Data cleaning

Amazon Fine Food Reviews Analysis

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

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

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

Attribute Information:

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

Objective:

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

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

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

Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

In [ ]:

```

```

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 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
```

[1]. Reading Data

1.Data Cleaning

Step1: Filtering only positive and negative reviews i.e.not taking into consideration those reviews with Score=3 as they are neutral

In [2]:

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')
#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3

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

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

#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 (525814, 10)
```

Out[2]:

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

In [ ]:

```

```

In [3]:

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

In [4]:

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

```
(80668, 7)
```

Out[4]:

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

In [5]:

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

Out[5]:

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

In [6]:

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

Out[6]:

```
393063
```

In [7]:

```
#Get the number of duplicate entries in the dataset.
filtered_data.duplicated(subset={"UserId","ProfileName","Time","Text"}).value_counts()
```

Out[7]:

```
False    364173
True     161641
dtype: int64
```

In [8]:

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

Out[8]:

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

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.

Problem 1:

There exist a lot of duplicates (161641) where the different products is reviewed by same user at the same time stamp. The product ID may be different but the product is similar with different variant

Solution to Problem 1

Data Cleaning: Deduplication

It is observed (as shown in the table above) 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 [9]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, k
```

In [10]:

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

Out[10]:

```
(364173, 10)
```

In [11]:

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

Out[11]:

```
69.25890143662969
```

Observation:- Percentage of data left after deduplication is 69 %

In [ ]:

```

```

In [12]:

```
data =final[final.HelpfulnessNumerator>final.HelpfulnessDenominator]
```

In [13]:

```
data
```

Out[13]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulness
59301	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
41159	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

Problem 2:

It was also seen that in two rows given above the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible

Solution to Problem 2:

Removing rows whoes HelpfulnessNumerator is greater than HelpfulnessDenominator

In [14]:

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

In [15]:

```
final.head()
```

Out[15]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	
138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	

In [16]:

```
#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()
```

```
(364171, 10)
```

Out[16]:

```
positive    307061
negative     57110
Name: Score, dtype: int64
```

Saving the data obtained after Data cleaning in final.sqlite database

In [17]:

```
conn = sqlite3.connect('final.sqlite')
sqlite_table = "Reviews"
final.to_sql(sqlite_table, conn, if_exists='replace')
conn.close
```

Out[17]:

```
<function Connection.close>
```

In [18]:

```
conn = sqlite3.connect('final.sqlite')
final_data = pd.read_sql_query(""" SELECT * FROM Reviews """, conn)
conn.close
```

Out[18]:

```
<function Connection.close>
```

In [19]:

```
final_data.head()
```

Out[19]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	
3	138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	
4	138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	

Analysis after Data_cleaning

Number of reviews which does not have any upvote

In [20]:

```
print("Number of reviews which does not have any upvote: ",final_data[final_data.Helpfulnes
```

```
Number of reviews which does not have any upvote:  171504
```

Total number of unique users

In [21]:

```
print("Total number of unique users: ",len(set(list(final_data.UserId))))
```

```
Total number of unique users:  243414
```

Total number of unique products

In [22]:

```
print("Total number of unique products: ",len(set(list(final_data.ProductId))))
```

```
Total number of unique products:  65442
```

In [ ]:

```

```