-------------+-----------+----------+
|          model           | alpha value | Train AUC | Test AUC |
+--------------------------+-------------+-----------+----------+
|  Naive Bayes using BoW   |      1      |   0.9169  |  0.9171  |
| Naives Bayes using TFIDF |     0.01    |   0.954   |  0.954   |
+--------------------------+-------------+-----------+----------+
Performance results for time based splitted data
+--------------------------+-------------+-----------+----------+
|          model           | alpha value | Train AUC | Test AUC |
+--------------------------+-------------+-----------+----------+
|  Naive Bayes using BoW   |      1      |   0.908   |  0.908   |
| Naives Bayes using TFIDF |     0.01    |   0.945   |  0.945   |
+--------------------------+-------------+-----------+----------+
```

Observation:

```
1. Upon comparing AUC score for random based and time based splitted data, they are almost the s
ame.
2. By seeing the confusion matrix, random based data predicts the positive and negative class wi
th less error than the latter.
3. But, the top positive and negative features are more meaningful in time based splitted data.
```