11 Amazon Fine Food Reviews Analysis_Truncated SVD

April 9, 2019

1 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.

2 [1]. Reading Data

2.1 [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 [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

from sklearn.decomposition import TruncatedSVD
from wordcloud import WordCloud
from sklearn.cluster import KMeans
from sklearn.metrics.pairwise import cosine_similarity
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect(os.path.join( os.getcwd(), '..', '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 point
# 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 5
# for tsne assignment you can take 5k data points

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

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negativ
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 (525814, 10)
```

```
Out[2]:    Id   ProductId          UserId                      ProfileName  \
        0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
        1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
        2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

           HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
        0                     1                       1      1  1303862400
        1                     0                       0      0  1346976000
        2                     1                       1      1  1219017600

                        Summary                                               Text
        0  Good Quality Dog Food  I have bought several of the Vitality canned d...
        1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
        2  "Delight" says it all  This is a confection that has been around a fe...
```

```
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  \
        0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
        3  #oc-R1105J5ZVQE25C  B005HG9ET0           Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B0070SBE1U   Christopher P. Presta  1348617600      1

                                                        Text  COUNT(*)
        0  Overall its just OK when considering the price...         2
        1  My wife has recurring extreme muscle spasms, u...         3
        2  This coffee is horrible and unfortunately not ...         2
        3  This will be the bottle that you grab from the...         3
        4  I didnt like this coffee. Instead of telling y...         2
```

```
In [5]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[5]:                 UserId   ProductId                       ProfileName        Time  \
        80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

               Score                                               Text  COUNT(*)
        80638      5  I was recommended to try green tea extract to ...         5
```

```
In [6]: display['COUNT(*)'].sum()
```

```
Out[6]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [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 [7]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
```

```
Out[7]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        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

   HelpfulnessDenominator  Score        Time  \
0                       2      5  1199577600
1                       2      5  1199577600
2                       2      5  1199577600
3                       2      5  1199577600
4                       2      5  1199577600

                             Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  LOACKER QUADRATINI VANILLA WAFERS
3  LOACKER QUADRATINI VANILLA WAFERS
4  LOACKER QUADRATINI VANILLA WAFERS

                                               Text
0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

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 [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

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

Out[9]: (364173, 10)

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

Out[10]: 69.25890143662969

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

In [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[11]:
```
      Id   ProductId          UserId              ProfileName  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     3                       1      5  1224892800
1                     3                       2      4  1212883200

                                     Summary  \
0             Bought This for My Son at College
1  Pure cocoa taste with crunchy almonds inside

                                                Text
0  My son loves spaghetti so I didn't hesitate or...
1  It was almost a 'love at first bite' - the per...
```

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
(364171, 10)
```

Out[13]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [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 [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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alo
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pre
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of thi
==================================================
```

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

print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
```

```
In [16]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
         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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pref
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only th
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of this
```

```
In [17]: # Sampling the data
         final = final.sample(n=100000, replace=True)
```

```
In [18]: # 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 [19]: sent_1500 = decontracted(sent_1500)
         print(sent_1500)
         print("="*50)
```

```
Great ingredients although, chicken should have been 1st rather than chicken broth, the only th
==================================================
```

```
In [20]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
         sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
         print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
```

```
In [21]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
         sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
         print(sent_1500)
```

```
Great ingredients although chicken should have been 1st rather than chicken broth the only thin
```

```
In [22]: # https://gist.github.com/sebleier/554280
         # we are removing the words from the stop words list: 'no', 'nor', 'not'
         # <br /><br /> ==> after the above steps, we are getting "br br"
         # we are including them into stop words list
         # instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

         stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
                     "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
                     'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 
                     'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
                     'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', '
                     'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
```

```
                'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
                's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
                've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
                "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mig
                "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                'won', "won't", 'wouldn', "wouldn't"])
```

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)
    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 stopwo
    preprocessed_reviews.append(sentance.strip())
```

```
100%|| 100000/100000 [00:39<00:00, 2518.55it/s]
```

In [24]:
```
preprocessed_reviews[1500]
```

Out[24]:
```
'little guy figured scratching post right away even though weeks old loves hiding insi
```

[3.2] Preprocessing Review Summary

In [25]:
```
## Similartly you can do preprocessing for review summary also.
```

In [26]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
for summary in tqdm(final['Summary'].values):
    summary = re.sub(r"http\S+", "", summary)
    summary = BeautifulSoup(summary, 'lxml').get_text()
    summary = decontracted(summary)
    summary = re.sub("\S*\d\S*", "", summary).strip()
    summary = re.sub('[^A-Za-z]+', ' ', summary)
    # https://gist.github.com/sebleier/554280
    summary = ' '.join(e.lower() for e in summary.split() if e.lower() not in stopword

    preprocessed_summary.append(summary.strip())
```

```
100%|| 100000/100000 [00:26<00:00, 3714.51it/s]
```

```
In [27]: final['CleanedText'] = preprocessed_reviews #adding a column of CleanedText which dis
         final['CleanedText'] = final['CleanedText'].astype('str')

         final['CleanedSummary'] = preprocessed_summary #adding a column of CleanedSummary whi
         final['CleanedSummary'] = final['CleanedSummary'].astype('str')

         final['Text_Summary'] = final['CleanedSummary'] + final['CleanedText']

         # # store final table into an SQlLite table for future.
         # conn = sqlite3.connect('final.sqlite')
         # c=conn.cursor()
         # conn.text_factory = str
         # final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
         #               index=True, index_label=None, chunksize=None, dtype=None)
         # conn.close()
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [28]: # #BoW
         # count_vect = CountVectorizer() #in scikit-learn
         # count_vect.fit(preprocessed_reviews)
         # print("some feature names ", count_vect.get_feature_names()[:10])
         # print('='*50)

         # final_counts = count_vect.transform(preprocessed_reviews)
         # print("the type of count vectorizer ",type(final_counts))
         # print("the shape of out text BOW vectorizer ",final_counts.get_shape())
         # print("the number of unique words ", final_counts.get_shape()[1])
```

5.2 [4.2] Bi-Grams and n-Grams.

```
In [29]: # #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/m

         # # 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_bigr
```

5.3 [4.3] TF-IDF

In [30]:
```
# tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
# tf_idf_vect.fit(preprocessed_reviews)
# print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_na
# print('='*50)

# final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
# print("the type of count vectorizer ",type(final_tf_idf))
# print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
# print("the number of unique words including both unigrams and bigrams ", final_tf_i
```

5.4 [4.4] Word2Vec

In [31]:
```
# # 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 [32]:
```
# w2v_words = list(w2v_model.wv.vocab)
# print("number of words that occured minimum 5 times ",len(w2v_words))
# print("sample words ", w2v_words[0:50])
```

In [33]:
```
# # Using Google News Word2Vectors

# # in this project we are using a pretrained model by google
# # its 3.3G file, once you load this into your memory
# # it occupies ~9Gb, so please do this step only if you have >12G of ram
# # we will provide a pickle file wich contains a dict ,
# # and it contains all our courpus words as keys and  model[word] as values
# # To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# # from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# # it's 1.9GB in size.


# # http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# # you can comment this whole cell
# # or change these varible according to your need

# is_your_ram_gt_16g=False
# want_to_use_google_w2v = False
# want_to_train_w2v = True

# if want_to_train_w2v:
#     # min_count = 5 considers only words that occured atleast 5 times
#     w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
#     print(w2v_model.wv.most_similar('great'))
#     print('='*50)
```

```
#     print(w2v_model.wv.most_similar('worst'))

# elif want_to_use_google_w2v and is_your_ram_gt_16g:
#     if os.path.isfile('GoogleNews-vectors-negative300.bin'):
#         w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300
#         print(w2v_model.wv.most_similar('great'))
#         print(w2v_model.wv.most_similar('worst'))
#     else:
#         print("you don't have gogole's word2vec file, keep want_to_train_w2v = True
```

5.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [34]:
```
# # 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]))
```

[4.4.1.2] TFIDF weighted W2v

In [35]:
```
# # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
# model = TfidfVectorizer()
# tf_idf_matrix = model.fit_transform(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 [36]:
```
# # 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 = tfi

# tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this
# row=0;
# for sent in tqdm(list_of_sentance): # for each review/sentence
#     sent_vec = np.zeros(50) # 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 = tf_idf_matrix[row, tfidf_feat.index(word)]
#             # to reduce the computation we are
#             # dictionary[word] = idf value of word in whole courpus
#             # sent.count(word) = tf valeus of word in this review
#             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
```

6 [5] Assignment 11: Truncated SVD

```
<li><strong>Apply Truncated-SVD on only this feature set:</strong>
    <ul>
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
<br>
<li><strong>Procedure:</strong>
    <ul>
<li>Take top 2000 or 3000 features from tf-idf vectorizers using idf_ score.</li>
<li>You need to calculate the co-occurrence matrix with the selected features (Note: X.X^T
```

doesn't give the co-occurrence matrix, it returns the covariance matrix, check these bolgs blog-1, blog-2 for more information)

```
        <li>You should choose the n_components in truncated svd, with maximum explained
```

variance. Please search on how to choose that and implement them. (hint: plot of cumulative explained variance ratio)

```
        <li>After you are done with the truncated svd, you can apply K-Means clustering and cho
```

the best number of clusters based on elbow method.

```
        <li> Print out wordclouds for each cluster, similar to that in previous assignment. </l
        <li>You need to write a function that takes a word and returns the most similar words u
```

cosine similarity between the vectors(vector: a row in the matrix after truncatedSVD)

```
    </ul>
</li>
<br>
```

6.1 Truncated-SVD

```
In [37]: # Source: https://docs.python.org/3/library/pickle.html

         # Saving data to pickle file
         def topicklefile(obj, file_name):
             pickle.dump(obj,open(file_name+'.pkl', 'wb'))

In [38]: # Data from pickle file
         def frompicklefile(file_name):
             data = pickle.load(open(file_name+'.pkl', 'rb'))
             return data

In [39]: # Sort 'Time' column
         final = final.sort_values(by='Time', ascending=True)

In [73]: # Applying BOW on train and test data and creating the
         from sklearn.preprocessing import StandardScaler
         from scipy.sparse import hstack

         #Source: https://stackoverflow.com/questions/41298073/how-to-get-the-most-representat
         def apply_vectorizer(train_data):

             #Applying TF-IDF on Train data
             count_vect = TfidfVectorizer(ngram_range=(1,1), min_df=10)

             #Applying BoW on Test data
             train_vect = count_vect.fit_transform(train_data)

             feature_names = np.array(count_vect.get_feature_names())

             idf_index = count_vect.idf_.argsort()

             feature_names = feature_names[idf_index]

             topicklefile(train_vect, 'train_vect')

             return count_vect, feature_names[:2000]

In [41]: def build_co_occurance_matrix(top_features, X, window_size):
             coocur_matrix = np.zeros((len(top_features),len(top_features)))
             # Iterate over all the review+summary texts from the dataset
             for x in tqdm(X):
                 # Splitting the string into list of words
                 text_corpus = x.split()
                 # Initializing the pointers to zeroth col and row in the co occurance matrix
                 for index1 in range(len(top_features)):
                     # Check in the word1 from the list is present in the corpus list of words
                     if top_features[index1] in text_corpus:
```

```
                    # Similar to word1, consider each word2 in the index range of index1
                    # As the matrix is symmetric for a given review in X, we can simultan
                    # The below loop will update the matrix on one side of the diagonal e
                    for index2 in range(index1):
                        # Initialize occur_count to 0, Based on the presence of the word2
                        occur_count = 0
                        # Check if the word2 is not equal to word1 and word2 is in corpus
                        if top_features[index2]!=top_features[index1] and top_features[in
                            # Collect all the indices of all the occurances of word1
                            word_index = [ind for ind,word in enumerate(text_corpus) if t
                            # Get all the words in the word windows of word1
                            for index in word_index:
                                window_words=[]
                                if index+1<len(text_corpus):
                                    window_words.extend(text_corpus[max(index-window_size

                                elif index == len(text_corpus):
                                    window_words.extend(text_corpus[index-window_size : i

                                # Count all the word2 occurances from the words obtained
                                occur_count += window_words.count(top_features[index2])
                            # Update the count in the symmetric cells of the co-occurence
                            coocur_matrix[index2][index1] += occur_count
                            coocur_matrix[index1][index2] += occur_count
                        else:
                            # If the word2 is not present in the corpus list of words add
                            coocur_matrix[index2][index1] += 0
                            coocur_matrix[index1][index2] += 0
                else:
                    # If the word1 is not present in the corpus list of words then add al
                    coocur_matrix[index1][:] += 0
        return coocur_matrix
```

```
In [42]: def apply_truncated_SVD(data, n_comp):
             t_svd = TruncatedSVD(n_components=n_comp)
             t_svd.fit(data)
             return t_svd, t_svd.explained_variance_ratio_
```

```
In [43]: def optimal_truncated_SVD(data, n_comp):
             t_svd = TruncatedSVD(n_components=n_comp)
             t_svd.fit(data)
             X_new = t_svd.fit_transform(data)
             return X_new
```

```
In [44]: #Source: https://chrisalbon.com/machine_learning/feature_engineering/select_best_numb
         def select_n_components(var_ratio, goal_var):
             # Set initial variance explained so far
             total_variance = 0.0
```

```
    # Set initial number of features
    n_components = 0

    # For the explained variance of each feature:
    for explained_variance in var_ratio:

        # Add the explained variance to the total
        total_variance += explained_variance

        # Add one to the number of components
        n_components += 1

        # If we reach our goal level of explained variance
        if total_variance >= goal_var:
            # End the loop
            break

    # Return the number of components
    return n_components
```

In [45]:
```
#Source: https://jakevdp.github.io/PythonDataScienceHandbook/05.09-principal-componen
def plot_cum_exp_var(t_svd):
    plt.plot(np.cumsum(t_svd.explained_variance_ratio_))
    plt.xlabel('number of components')
    plt.ylabel('cumulative explained variance')
    plt.show()
```

In [46]:
```
#Source: https://www.datasciencecentral.com/profiles/blogs/python-implementing-a-k-me
# https://jakevdp.github.io/PythonDataScienceHandbook/05.11-k-means.html
def apply_kmeans(data, clusters):
#    clusters = [i for in range(2,10,2)]
    inertias = []

    for cluster in clusters:
        kmeans = KMeans(n_clusters=cluster, n_jobs=-1)
        kmeans.fit(data)
        inertias.append(kmeans.inertia_)
    print('inertias: ',inertias)
    return inertias
```

In [47]:
```
def plot_scores_vs_clusters(clusters, inertias):
    plt.plot(clusters, inertias)
    plt.xlabel('n_clusters')
    plt.ylabel('Scores')
    plt.title('Elbow Plot')
    plt.show()
```

In [48]:
```
def retrain_kmeans(cluster, data):
    kmeans = KMeans(n_clusters=cluster, n_jobs=-1)
```

```
        kmeans.fit(data)
        labels = kmeans.labels_
        return labels
```

In [49]:
```
    #https://andrew47.github.io/scikitlearn-cluster.html
    from collections import Counter
    def build_wordclouds(X, labels):
        review_labels = pd.DataFrame({'Top Features':X, 'labels':labels})

        for cluster in review_labels['labels'].unique():
            review_labels1 = review_labels[review_labels['labels']==cluster]

            if len(review_labels1) != 0:
                text = ' '.join(review_labels1['Top Features'])
                text = text.split()

                counts = Counter(text)
                counts = dict(counts)

                wordcloud = WordCloud(background_color = 'white')
                kMeansWordCloud = wordcloud.generate_from_frequencies(counts)
                plt.figure()
                plt.imshow(kMeansWordCloud)
                plt.axis("off")

        return review_labels
```

In [50]:
```
    def sim_words_cosine_sim(input_word, X_new, review_labels):
        review_labels
        label = review_labels[review_labels['Top Features']==input_word]['labels'].values

        review_labels1 = review_labels[review_labels['labels']==label]

        input_word_index = list(top_features).index(input_word)

        sim_words_in_cluster = list(review_labels1['Top Features'])

        sim_words_in_cluster_index=[]

        for word in sim_words_in_cluster:
            sim_words_in_cluster_index.append(list(top_features).index(word))

        cosine_similarities = []

        for index in sim_words_in_cluster_index:
            cos_sim = float(cosine_similarity(X_new[input_word_index].reshape(1, -1), X_ne
            cosine_similarities.append(cos_sim)
```

```
        features_cos_sim = pd.DataFrame({'Features':sim_words_in_cluster, 'Cosine Similar

        return features_cos_sim
```

6.1.1 [5.1] Taking top features from TFIDF, SET 2

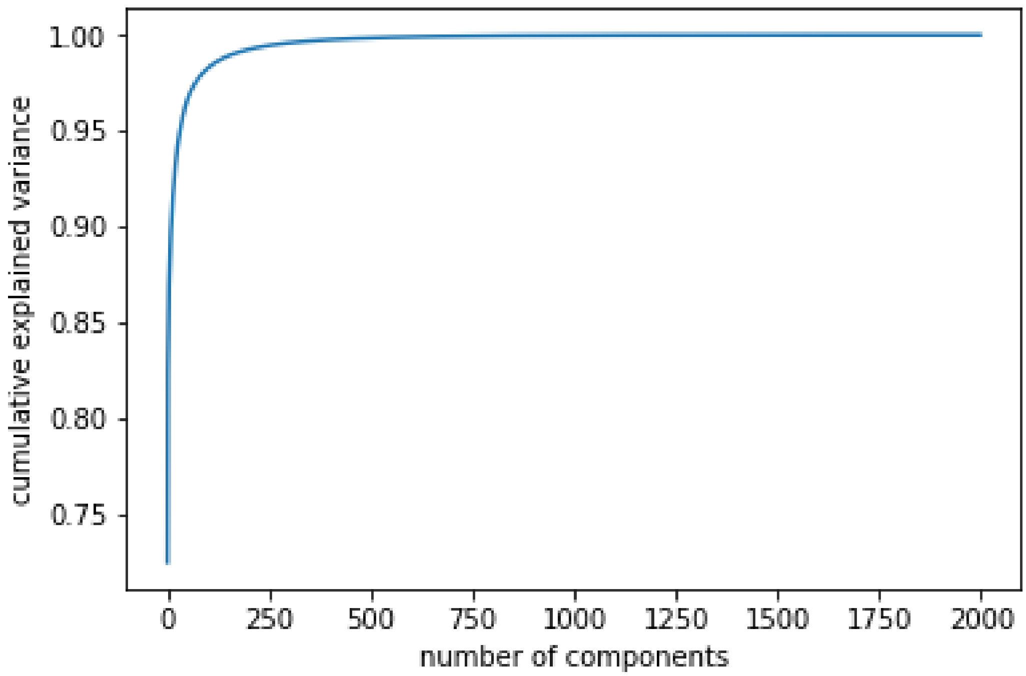
```
In [51]: # Please write all the code with proper documentation

In [74]: X = np.array(final['Text_Summary'])
         count_vect, top_features = apply_vectorizer(X)

In [75]: train_vect = frompicklefile('train_vect')
```

6.1.2 [5.2] Calulation of Co-occurrence matrix

```
In [76]: # Please write all the code with proper documentation

In [77]: coocur_matrix = build_co_occurance_matrix(list(top_features), X, 5)

100%|| 100000/100000 [1:27:15<00:00, 19.10it/s]


In [78]: coocur_matrix

Out[78]: array([[0.0000e+00, 6.0330e+03, 1.6068e+04, ..., 7.2000e+01, 6.9000e+01,
                 8.0000e+01],
                [6.0330e+03, 0.0000e+00, 2.3480e+03, ..., 1.0000e+01, 1.1000e+01,
                 2.3000e+01],
                [1.6068e+04, 2.3480e+03, 0.0000e+00, ..., 1.3000e+01, 3.1000e+01,
                 5.3000e+01],
                ...,
                [7.2000e+01, 1.0000e+01, 1.3000e+01, ..., 0.0000e+00, 2.0000e+00,
                 1.0000e+00],
                [6.9000e+01, 1.1000e+01, 3.1000e+01, ..., 2.0000e+00, 0.0000e+00,
                 0.0000e+00],
                [8.0000e+01, 2.3000e+01, 5.3000e+01, ..., 1.0000e+00, 0.0000e+00,
                 0.0000e+00]])
```

6.1.3 [5.3] Finding optimal value for number of components (n) to be retained.

```
In [79]: # Please write all the code with proper documentation

In [80]: t_svd, tsvd_exp_var_ratio_ = apply_truncated_SVD(coocur_matrix, len(top_features)-1)

In [81]: plot_cum_exp_var(t_svd)
```




```
In [82]: n_comp= select_n_components(tsvd_exp_var_ratio_, 0.90)
         print(n_comp)
```

```
11
```

```
In [83]: X_new = optimal_truncated_SVD(coocur_matrix, n_comp)
         X_new.shape
```

```
Out[83]: (2000, 11)
```

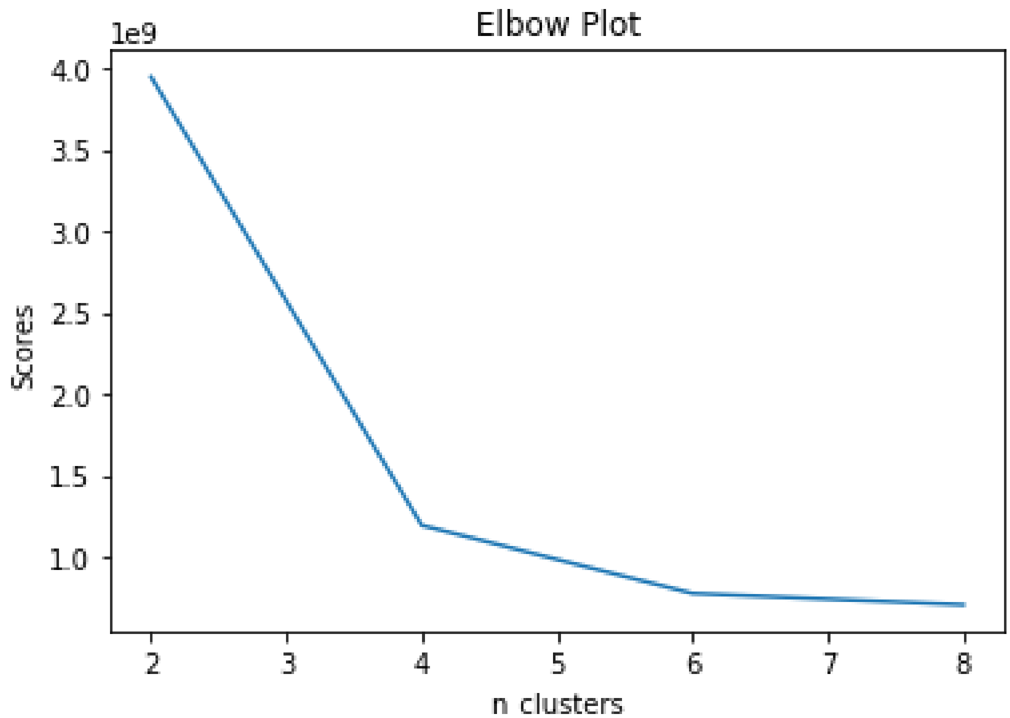
6.1.4 [5.4] Applying k-means clustering

```
In [84]: # Please write all the code with proper documentation
```

```
In [85]: clusters = [i for i in range(2,10,2)]
         inertias = apply_kmeans(X_new, clusters)
```

```
inertias:  [3947942773.255795, 1192518958.736823, 775065156.6024526, 705505792.8484215]
```

```
In [86]: plot_scores_vs_clusters(clusters, inertias)
```




```
In [87]: labels = retrain_kmeans(6, X_new)
```

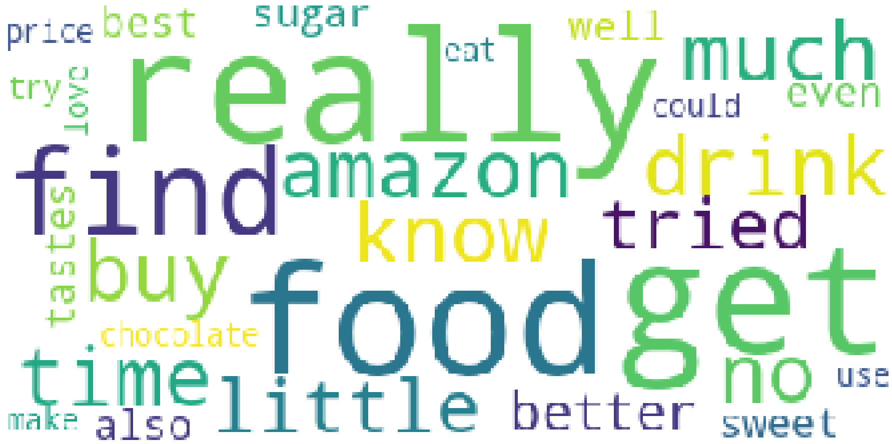
6.1.5 [5.5] Wordclouds of clusters obtained in the above section

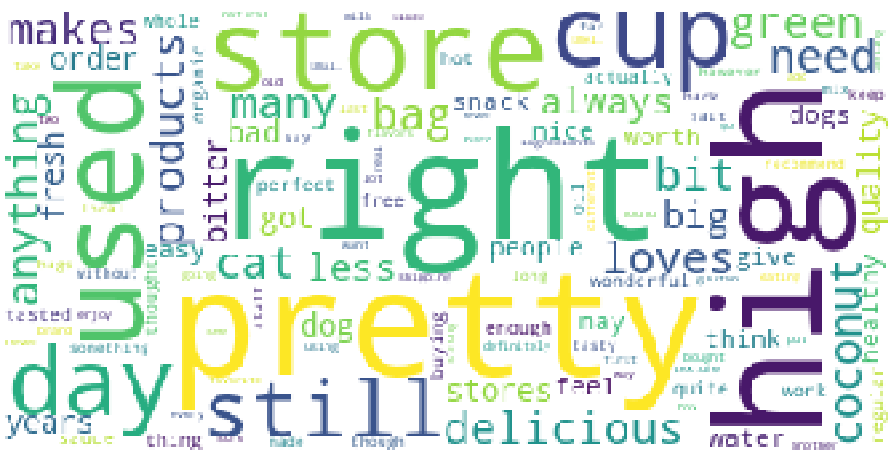
```
In [88]: # Please write all the code with proper documentation
```

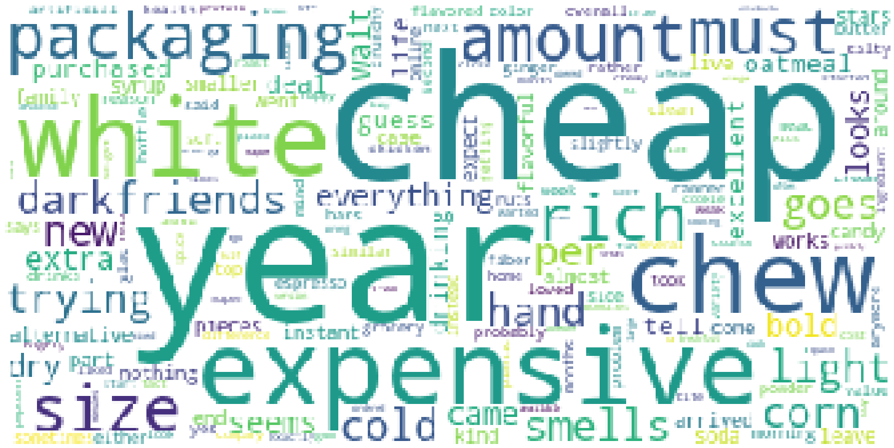
```
In [89]: print(type(X_new))
         review_labels = build_wordclouds(top_features, labels)
```

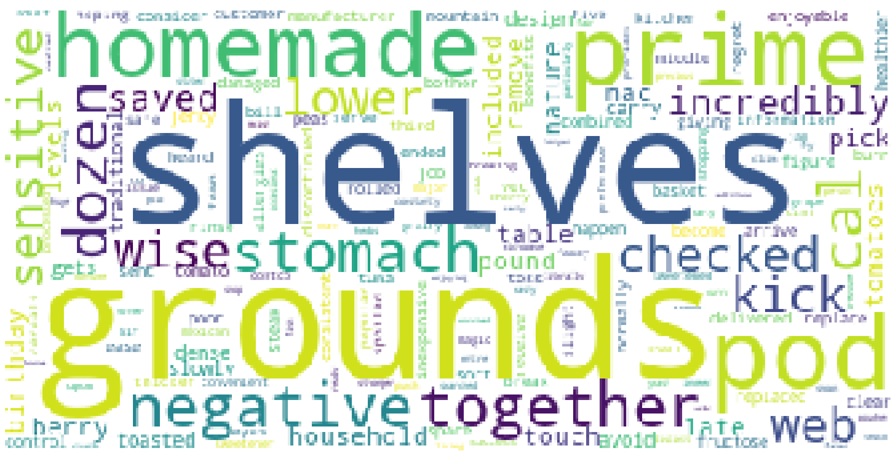
```
<class 'numpy.ndarray'>
```


not
coffee
tea
flavor
great
like
good
one
would
taste
product


really
food
get
find
amazon
drink
much
know
tried
buy
time
little
better
no
sweet
also
chocolate
tastes
price
best
sugar
well
eat
could
even
try
love
make
use


pretty
right
high
store
used
cup
day
still
delicious
green
need
makes
order
products
anything
fresh
many
bag
always
bit
big
quality
coconut
healthy
loves
less
cat
dog
bitter
bad
nice
worth
snack
dogs
people
give
think
water
years
stores
feel
may
enough
perfect
free
got
easy
tasted
wonderful
something
thing





6.1.6 [5.6] Function that returns most similar words for a given word.

```
In [90]: # Please write all the code with proper documentation

In [92]: features_cos_sim = sim_words_cosine_sim('food', X_new, review_labels)

In [93]: features_cos_sim

Out[93]:    Cosine Similarities  Features
         0             0.889184      love
         1             0.909744       get
```

```
2                 0.872552          no
3                 0.810749        best
4                 0.796198      amazon
5                 0.879702      really
6                 0.887681        much
7                 0.895720        also
8                 0.906809        time
9                 0.895487         buy
10                0.858513         use
11                0.867409        find
12                0.872336      little
13                0.775903       price
14                0.904468        even
15                0.870313        make
16                0.861497      better
17                0.906856        well
18                0.925004         try
19                0.902269       tried
20                1.000000        food
21                0.882998       could
22                0.962322         eat
23                0.715576      tastes
24                0.807125       sweet
25                0.820809       sugar
26                0.874458        know
27                0.743588       drink
28                0.827687   chocolate
```

7 [6] Conclusions

```
In [94]: # Please write down few lines about what you observed from this assignment.
         # Also please do mention the optimal values that you obtained for number of component
```

7.1 [6.1] Observations:

1. 2000 important features from TF-IDF vectorizer is obtained using _idf score.
2. Co-occurence matrix is built for 2000 important features.
3. '11' n_components is obtained when Truncated SVD is applied on the Co-occurence matrix U(n*n).
4. New matrix U' with n*k dimensions is obtained and K-menas clustering is applied on it.
5. The optimal number of clusters obtained is 6.
6. Building wordclouds for all the clusters.

7) Each wordcloud represents the following: a) WC1: only 'not' b) WC2: This cluster contains about coffee, tea and their attributes like taste, flavour. c) WC3: This cluster contains words

like food, drink, sugar, sweet,tastes, better and etc. d) WC4: This clusters contains words like pretty, right, store, cup and also about food products and their attributes like delicious, taste, bitter and etc. e) WC5: This cluster contains words related to buying products on Amazon. f) WC6: This cluster contains words related to home and homemade products