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 [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
```

```
C:\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows; aliasing chunk
ize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:

```
# using SQLite Table to read data.
con = sqlite3.connect('C:/Users/sesha/OneDrive/Desktop/IMP/before/MINIPJ/Personal/AMAZON food revi
ew dataset/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""", co
n)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5000""", 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 (5000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all

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
```

[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 [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	HelpfulnessDenominator	Score	Time	Summ
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRA VANI WAFE
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRA VANI WAFE
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRA VANI WAFE
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRA VANI WAFE
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRA VANI WAFE

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=False, kind='qui
cksort', na_position='last')
```

In [9]:

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

Out[9]:

```
(4986, 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]:

```
99.72
```

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	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892800	Bought This for My Son at College
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside

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()
```

```
(4986, 10)
```

Out[13]:

```
1    4178
0     808
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 [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)
```

```
Why is this $[...] when the same product is available for $[...] here?<br
/>http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<br /><br />The Victor M380 and
M502 traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The best t
hing was that there were a lot of "brown" chips in the bsg (my favorite), so I bought some more th
rough amazon and shared with family and friends.  I am a little disappointed that there are not, s
o far, very many brown chips in these bags, but the flavor is still very good.  I like them better
than the yogurt and green onion flavor because they do not seem to be as salty, and the onion flav
or is better.  If you haven't eaten Kettle chips before, I recommend that you try a bag before buy
ing bulk.  They are thicker and crunchier than Lays but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the other
wants crispy cookies.  Hey, I'm sorry; but these reviews do nobody any good beyond reminding us to
look  before ordering.<br /><br />These are chocolate-oatmeal cookies.  If you don't like that com
bination, don't order this type of cookie.  I find the combo quite nice, really.  The oatmeal sort
of "calms" the rich chocolate flavor and gives the cookie sort of a coconut-type consistency.  Now
let's also remember that tastes differ; so, I've given my opinion.<br /><br />Then, these are soft
, chewy cookies -- as advertised.  They are not "crispy" cookies, or the blurb would say "crispy,"
rather than "chewy."  I happen to like raw cookie dough; however, I don't see where these taste li
ke raw cookie dough.  Both are soft, however, so is this the confusion?  And, yes, they stick toge
ther.  Soft cookies tend to do that.  They aren't individually wrapped, which would add to the
cost.  Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br /><br />So, if you want
something hard and crisp, I suggest Nabiso's Ginger Snaps.  If you want a cookie that's soft, chew
y and tastes like a combination of chocolate and oatmeal, give these a try.  I'm here to place my
second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />This k cup is great coffee.  d
caf is very good as well
==================================================
```

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)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor M3
80 and M502 traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearb
y.
```

In [16]:

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

```
Why is this $[...] when the same product is available for $[...] here? />The Victor M380 and M502
traps are unreal, of course -- total fly genocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The best t
hing was that there were a lot of "brown" chips in the bsg (my favorite), so I bought some more th
rough amazon and shared with family and friends.  I am a little disappointed that there are not, s
o far, very many brown chips in these bags, but the flavor is still very good.  I like them better
than the yogurt and green onion flavor because they do not seem to be as salty, and the onion flav
or is better.  If you haven't eaten Kettle chips before, I recommend that you try a bag before buy
ing bulk.  They are thicker and crunchier than Lays but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the other
wants crispy cookies.  Hey, I'm sorry; but these reviews do nobody any good beyond reminding us to
look  before ordering.These are chocolate-oatmeal cookies.  If you don't like that combination, do
n't order this type of cookie.  I find the combo quite nice, really.  The oatmeal sort of "calms"
the rich chocolate flavor and gives the cookie sort of a coconut-type consistency.  Now let's also
remember that tastes differ; so, I've given my opinion.Then, these are soft, chewy cookies -- as
advertised.  They are not "crispy" cookies, or the blurb would say "crispy," rather than "chewy."
I happen to like raw cookie dough; however, I don't see where these taste like raw cookie dough.
Both are soft, however, so is this the confusion?  And, yes, they stick together.  Soft cookies te
nd to do that.  They aren't individually wrapped, which would add to the cost.  Oh yeah, chocolate
chip cookies tend to be somewhat sweet.So, if you want something hard and crisp, I suggest Nabiso'
s Ginger Snaps.  If you want a cookie that's soft, chewy and tastes like a combination of
chocolate and oatmeal, give these a try.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cup is great coffee.  dcaf is
very good as well
```

In [17]:

```
# 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"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [18]:

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

```
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the other
wants crispy cookies.  Hey, I am sorry; but these reviews do nobody any good beyond reminding us t
o look  before ordering.<br /><br />These are chocolate-oatmeal cookies.  If you do not like that
combination, do not order this type of cookie.  I find the combo quite nice, really.  The oatmeal
sort of "calms" the rich chocolate flavor and gives the cookie sort of a coconut-type consistency.
Now let is also remember that tastes differ; so, I have given my opinion.<br /><br />Then, these a
re soft, chewy cookies -- as advertised.  They are not "crispy" cookies, or the blurb would say "c
rispy," rather than "chewy."  I happen to like raw cookie dough; however, I do not see where these
taste like raw cookie dough.  Both are soft, however, so is this the confusion?  And, yes, they st
ick together.  Soft cookies tend to do that.  They are not individually wrapped, which would add t
o the cost.  Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br /><br />So, if you want
something hard and crisp, I suggest Nabiso is Ginger Snaps.  If you want a cookie that is soft, ch
ewy and tastes like a combination of chocolate and oatmeal, give these a try.  I am here to place
my second order.
==================================================
```

In [19]:

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

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

In [20]:

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

```
Wow So far two two star reviews One obviously had no idea what they were ordering the other wants
crispy cookies Hey I am sorry but these reviews do nobody any good beyond reminding us to look bef
ore ordering br br These are chocolate oatmeal cookies If you do not like that combination do not
order this type of cookie I find the combo quite nice really The oatmeal sort of calms the rich ch
ocolate flavor and gives the cookie sort of a coconut type consistency Now let is also remember th
at tastes differ so I have given my opinion br br Then these are soft chewy cookies as advertised
They are not crispy cookies or the blurb would say crispy rather than chewy I happen to like raw c
ookie dough however I do not see where these taste like raw cookie dough Both are soft however so
is this the confusion And yes they stick together Soft cookies tend to do that They are not indivi
dually wrapped which would add to the cost Oh yeah chocolate chip cookies tend to be somewhat
sweet br br So if you want something hard and crisp I suggest Nabiso is Ginger Snaps If you want a
cookie that is soft chewy and tastes like a combination of chocolate and oatmeal give these a try
I am here to place my second order
```

In [21]:

```
# 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', 'ourselves', 'you', "y
ou're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having'
```

```
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', '
while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during',
'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under'
, 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'e
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll'
, 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "d
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [22]:

```
# 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())
```

```
100%|████████████████████████████████████████████████████████████████████████████| 4986/4986
[00:01<00:00, 3256.88it/s]
```

In [23]:

```
preprocessed_reviews[1500]
```

Out[23]:

```
'wow far two two star reviews one obviously no idea ordering wants crispy cookies hey sorry review
s nobody good beyond reminding us look ordering chocolate oatmeal cookies not like combination not
order type cookie find combo quite nice really oatmeal sort calms rich chocolate flavor gives
cookie sort coconut type consistency let also remember tastes differ given opinion soft chewy cook
ies advertised not crispy cookies blurb would say crispy rather chewy happen like raw cookie dough
however not see taste like raw cookie dough soft however confusion yes stick together soft cookies
tend not individually wrapped would add cost oh yeah chocolate chip cookies tend somewhat sweet wa
nt something hard crisp suggest nabiso ginger snaps want cookie soft chewy tastes like combination
chocolate oatmeal give try place second order'
```

[3.2] Preprocessing Review Summary

In [24]:

```
## Similartly you can do preprocessing for review summary also.
preprocessed_summary = []
# tqdm is for printing the status bar
for summary in tqdm(final['Summary'].values):
    summary = re.sub(r"http\S+", "", summary) # remove urls from text python:
https://stackoverflow.com/a/40823105/4084039
    summary = BeautifulSoup(summary, 'lxml').get_text() #
https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-tags-from-an-e
lement
    summary = decontracted(summary)
    summary = re.sub("\S*\d\S*", "", summary).strip() #remove words with numbers python: https://st
ackoverflow.com/a/18082370/4084039
```

```
    summary = re.sub('[^A-Za-z]+', ' ', summary) #remove spacial character:
https://stackoverflow.com/a/5843547/4084039
    # https://gist.github.com/sebleier/554280
    summary = ' '.join(e.lower() for e in summary.split() if e.lower() not in stopwords)
    preprocessed_summary.append(summary.strip())
```

```
100%|████████████████████████████████████████████████████████████████| 4986/4986
[00:00<00:00, 5018.41it/s]
```

In [25]:

```
preprocessed_reviews = [i + ' ' + j for i, j in zip(preprocessed_reviews,preprocessed_summary)]
print(preprocessed_reviews[1500])
```

```
wow far two two star reviews one obviously no idea ordering wants crispy cookies hey sorry reviews
nobody good beyond reminding us look ordering chocolate oatmeal cookies not like combination not o
rder type cookie find combo quite nice really oatmeal sort calms rich chocolate flavor gives
cookie sort coconut type consistency let also remember tastes differ given opinion soft chewy cook
ies advertised not crispy cookies blurb would say crispy rather chewy happen like raw cookie dough
however not see taste like raw cookie dough soft however confusion yes stick together soft cookies
tend not individually wrapped would add cost oh yeah chocolate chip cookies tend somewhat sweet wa
nt something hard crisp suggest nabiso ginger snaps want cookie soft chewy tastes like combination
chocolate oatmeal give try place second order reviewing mistakes cookies
```

In [26]:

```
final ['CleanText']= preprocessed_reviews
final.head(5)
```

Out[26]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summa
2546	2774	B00002NCJC	A196AJHU9EASJN	Alex Chaffee	0	0	1	1282953600	thi buck
2547	2775	B00002NCJC	A13RRPGE79XFFH	reader48	0	0	1	1281052800	Fli Bego
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	10	1	962236800	WC Ma your ov 'slicker
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	7	1	961718400	Gre Prodi
2942	3204	B000084DVR	A1UGDJP1ZJWVPF	T. Moore "thoughtful reader"	1	1	1	1177977600	Go stu

In [27]:

```
##Sorting data for Time Based Splitting
final = final.sort_values('Time',axis= 0,inplace = False , na_position = 'last',ascending = True)
X_train = final['CleanText'].values
X_train = X_train[:50000]
print(X_train.shape)
```

```
(4986,)
```

TF-IDF

In [28]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,1),use_idf=True, min_df=10, max_features = 2000)
tf_idf_vect.fit(X_train)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(X_train)
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_idf.get_shape()[
1])
```

```
some sample features(unique words in the corpus) ['able', 'absolute', 'absolutely', 'according', '
acid', 'acidic', 'across', 'active', 'actual', 'actually']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 2000)
the number of unique words including both unigrams and bigrams  2000
```

[5] Assignment 11: Truncated SVD

1. **Apply Truncated-SVD on only this feature set:**

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

   - **Procedure:**
     - Take top 2000 or 3000 features from tf-idf vectorizers using idf_ score.
     - 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)
     - 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)
     - After you are done with the truncated svd, you can apply K-Means clustering and choose the best number of clusters based on elbow method.
     - Print out wordclouds for each cluster, similar to that in previous assignment.
     - You need to write a function that takes a word and returns the most similar words using cosine similarity between the vectors(vector: a row in the matrix after truncatedSVD)

Truncated-SVD

[5.1] Taking top features from TFIDF, SET 2

In [29]:

```
def top_ft(tf_idf_vect, ft_names, top_n_ft):
    # returns top n features :
    ft_index = np.argsort(tf_idf_vect.idf_)
    top_ft = [(ft_names[i], tf_idf_vect.idf_[i]) for i in ft_index[:top_n_ft]]
    data_topFt = pd.DataFrame(data=top_ft, columns = ['Top Words','TFIDF Values'])
    return data_topFt

#Get TF-IDF Scores mean:
tfidf_mean = np.mean(final_tf_idf, axis = 0)
tfidf_mean = np.array(tfidf_mean)[0].tolist()

#List feature names:
ft_names = tf_idf_vect.get_feature_names()

#Top TFIDF words with their scores:
top_n_ft = 3000
top_ft = top_ft(tf_idf_vect, ft_names, top_n_ft)

#Print the top 20 features.
```

```
top_ft.head(20)
```

Out[29]:

	Top Words	TFIDF Values
0	not	1.609886
1	great	2.121942
2	good	2.153850
3	like	2.227029
4	taste	2.498877
5	love	2.576305
6	product	2.587032
7	one	2.600852
8	would	2.654975
9	flavor	2.689130
10	best	2.740366
11	no	2.921545
12	really	2.928418
13	get	2.975004
14	much	3.010302
15	buy	3.062541
16	tried	3.094595
17	time	3.101131
18	find	3.112673
19	little	3.134467

[5.2] Calulation of Co-occurrence matrix

In [30]:

```
# Please write all the code with proper documentation
def co_Mat(X_train, top_ft, window):
    print("Generate the Co-Occurence Matrix....")
    dim=top_ft.shape[0]
    square_matrix = np.zeros((dim,dim),int)

    values = [i for i in range(0,top_ft.shape[0])]
    keys = [str(i) for i in top_ft['Top Words']]
    lookup_dict = dict(zip(keys,values))

    top_words= keys

    for row in tqdm(X_train):
        #Split each review into words
        words_in_row = row.split()
        lnt = len(words_in_row)
        for i in range(0,len(words_in_row),1):
            idx_of_neigbors= []
            if((i-window >= 0) and (i+window < lnt)):
                idx_of_neigbors = np.arange(i-window,i+window+1)
            elif((i-window < 0) and (i+window < lnt)):
                idx_of_neigbors = np.arange(0, i+window+1)
            elif((i-window >= 0) and (i+window >= lnt)):
                idx_of_neigbors = np.arange(i-window, lnt)
            else:
                pass

            #neigh = [words_in_row[x] for x in idx_of_neigbors]
            #print(words_in_row[i],"********",neigh)
            #print(idx_of_neigbors)
```

```
            for j in idx_of_neigbors:
                if((words_in_row[j] in top_words) and (words_in_row[i] in top_words)):
                    row_idx = lookup_dict[words_in_row[i]]
                    col_idx = lookup_dict[words_in_row[j]]
                    square_matrix[row_idx,col_idx] += 1
                else:
                    pass

    np.fill_diagonal(square_matrix, 0)
    print("Generate Co-Oc Matrix")

    #Create a co-occurence df.
    co_Mat_df=pd.DataFrame(data=square_matrix, index=keys, columns=keys)
    return co_Mat_df

co_Mat = co_Mat(X_train, top_ft, window=5)

co_Mat.to_csv('coc_Mat.csv')
```

```
Generate the Co-Occurence Matrix....
```

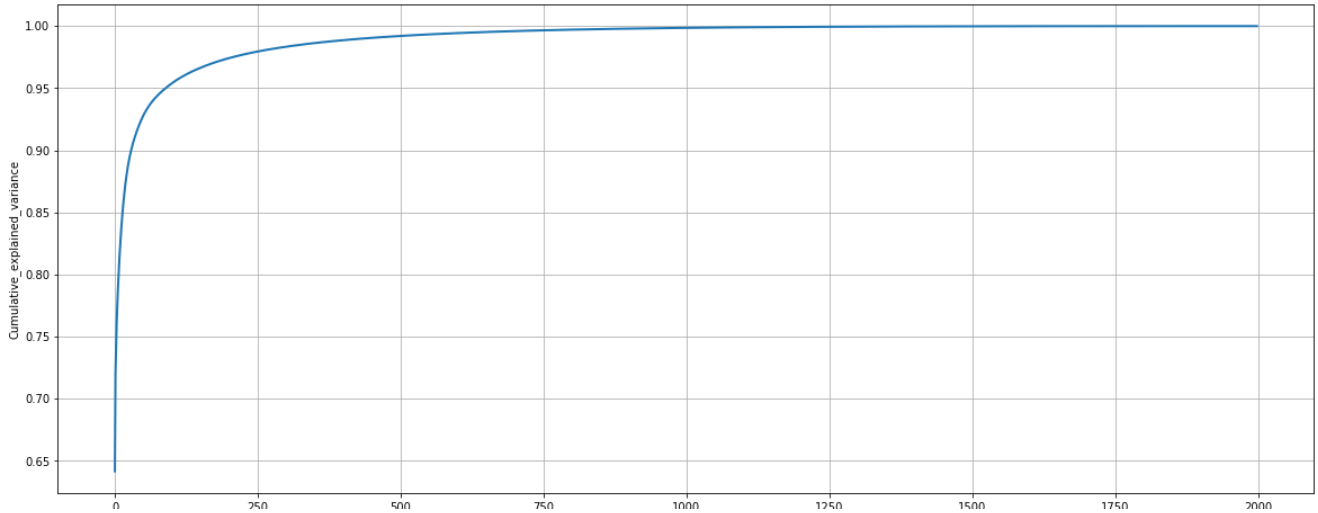
```
100%|████████████████████████████████████████████████████████████████████████████| 4986/4986
[00:31<00:00, 159.42it/s]
```

```
Generate Co-Oc Matrix
```

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

In [31]:

```
from sklearn.decomposition import TruncatedSVD

n = co_Mat.shape[0]-1

#Inititalizing truncated SVD.
svd = TruncatedSVD(n_components=n,
                   algorithm='randomized',
                   n_iter=7,
                   random_state=42)
svd_tfidf=svd.fit_transform(co_Mat)

cum_var_explained = np.cumsum(svd.explained_variance_ratio_)

# Plot the SVD
plt.figure(1, figsize=(20, 8))
plt.plot(cum_var_explained, linewidth=2)
plt.grid()
plt.axis('tight')
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
```



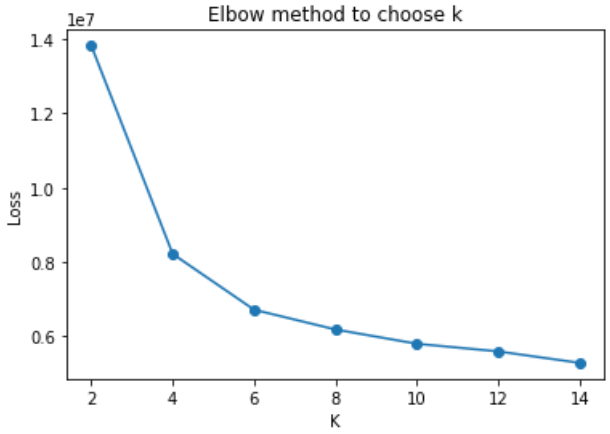
[5.4] Applying k-means clustering

In [32]:

```
# Please write all the code with proper documentation
# Elbow method to find K
from sklearn.cluster import KMeans
def find_optimal_k(svd_tfidf):
    inertia = []
    k = [2,4,6,8,10,12,14]
    for i in k:
        km = KMeans(n_clusters = i)
        km.fit(svd_tfidf)
        inertia.append(km.inertia_)
    plt.plot(k, inertia, "-o")
    plt.title("Elbow method to choose k")
    plt.xlabel("K")
    plt.ylabel("Loss")
    plt.show()
```

In [33]:

```
find_optimal_k(svd_tfidf)
```



In [34]:

```
model = KMeans(n_clusters=50, random_state=42, n_init=50)
model.fit(svd_tfidf)


#Get the cluster centroid values.
print("The cluster centroids:")
print(model.cluster_centers_)
```

```
The cluster centroids:
[[ 7.19558996e+01 -1.23897618e+01  5.63425666e-01 ...  5.17716496e-06
   2.82494491e-05  4.47815570e-06]
 [ 5.72825721e+02 -7.91255858e+01  2.18276065e+01 ...  1.10429737e-04
   1.16483503e-04 -8.69146832e-05]
 [ 9.60446612e+00 -1.15493456e+00  6.69622526e-01 ... -3.04620877e-05
  -1.57309328e-05  6.90872473e-06]
 ...
 [ 3.07090468e+02 -5.18418541e+01 -8.86071940e+00 ...  6.91749582e-05
  -6.73922133e-05  6.01444149e-05]
 [ 1.81310433e+02 -8.91578331e+00 -1.57912293e+00 ... -1.17048905e-04
  -9.86056793e-05 -1.74098080e-05]
 [ 1.96346062e+02 -2.13797593e+01  3.66249713e+01 ... -2.39042017e-05
  -1.04606100e-05 -7.07041933e-06]]
```

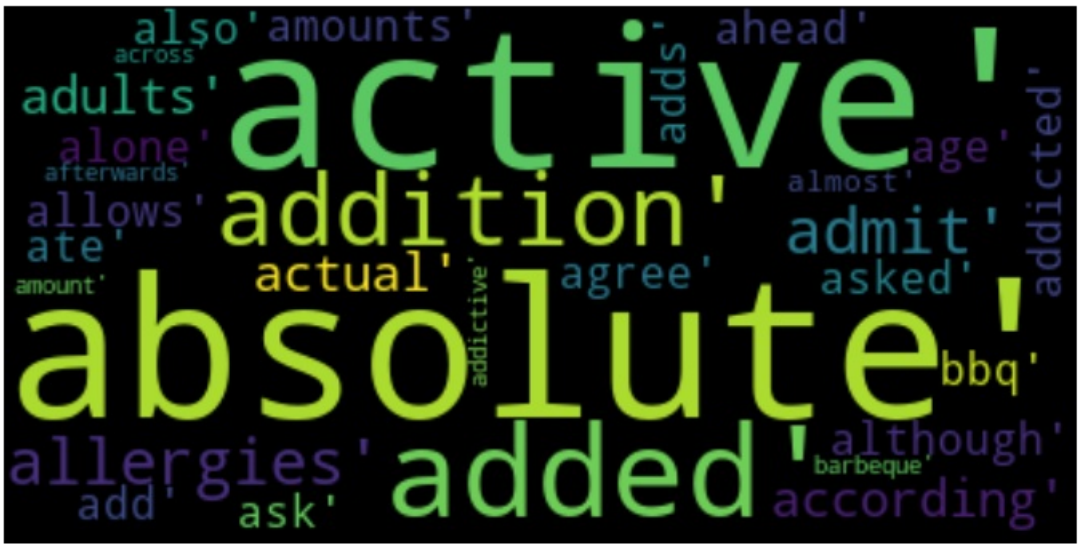
[5.5] Wordclouds of clusters obtained in the above section

[3.5] Wordclouds of clusters obtained in the above section

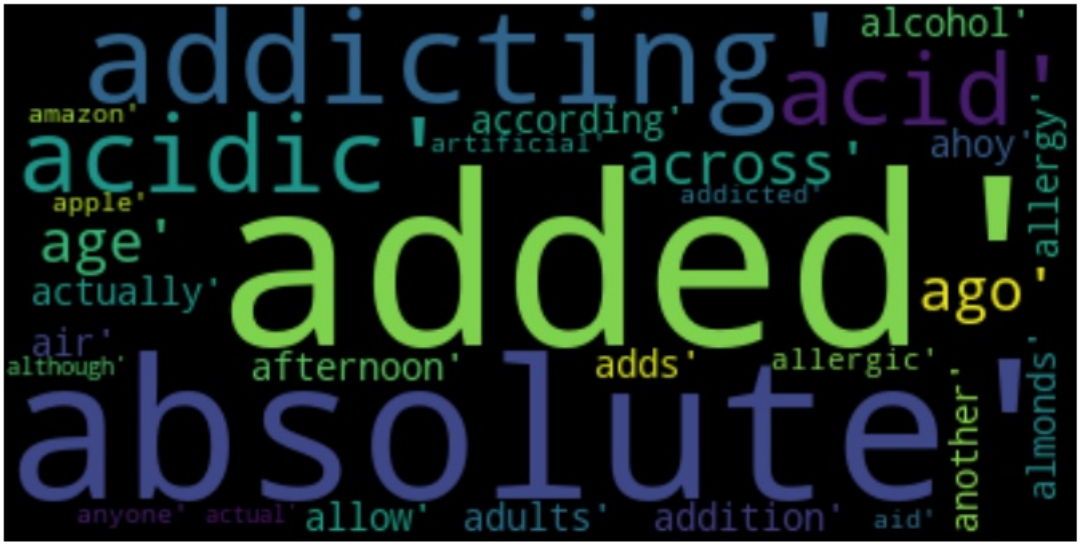
In [35]:

```
# Please write all the code with proper documentation
from wordcloud import WordCloud


centroids = model.cluster_centers_.argsort() # function for printing top 30 feature names with eac
h cluster

terms = tf_idf_vect.get_feature_names()

list1 = []

for i in range(10):
    print("Cluster %d:" % i, end='')
    for j in centroids[i, :30]:
        list1.append(terms[j])
    wc = WordCloud(background_color="black", max_words=len(str(list1)))
    wc.generate(str(list1))
    print("Word Cloud for KMeans Cluster:", i)
    plt.figure(figsize = (12,12), facecolor = None)
    plt.imshow(wc, interpolation='bilinear')
    plt.axis("off")
    plt.show()
    list1.clear()
```

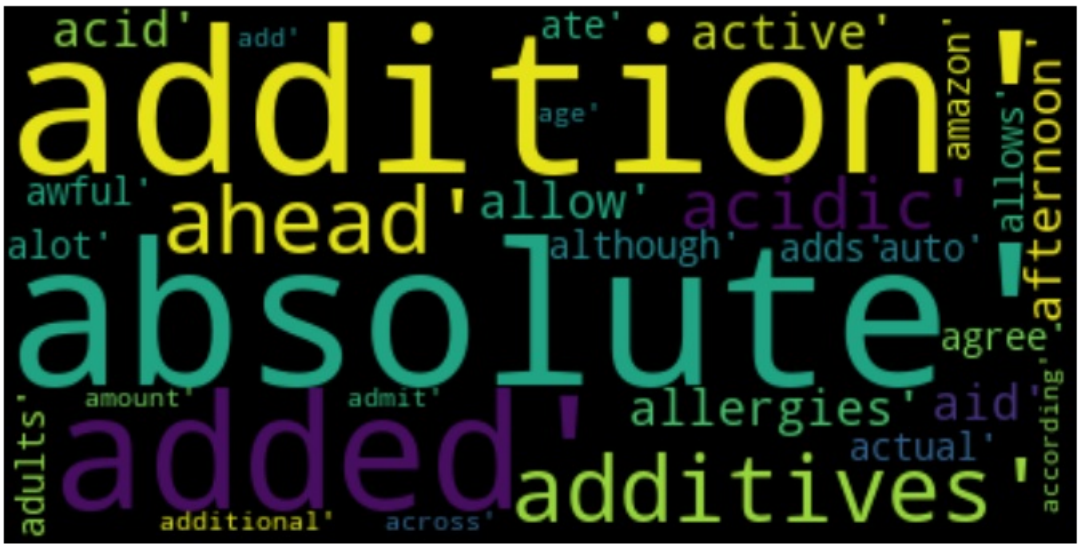
Cluster 0:Word Cloud for KMeans Cluster: 0



Cluster 1:Word Cloud for KMeans Cluster: 1



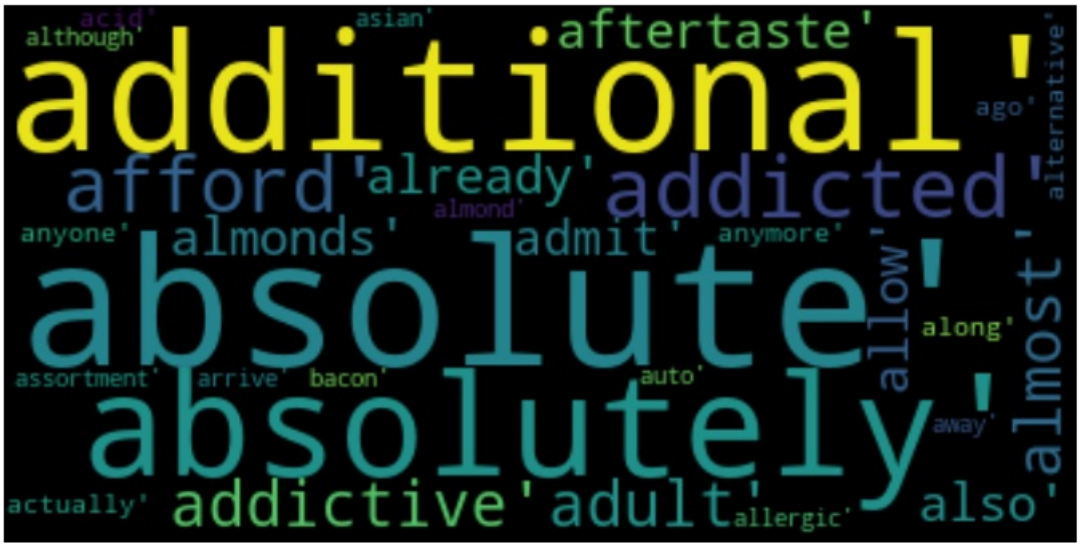
Cluster 2:Word Cloud for KMeans Cluster: 2



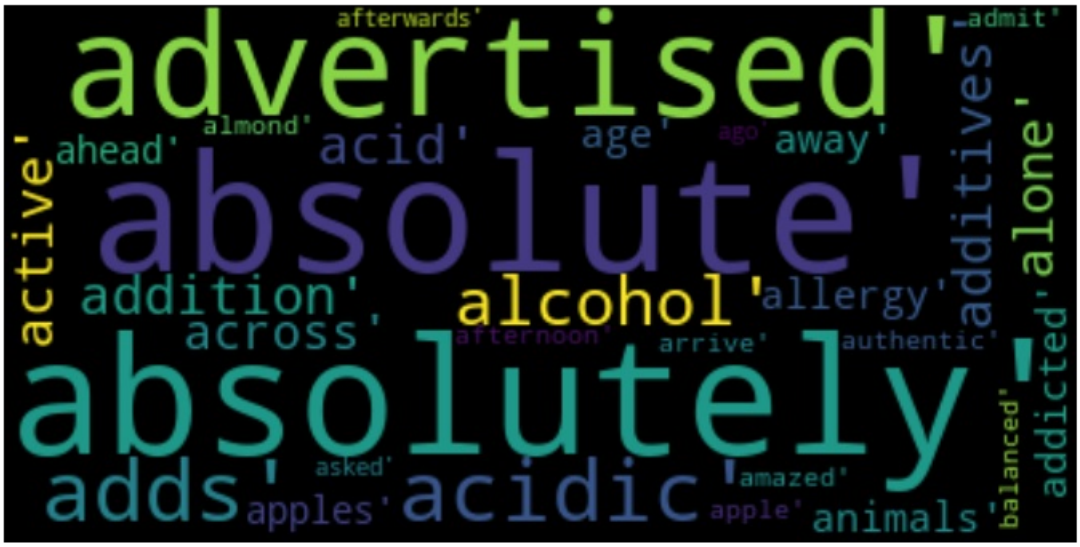
Cluster 3:Word Cloud for KMeans Cluster: 3

Cluster 4:Word Cloud for KMeans Cluster: 4

Cluster 5:Word Cloud for KMeans Cluster: 5

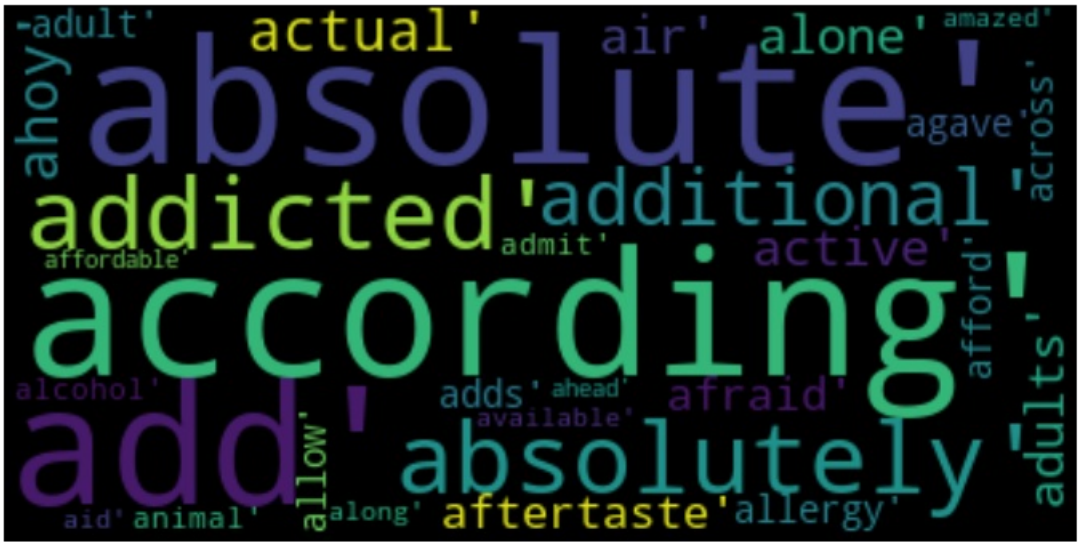


Cluster 6:Word Cloud for KMeans Cluster: 6

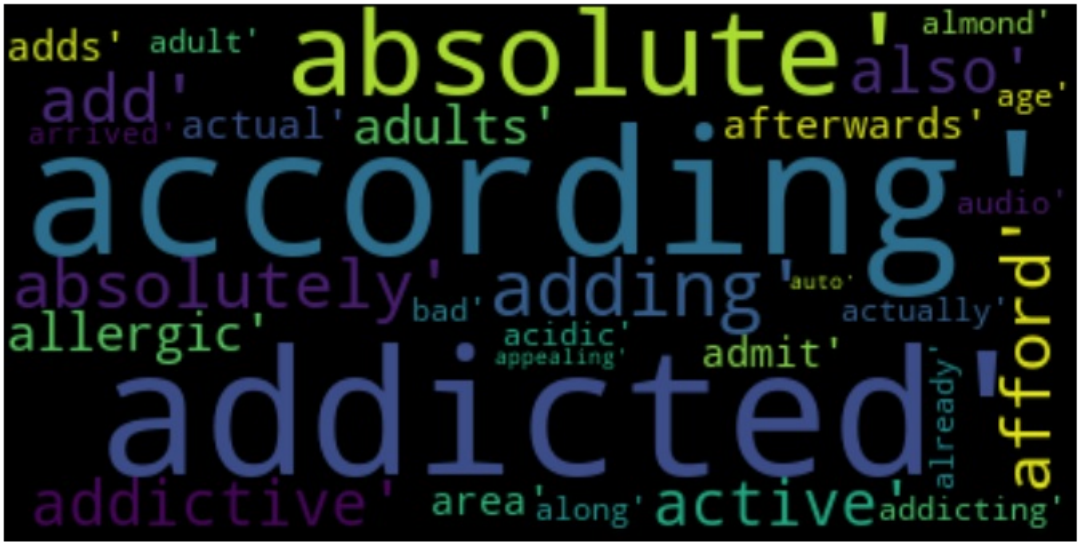


Cluster 7:Word Cloud for KMeans Cluster: 7

Cluster 8:Word Cloud for KMeans Cluster: 8



Cluster 9:Word Cloud for KMeans Cluster: 9



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

In [36]:

```
top_ft = tf_idf_vect.get_feature_names()
```

In [37]:

```
# Please write all the code with proper documentation
from sklearn.metrics.pairwise import cosine_similarity
def similar_word(word):
    similarity = cosine_similarity(co_Mat)
    word_vect = similarity[top_ft.index(word)]
    print("Similar Word to",word)
    index = word_vect.argsort()[::-1][1:21]
    for j in range(len(index)):
        print((j+1),"Word",top_ft[index[j]] ,"is similar to",word,"\n")
```

In [38]:

```
similar_word(top_ft[1])
```

```
Similar Word to absolute
1 Word american is similar to absolute

2 Word absolutely is similar to absolute

3 Word acidic is similar to absolute

4 Word afterwards is similar to absolute

5 Word ago is similar to absolute

6 Word added is similar to absolute

7 Word baked is similar to absolute

8 Word addicting is similar to absolute

9 Word ball is similar to absolute

10 Word adults is similar to absolute

11 Word amounts is similar to absolute

12 Word according is similar to absolute

13 Word became is similar to absolute

14 Word aid is similar to absolute

15 Word chocolate is similar to absolute

16 Word ate is similar to absolute

17 Word afford is similar to absolute

18 Word allowed is similar to absolute

19 Word asian is similar to absolute

20 Word benefit is similar to absolute
```

[6] Conclusions

-The optimal value of K from the elbow plot is 6.

-The word clouds obtained do make sense.