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)

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (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
from scipy import sparse
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.decomposition import TruncatedSVD
from sklearn.cluster import KMeans
from sklearn.feature_extraction.text import CountVectorizer

from sklearn import metrics
from wordcloud import WordCloud

from nltk.stem.porter import PorterStemmer
from datetime import datetime
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
import tabulate

from tqdm import tqdm
import os
```

In [0]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000
data points
# you can change the number to any other number based on your computing pow
er

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score !
= 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score !=
 3 LIMIT 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[0]:

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

In [0]:

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

In [0]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[0]:

	UserId	ProductId	ProfileName	Time	Score	Text	COU
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [0]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[0]:

	UserId	ProductId	ProfileName	Time	Score	Text
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...

In [0]:
```
display['COUNT(*)'].sum()
```

Out[0]: 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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[0]:

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

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 [0]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True,
inplace=False, kind='quicksort', na_position='last')
```

In [0]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Te
xt"}, keep='first', inplace=False)
final.shape
```

Out[0]: (4986, 10)

In [0]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[0]: 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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [0]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [0]:
```
#Before starting the next phase of preprocessing lets see the number of ent
ries left
print(final.shape)

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

```
(4986, 10)
```

Out[0]:
```
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 [0]:
```
# 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 thing was that there were a lot of "brown" chips in the bsg (my favorite), so I bought some more through amazon and shared with family and friends.  I am a little disappointed that there are not, so 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 flavor is better.  If you haven't eaten Kettle chips before, I recommend that you try a bag before buying 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 combination, 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 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 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, 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.<br />This k cup is great coffee.  dcaf is very good as well
==================================================
```

In [0]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/408403
9
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 M380 and M502 traps are unreal, of course -- total fly
genocide. Pretty stinky, but only right nearby.
```

In [0]:
```
# 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? />Th
e Victor M380 and M502 traps are unreal, of course -- total fly genocide. P
retty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious these
chips are.  The best thing was that there were a lot of "brown" chips in th
e bsg (my favorite), so I bought some more through amazon and shared with f
amily and friends.  I am a little disappointed that there are not, so 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 flavor is better.  If you haven't eaten
Kettle chips before, I recommend that you try a bag before buying bulk.  Th
ey are thicker and crunchier than Lays but just as fresh out of the bag.
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re ordering; the other wants crispy cookies.  Hey, I'm sorry; but these rev
iews do nobody any good beyond reminding us to look  before ordering.These
are chocolate-oatmeal cookies.  If you don't like that combination, don't o
rder this type of cookie.  I find the combo quite nice, really.  The oatmea
l 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 the
se taste like raw cookie dough.  Both are soft, however, so is this the con
fusion?  And, yes, they stick together.  Soft cookies tend to do that.  The
y aren't individually wrapped, which would add to the cost.  Oh yeah, choco
late 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 so
ft, chewy and tastes like a combination of chocolate and oatmeal, give thes
e 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 [0]:

```python
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [0]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what they we
re ordering; the other wants crispy cookies.  Hey, I am sorry; but these re
views do nobody any good beyond reminding us to look  before ordering.<br /
><br />These are chocolate-oatmeal cookies.  If you do not like that combin
ation, do not order this type of cookie.  I find the combo quite nice, real
ly.  The oatmeal sort of "calms" the rich chocolate flavor and gives the co
okie sort of a coconut-type consistency.  Now let is also remember that tas
tes differ; so, I have given my opinion.<br /><br />Then, these are soft, c
hewy cookies -- as advertised.  They are not "crispy" cookies, or the blurb
would say "crispy," rather than "chewy."  I happen to like raw cookie doug
h; 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.  S
oft cookies tend to do that.  They are not individually wrapped, which woul
d add to the cost.  Oh yeah, chocolate chip cookies tend to be somewhat swe
et.<br /><br />So, if you want something hard and crisp, I suggest Nabiso i
s 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 [0]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/408
4039
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  and  traps are unreal, of course -- total fly genocid
e. Pretty stinky, but only right nearby.
```

In [0]:
```
#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 or
dering the other wants crispy cookies Hey I am sorry but these reviews do n
obody any good beyond reminding us to 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 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 do not see where these taste like raw cooki
e dough Both are soft however so is this the confusion And yes they stick t
ogether Soft cookies tend to do that They are not individually wrapped whic
h 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 Gin
ger Snaps If you want a cookie that is soft chewy and tastes like a combina
tion of chocolate and oatmeal give these a try I am here to place my second
order
```

In [0]:
```
# 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', "you'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', 'be
cause', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'int
o', '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', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so',
'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "sho
uld've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'did
n', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't",
'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "sh
ouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [0]:
```
# 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() no
t in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████████████████████████
██████| 4986/4986 [00:01<00:00, 3137.37it/s]
```

In [0]:
```
preprocessed_reviews[1500]
```

Out[0]:
```
'wow far two two star reviews one obviously no idea ordering wants crispy c
ookies hey sorry reviews nobody good beyond reminding us look ordering choc
olate oatmeal cookies not like combination not order type cookie find combo
quite nice really oatmeal sort calms rich chocolate flavor gives cookie sor
t coconut type consistency let also remember tastes differ given opinion so
ft chewy cookies advertised not crispy cookies blurb would say crispy rathe
r chewy happen like raw cookie dough however not see taste like raw cookie 
dough soft however confusion yes stick together soft cookies tend not indiv
idually wrapped would add cost oh yeah chocolate chip cookies tend somewhat
sweet want something hard crisp suggest nabiso ginger snaps want cookie sof
t chewy tastes like combination chocolate oatmeal give try place second ord
er'
```

[3.2] Preprocessing Review Summary

In [0]:
```
## Similartly you can do preprocessing for review summary also.
```

[4] Featurization

[4.1] BAG OF WORDS

In [0]:
```
#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])
```

```
some feature names  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abbot
t', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[4.2] Bi-Grams and n-Grams.

In [0]:
```
#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/modules/generated/sklearn.feature_extraction.text.CountVectorizer.ht
ml

# 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=500
0)
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 ", fi
nal_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.3] TF-IDF

In [0]:
```
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_fe
ature_names()[0:10])
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 ", fi
nal_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'able
find', 'able get', 'absolute', 'absolutely', 'absolutely delicious', 'absol
utely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.4] Word2Vec

In [0]:
```
# 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 [0]:
```
# 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/#.W17SRFA
zZPY
# 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-neg
ative300.bin', binary=True)
        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_w2
v = True, to train your own w2v ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wonderfu
l', 0.9946032166481018), ('excellent', 0.9944332838058472), ('especially',
0.9941144585609436), ('baked', 0.9940600395202637), ('salted', 0.9940472245
21637), ('alternative', 0.9937226176261902), ('tasty', 0.9936816692352295),
('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('popco
rn', 0.9992750883102417), ('de', 0.9992610216140747), ('miss', 0.9992451071
739197), ('melitta', 0.999218761920929), ('choice', 0.9992102384567261),
('american', 0.9991837739944458), ('beef', 0.9991780519485474), ('finish',
0.9991567134857178)]
```

In [0]:
```
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])
```

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'stink
y', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'received', 's
hipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'instead', 'rem
oved', 'easily', 'daughter', 'designed', 'printed', 'use', 'car', 'window
s', 'beautifully', 'shop', 'program', 'going', 'lot', 'fun', 'everywhere',
'like', 'tv', 'computer', 'really', 'good', 'idea', 'final', 'outstanding',
'window', 'everybody', 'asks', 'bought', 'made']
```

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

[4.4.1.1] Avg W2v

In [0]:
```
# 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 mi
ght need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████████████████████████████████████████████████████████████████
██████| 4986/4986 [00:03<00:00, 1330.47it/s]

4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [0]:
```
# 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 [0]:
```
# 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_v
al = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored
in this list
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/revie
w
    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
```

```
100%|██████████████████████████████████████████████████████████████████████
███████| 4986/4986 [00:20<00:00, 245.63it/s]
```

[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, (https://medium.com/data-science-group-iitr/word-embedding-2d05d270b285)](https://medium.com/data-science-group-iitr/word-embedding-2d05d270b285) [blog-2 (https://www.analyticsvidhya.com/blog/2017/06/word-embeddings-count-word2veec/)](https://www.analyticsvidhya.com/blog/2017/06/word-embeddings-count-word2veec/)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 [0]:
```
# Please write all the code with proper documentation
```

The code for generating top features is in the code shown in Section 5.2

[5.2] Calulation of Co-occurrence matrix

In [0]:
```
# Please write all the code with proper documentation
```

In [ ]:
```
#%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np

import scipy


import matplotlib.pyplot as plt

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.preprocessing import StandardScaler

from bs4 import BeautifulSoup
import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
import nltk
from nltk import word_tokenize, sent_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
import re
import pickle

from tqdm import tqdm
import os
import time

class asign_11_dtcrea:

        def __init__(self):
                self.X_train = pd.DataFrame()
                self.feat_names = []
                self.top2000feat = []
                self.vocablry = {}
                self.max_features = None
                self.row = []
                self.col = []
                self.data = []
                self.tgt_word_count = 0

        #gridsearchcv parameters -- start
        @property
        def X_train(self):
            return self._X_train

        @X_train.setter
        def X_train(self,new_X_train):
            self._X_train = new_X_train
```

```
        # Give reviews with Score>3 a positive rating(1), and reviews with
 a score<3 a negative rating(0).
        def partition(self,x):
                if x < 3:
                        return 0
                return 1

        def write_ft_data(self,fnme,opdata):

                #fname = 'E:/appliedaicourse/assignments/dblite/kdtree_50
k/' + fnme
                fname = 'E:/appliedaiacourse/assignments/dblite/asign-11-ts
vd' + fnme
                with open(fname, 'wb') as fp:
                        pickle.dump(opdata, fp)

        def write_data(self,fnme,opdata):

                #fname = 'E:/appliedaicourse/assignments/dblite/kdtree_50
k/' + fnme

                #fname = 'E:/appliedaiacourse/assignments/dblite/asign-11-t
svd' + fnme
                fname = 'D:/data/asign-11-tsvd'+ fnme
                print(fname)
                with open(fname, 'wb') as fp:
                        pickle.dump(opdata, fp)


        def decontracted(self,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



        # Combining all the above statements
        def rw_preproc(self,xdata):
                stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'w
e', 'our', 'ours', 'ourselves', 'you', "you're", "you've",\
                "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
                'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
```

```
s', 'itself', 'they', 'them', 'their',\
                'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
                'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', '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', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
                'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
                's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
                've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
                "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n'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"])

                preprocessed_reviews = []

                # tqdm is for printing the status bar

                for sentance in tqdm(xdata.values):
                        sentance = re.sub(r"http\S+", "", sentance)
                        sentance = BeautifulSoup(sentance, 'lxml').get_text
()
                        sentance = self.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.spl
it() if e.lower() not in stopwords)
                        preprocessed_reviews.append(sentance.strip())
                return preprocessed_reviews


        def getreviews(self, nrows):
                X_trn = pd.DataFrame()
                # using SQLite Table to read data.
                filepath = os.path.abspath('E:/appliedaiacourse/assignment
s/dblite/database.sqlite')
                assert os.path.exists(filepath), 'the file does not exist'
                con = sqlite3.connect(filepath)
                #filtered_data = pd.read_sql_query(""" SELECT * FROM Review
s WHERE Score != 3 LIMIT 50000""", con)
                if nrows == -1 :
                        # fetch all rows
                        filtered_data = pd.read_sql_query(""" SELECT * FROM
Reviews WHERE Score != 3 """ , con)
                else:
```

```
                        filtered_data = pd.read_sql_query(""" SELECT * FROM 
Reviews WHERE Score != 3 LIMIT """ + str(nrows), con)

                #changing reviews with score less than 3 to be positive and 
vice-versa
                actualScore = filtered_data['Score']
                positiveNegative = actualScore.map(self.partition)
                filtered_data['Score'] = positiveNegative
                #Sorting data according to ProductId in ascending order
                sorted_data=filtered_data.sort_values('ProductId', axis=0, 
ascending=True, inplace=False, kind='quicksort', na_position='last')
                #Deduplication of entries
                final=sorted_data.drop_duplicates(subset={"UserId","Profile
Name","Time","Text"}, keep='first', inplace=False)
                final.shape

                final=final[final.HelpfulnessNumerator<=final.HelpfulnessDe
nominator]

                #Before starting the next phase of preprocessing lets see t
he number of entries left
                print(final.shape)

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

                self.X_train = self.rw_preproc(final['Text'])

        def TFIDFVectorizer(self):
                X_v_train = []
                tidfXtrain_scaled = []

                #this is for gridsearchcv
                tf_idf_vect_1 = TfidfVectorizer(ngram_range=(1,1), min_df=4
, max_features=4000) #in scikit-learn
                X_v_train = tf_idf_vect_1.fit_transform(self.X_train)

                self.feat_names = tf_idf_vect_1.get_feature_names()
                self.write_ft_data('/tfidfvectorizer/tfidf_feat',tf_idf_vec
t_1.get_feature_names())
                print("some sample features(unique words in the corpus)",tf
_idf_vect_1.get_feature_names()[0:10])
                print('='*50)

                idf_idx = np.argsort(tf_idf_vect_1.idf_)[::-1]

                top_n = 2000
                self.top2000feat = [self.feat_names[i] for i in idf_idx[:to
p_n]]

                idf_rev_list = []
                for i in idf_idx[:top_n]:
                        idf_rev_list.append(tf_idf_vect_1.idf_[i])

                self.write_data('/tfidfvectorizer/idf_rev_lst.pkl',idf_rev_
```

```
list)
                self.write_data('/tfidfvectorizer/idf_rev_ft.pkl',self.top2
000feat)

        def create_feat_dict(self):
                for ftname in self.top2000feat:
                        self.vocablry.setdefault(ftname,len(self.vocablry))
                #print(self.vocablry)


        def crea_sent_contxt_wrd(self,sentence):
                window=2
                focus_contxt = ()
                sent_contxt_wrds = []
                rvw = sentence.split()
                for i in range(0,len(rvw)):
                        focus_wrd = rvw[i]
                        low = max(0,i - window)
                        high = min(len(rvw), i + window +1)
                        #low = max(0,low)
                        #print('Context:',rvw[low:high])
                        focus_contxt = (focus_wrd, rvw[low:high])
                        sent_contxt_wrds.append(focus_contxt)
                return sent_contxt_wrds

        def crea_cocur_mtx(self):
                self.row =[]
                self.col = []
                self.data = []

                for j,review in enumerate(self.X_train):
                        sent_contxt_wrd = self.crea_sent_contxt_wrd(review)
                        print(sent_contxt_wrd)
                        #print(review)
                        rvw = review.split()
                        for i,word in enumerate(rvw):
                                print('next focus word', word)
                                rw = self.vocablry.get(word,'Not Found')
                                if rw == 'Not Found':

                                        continue
                                else:
                                        print('row found',word)
                                        context = sent_contxt_wrd[i][1]
                                        print(context)
                                        for wrd in context:
                                                if word == wrd:
                                                        continue
                                                cl = self.vocablry.get(wrd,
'Not Found')
                                                #print('word2', wrd,cl)
                                                if cl=='Not Found':
                                                        #print('col not fou
nd',wrd)
                                                        continue
                                                else:
                                                        print('insertion',w
```

```
rd,rw,cl)
                                                        self.row.append(rw)
                                                        self.col.append(cl)
                                                        self.data.append(1.
)
                        print('Processed  :',j,' review',review)

                if len(self.row) > 0 and len(self.col) > 0:
                        cocur_mtx = scipy.sparse.coo_matrix((self.data, (se
lf.row, self.col)))
                        print('-'*50)
                        print('finished creating coo_matrix')
                        self.write_data('/tfidfvectorizer/cocurmtx.pkl',coc
ur_mtx)
                        self.write_data('/tfidfvectorizer/vocab.pkl',self.v
ocablry)
                else:
                        print('No coo_matrix',self.row,self.col)




if __name__ == "__main__" :

        print('Process Starting')

        tsvd = asign_11_dtcrea()

        tsvd.getreviews(5000)
        tsvd.max_features = 2000

        tsvd.TFIDFVectorizer()
        tsvd.create_feat_dict()
        tsvd.crea_cocur_mtx()
```

In [2]:

```
import pickle
fname = 'D:/data/asign-11-tsvd/tfidfvectorizer/cocurmtx.pkl'
with open(fname,'rb') as fp:
    cocur_mtx = pickle.load(fp)
#print(cocur_mtx.todense())

fname = 'D:/data/asign-11-tsvd/tfidfvectorizer/vocab.pkl'
with open(fname, 'rb') as fp:
    vocab = pickle.load(fp)
#print(vocab)

fname = 'D:/data/asign-11-tsvd/tfidfvectorizer/idf_rev_ft.pkl'
with open(fname, 'rb') as fp:
    tfidfeat = pickle.load(fp)
```

[5.2.1] Testing Co-occurance matrix

In [2]:
```
def crea_sent_contxt_wrd(sentence):
    window=2
    focus_contxt = ()
    sent_contxt_wrds = []
    rvw = sentence.split()
    for i in range(0,len(rvw)):
        focus_wrd = rvw[i]
        low = max(0,i - window)
        high = min(len(rvw), i + window +1)
        #low = max(0,low)
        #print('Context:',rvw[low:high])
        focus_contxt = (focus_wrd, rvw[low:high])
        sent_contxt_wrds.append(focus_contxt)
    return sent_contxt_wrds
```

In [3]:
```
def crea_cocur_mtx():
    row =[]
    col = []
    data = []

    for review in reviews:
        sent_contxt_wrd = crea_sent_contxt_wrd(review)
        print(sent_contxt_wrd)
        print(review)
        rvw = review.split()
        for i,word in enumerate(rvw):
            print('next focus word', word)
            rw = top2000.get(word,'Not Found')
            if rw == 'Not Found':
                continue
            else:
                context = sent_contxt_wrd[i][1]
                print(context)
                for wrd in context:
                    if word == wrd:
                        continue
                    cl = top2000.get(wrd,'Not Found')
                    if cl=='Not Found':
                        continue
                    else:
                        row.append(rw)
                        col.append(cl)
                        data.append(1.)
    print(row,col)
    cocur_mtx = sparse.coo_matrix((data, (row, col)))
    print(cocur_mtx.todense())
```

In [4]:
```
top2000 = {'abc':0,'def':1,'pqr':2}
reviews = ["abc def ijk pqr",
          "pqr klm opq",
          "lmn pqr xyz abc def pqr abc"]
```

In [7]:
```
crea_cocur_mtx()
```

```
[('abc', ['abc', 'def', 'ijk']), ('def', ['abc', 'def', 'ijk', 'pqr']), ('i
jk', ['abc', 'def', 'ijk', 'pqr']), ('pqr', ['def', 'ijk', 'pqr'])]
abc def ijk pqr
next focus word abc
['abc', 'def', 'ijk']
next focus word def
['abc', 'def', 'ijk', 'pqr']
next focus word ijk
next focus word pqr
['def', 'ijk', 'pqr']
[('pqr', ['pqr', 'klm', 'opq']), ('klm', ['pqr', 'klm', 'opq']), ('opq',
['pqr', 'klm', 'opq'])]
pqr klm opq
next focus word pqr
['pqr', 'klm', 'opq']
next focus word klm
next focus word opq
[('lmn', ['lmn', 'pqr', 'xyz']), ('pqr', ['lmn', 'pqr', 'xyz', 'abc']), ('x
yz', ['lmn', 'pqr', 'xyz', 'abc', 'def']), ('abc', ['pqr', 'xyz', 'abc', 'd
ef', 'pqr']), ('def', ['xyz', 'abc', 'def', 'pqr', 'abc']), ('pqr', ['abc',
'def', 'pqr', 'abc']), ('abc', ['def', 'pqr', 'abc'])]
lmn pqr xyz abc def pqr abc
next focus word lmn
next focus word pqr
['lmn', 'pqr', 'xyz', 'abc']
next focus word xyz
next focus word abc
['pqr', 'xyz', 'abc', 'def', 'pqr']
next focus word def
['xyz', 'abc', 'def', 'pqr', 'abc']
next focus word pqr
['abc', 'def', 'pqr', 'abc']
next focus word abc
['def', 'pqr', 'abc']
[0, 1, 1, 2, 2, 0, 0, 0, 1, 1, 1, 2, 2, 2, 0, 0] [1, 0, 2, 1, 0, 2, 1, 2,
0, 2, 0, 0, 1, 0, 1, 2]
[[0. 3. 3.]
 [3. 0. 2.]
 [3. 2. 0.]]
```

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

In [0]:
```
# Please write all the code with proper documentation
```

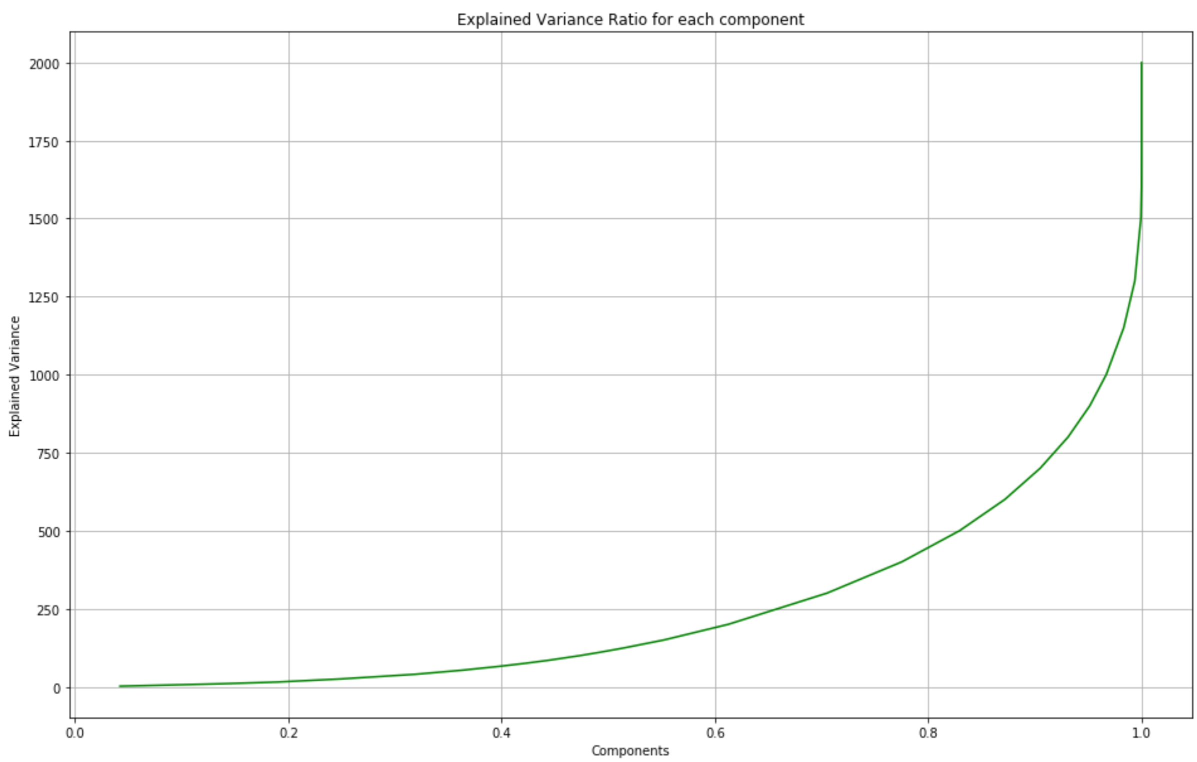
In [22]:
```
ncomp =[2,5,10,15,25,40,53,65,75,85,100,110,120,125,150,200,300,400,500,600
,700,800,900,1000,1150,1300,1500,1600,\
       1700,1800,1900,1999]
start_tme = datetime.now()
expl_var_ratio = []
print("find expl var process starts",start_tme)
for i in ncomp:
    tsvd = TruncatedSVD(n_components=i,random_state=42)
    tsvd.fit(cocur_mtx.todense())
    expl_var_ratio.append(np.sum(tsvd.explained_variance_ratio_))
    print('Finished processing component:#', i ,' Now: ', datetime.now(), '
Duration: ', datetime.now()-start_tme)
```

```
find expl var process starts 2019-09-27 12:19:42.256233
Finished processing component:# 2  Now:  2019-09-27 12:19:42.436243  Durati
on:  0:00:00.180010
Finished processing component:# 5  Now:  2019-09-27 12:19:44.649370  Durati
on:  0:00:02.393137
Finished processing component:# 10  Now:  2019-09-27 12:19:45.203401  Durat
ion:  0:00:02.947168
Finished processing component:# 15  Now:  2019-09-27 12:19:47.278520  Durat
ion:  0:00:05.022287
Finished processing component:# 25  Now:  2019-09-27 12:19:49.567651  Durat
ion:  0:00:07.311418
Finished processing component:# 40  Now:  2019-09-27 12:19:51.947787  Durat
ion:  0:00:09.691554
Finished processing component:# 53  Now:  2019-09-27 12:19:55.985018  Durat
ion:  0:00:13.728785
Finished processing component:# 65  Now:  2019-09-27 12:19:58.380155  Durat
ion:  0:00:16.123922
Finished processing component:# 75  Now:  2019-09-27 12:20:01.548336  Durat
ion:  0:00:19.292103
Finished processing component:# 85  Now:  2019-09-27 12:20:03.982476  Durat
ion:  0:00:21.726243
Finished processing component:# 100  Now:  2019-09-27 12:20:06.541622  Dura
tion:  0:00:24.285389
Finished processing component:# 110  Now:  2019-09-27 12:20:09.389785  Dura
tion:  0:00:27.133552
Finished processing component:# 120  Now:  2019-09-27 12:20:12.449960  Dura
tion:  0:00:30.193727
Finished processing component:# 125  Now:  2019-09-27 12:20:15.348126  Dura
tion:  0:00:33.091893
Finished processing component:# 150  Now:  2019-09-27 12:20:19.100340  Dura
tion:  0:00:36.844107
Finished processing component:# 200  Now:  2019-09-27 12:20:22.198517  Dura
tion:  0:00:39.942284
Finished processing component:# 300  Now:  2019-09-27 12:20:25.699718  Dura
tion:  0:00:43.443485
Finished processing component:# 400  Now:  2019-09-27 12:20:29.586940  Dura
tion:  0:00:47.330707
Finished processing component:# 500  Now:  2019-09-27 12:20:35.049252  Dura
tion:  0:00:52.793019
Finished processing component:# 600  Now:  2019-09-27 12:20:39.414502  Dura
tion:  0:00:57.158269
Finished processing component:# 700  Now:  2019-09-27 12:20:44.125772  Dura
tion:  0:01:01.869539
Finished processing component:# 800  Now:  2019-09-27 12:20:49.637087  Dura
tion:  0:01:07.380854
Finished processing component:# 900  Now:  2019-09-27 12:20:55.382415  Dura
tion:  0:01:13.126182
Finished processing component:# 1000  Now:  2019-09-27 12:21:02.273810  Dur
ation:  0:01:20.017577
Finished processing component:# 1150  Now:  2019-09-27 12:21:11.904360  Dur
ation:  0:01:29.648127
Finished processing component:# 1300  Now:  2019-09-27 12:21:21.075885  Dur
ation:  0:01:38.819652
Finished processing component:# 1500  Now:  2019-09-27 12:21:31.434478  Dur
ation:  0:01:49.178245
Finished processing component:# 1600  Now:  2019-09-27 12:21:43.507168  Dur
ation:  0:02:01.250935
```

```
Finished processing component:# 1700  Now:  2019-09-27 12:21:55.711866  Dur
ation:  0:02:13.455633
Finished processing component:# 1800  Now:  2019-09-27 12:22:08.549600  Dur
ation:  0:02:26.293367
Finished processing component:# 1900  Now:  2019-09-27 12:22:22.064373  Dur
ation:  0:02:39.808140
Finished processing component:# 1999  Now:  2019-09-27 12:22:36.861220  Dur
ation:  0:02:54.604987
```

In [23]:

```
fig, ax = plt.subplots(figsize=(16,10))
ax.plot(expl_var_ratio,ncomp,c='g')
#for i, txt in enumerate(np.round(expl_var_ratio,3)):
#    ax.annotate((ncomp[i],np.round(txt,3)), (ncomp[i],expl_var_ratio[i]))
plt.grid()
plt.title("Explained Variance Ratio for each component")
plt.xlabel("Components")
plt.ylabel("Explained Variance")
plt.show()
```



Using optimal number of components = 100

In [3]:
```
tsvd = TruncatedSVD(n_components=100,random_state=42)
tsvd.fit(cocur_mtx.todense())
print(tsvd.explained_variance_ratio_)
```

```
[0.02123773 0.02086919 0.01358581 0.01283822 0.01283544 0.01285449
 0.01274992 0.01190114 0.01144402 0.01128598 0.01072778 0.01048864
 0.0090681  0.00868028 0.00822102 0.00691167 0.00687163 0.00677654
 0.0060346  0.00599213 0.00587185 0.00580697 0.00547829 0.00548577
 0.00533295 0.0052521  0.00526914 0.0051846  0.0051383  0.00504399
 0.00503552 0.00485772 0.00475201 0.00448371 0.00439867 0.00441069
 0.00436148 0.00424011 0.00400542 0.00393701 0.00369986 0.00359941
 0.00366661 0.00364522 0.00361424 0.00338413 0.00334182 0.00326977
 0.00328351 0.00317204 0.00310739 0.00312874 0.00311357 0.00308139
 0.00305516 0.00297469 0.00297292 0.00282504 0.00278603 0.00278392
 0.00278049 0.00270919 0.00272544 0.00272126 0.00268547 0.00266481
 0.00265433 0.00259652 0.00257113 0.00257522 0.00255505 0.00243987
 0.00245269 0.00242691 0.00241903 0.0023853  0.00238257 0.00228043
 0.00223868 0.00220762 0.00214516 0.00215516 0.00215167 0.00213827
 0.00210367 0.0020558  0.00201867 0.00201059 0.00201477 0.00198286
 0.00195497 0.00190389 0.00189265 0.0018581  0.00183435 0.00181516
 0.00179428 0.00178097 0.00175093 0.00174431]
```

Transforming the original matrix from higher to lower dimension

In [4]:
```
new_mtx=tsvd.transform(cocur_mtx.todense())
```

[5.4] Applying k-means clustering

In [0]:
```
# Please write all the code with proper documentation
```

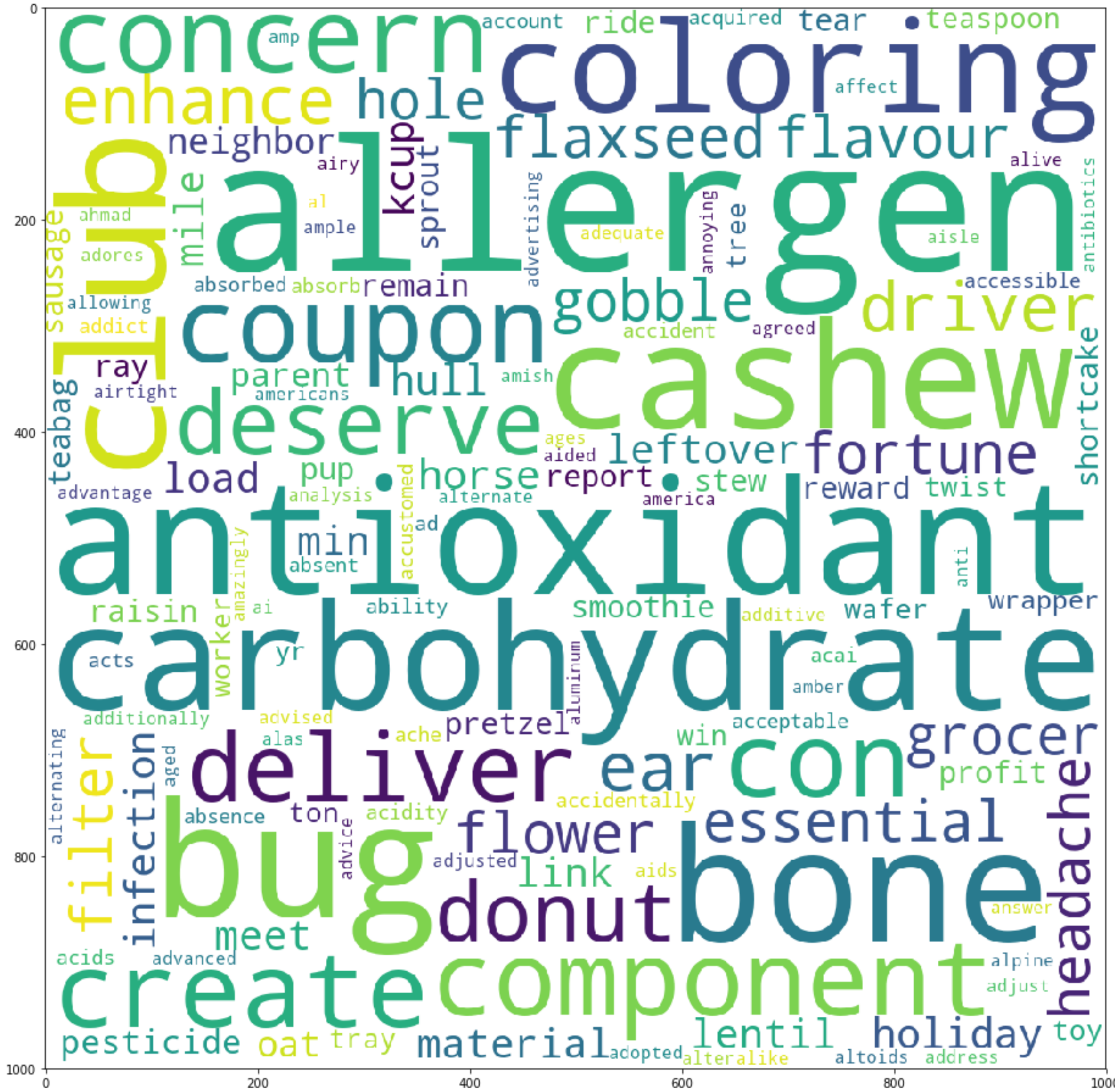
In [165]:
```
kmeans = KMeans(n_clusters=10,n_jobs=3, random_state=42, verbose=200)
kmeans.fit(new_mtx)
labels = kmeans.labels_

tfidflblftnme = sorted(zip(labels,tfidfeat))

tfidfwrdcld = [word for word in tfidflblftnme]
df = pd.DataFrame(tfidfwrdcld, columns =['lbl', 'ftname'])
```

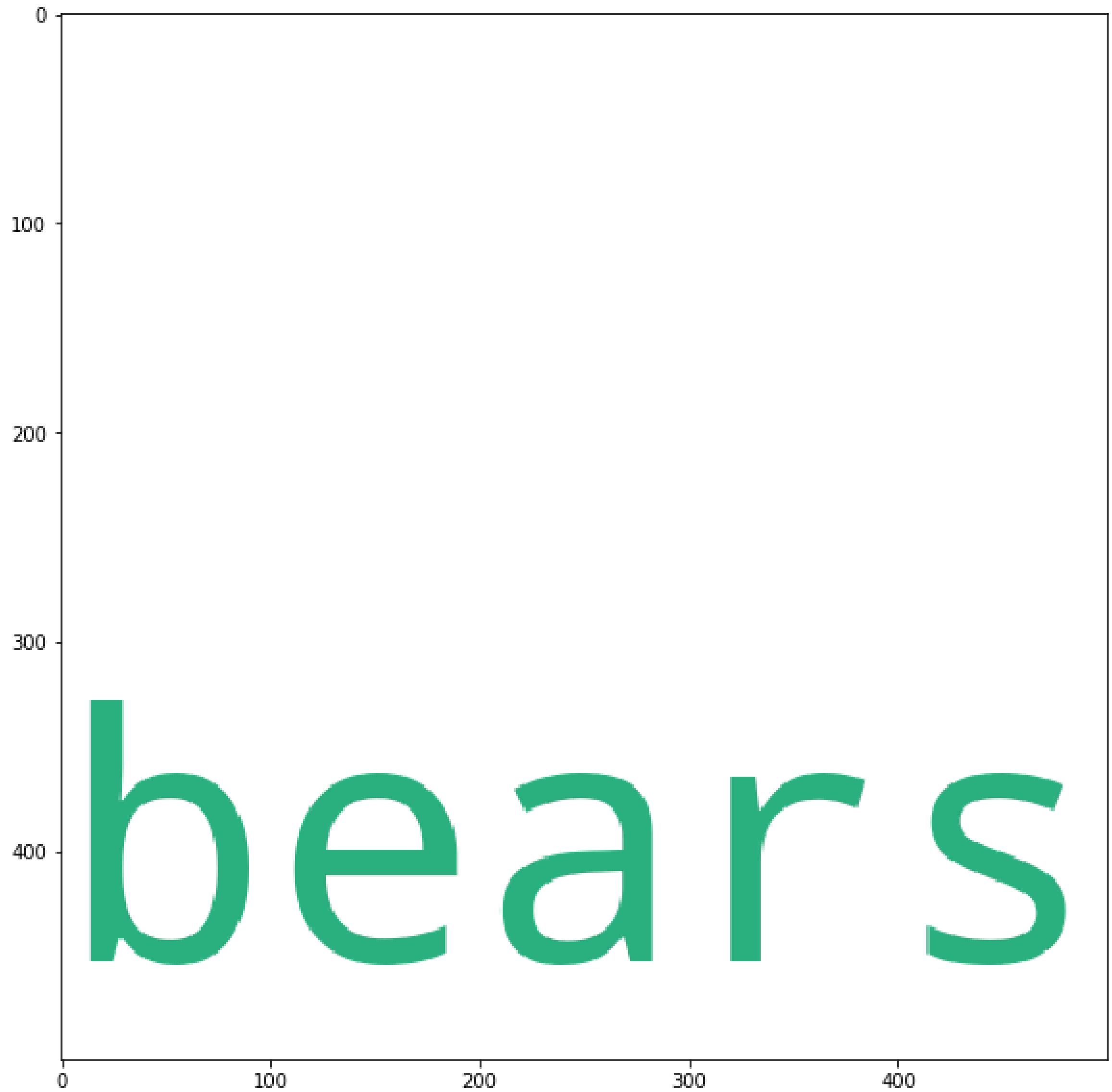
In [47]:
```
 optk = list(np.unique(labels))
```

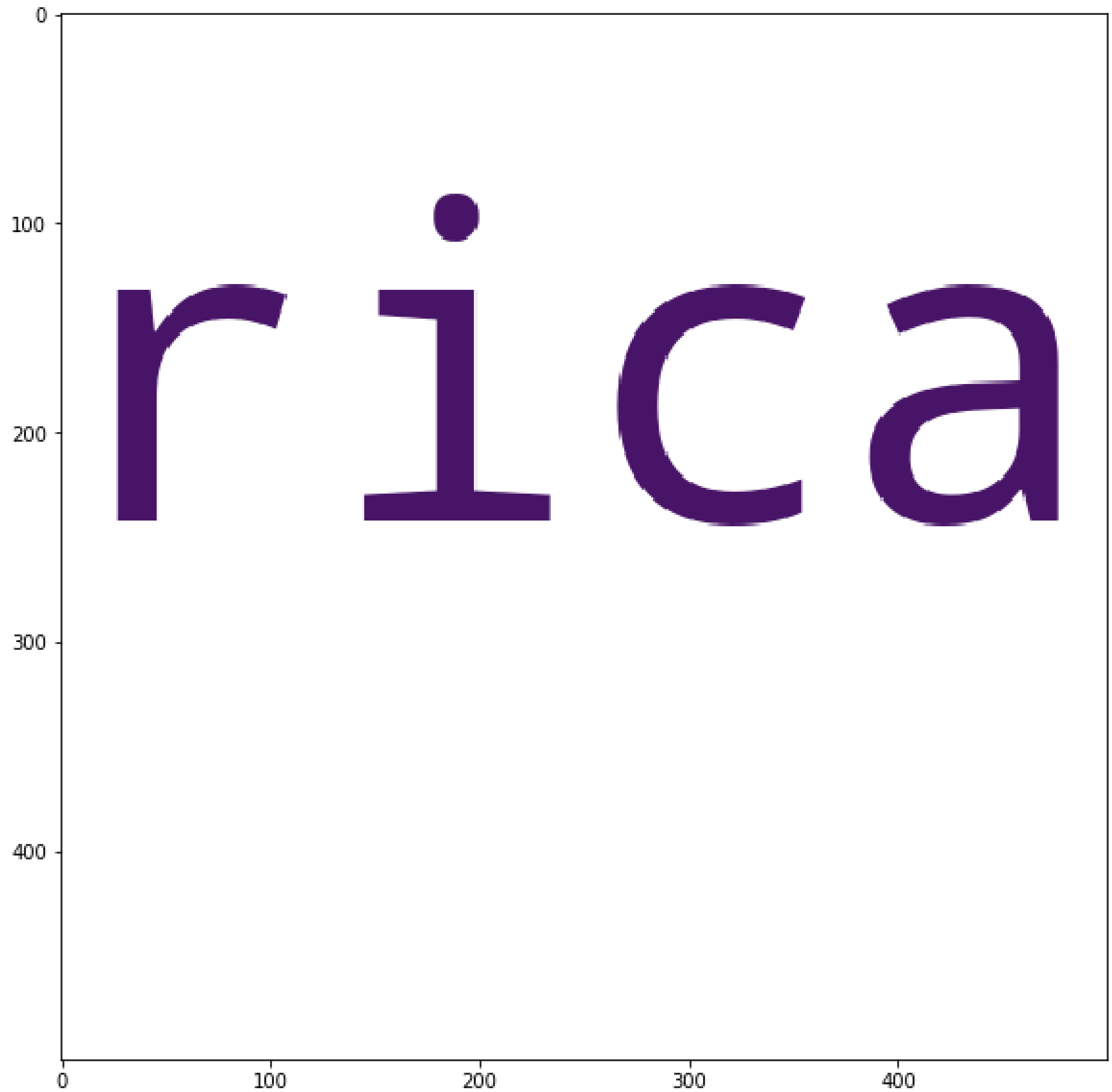
[5.5] Wordclouds of clusters obtained in the above section

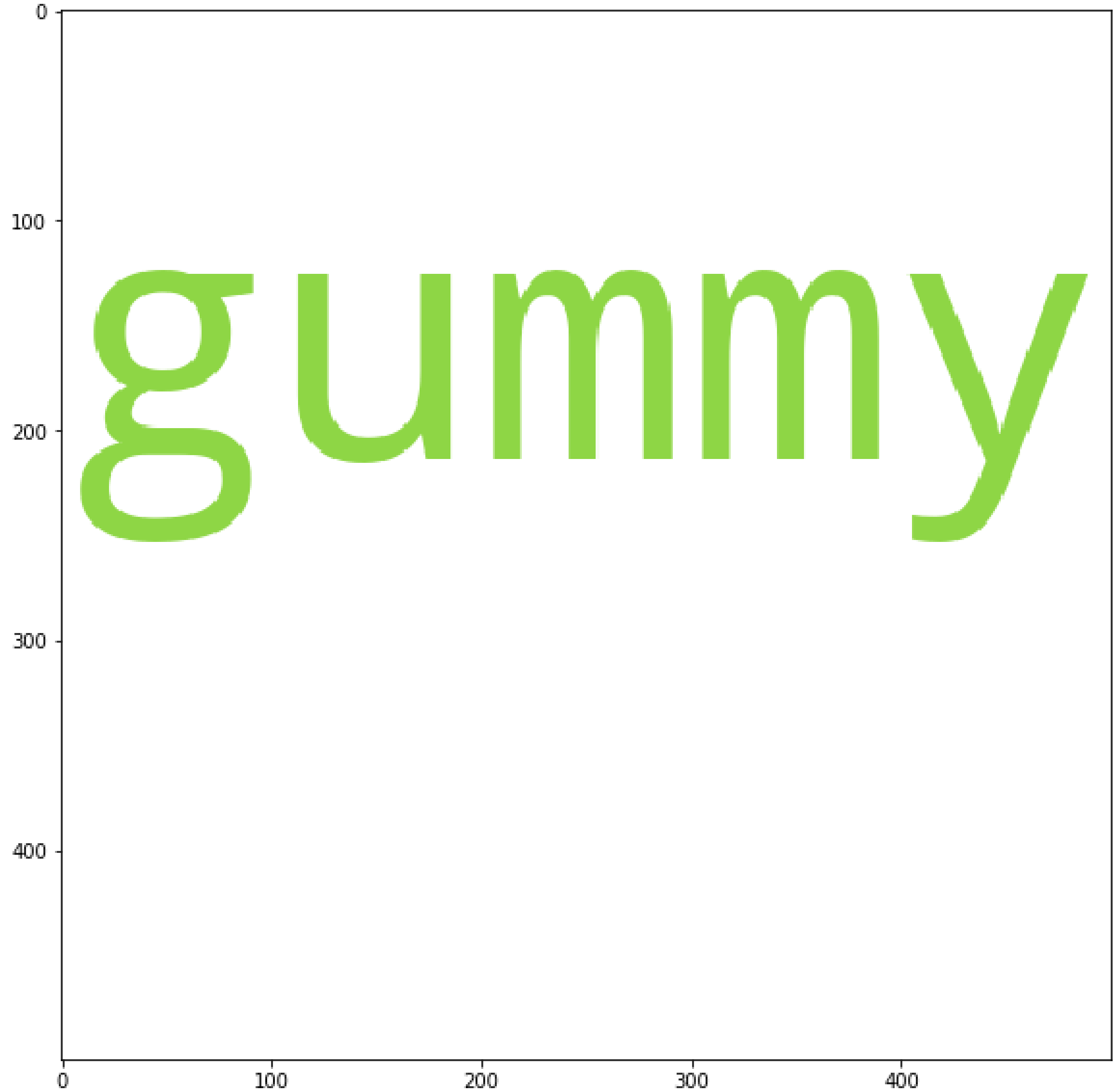
In [0]:
```
# Please write all the code with proper documentation
```

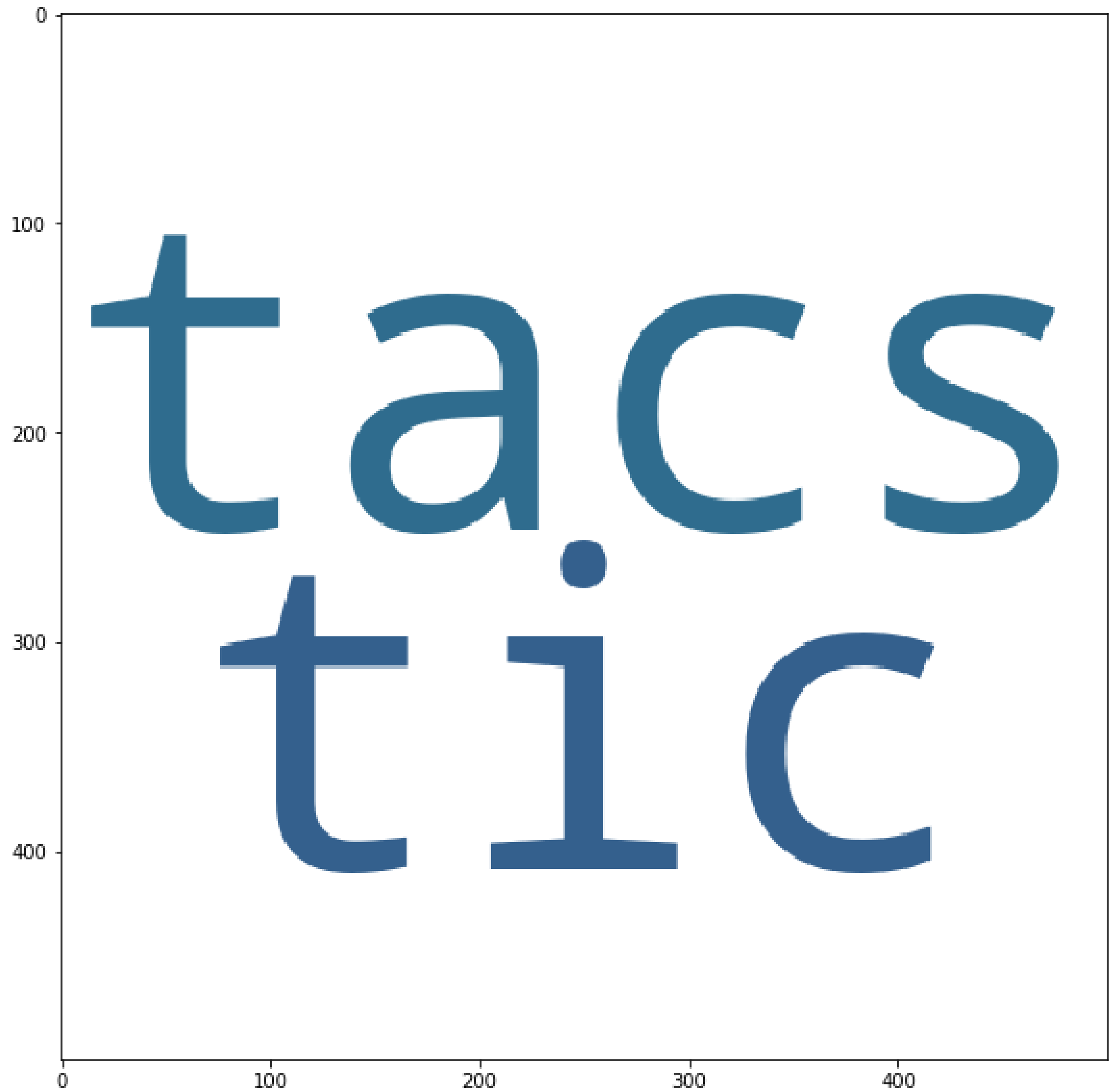
In [49]:
```
for i in optk:
    a= list(df[df.lbl == i]['ftname'])
    str1 = ' '.join(str(e) for e in a)
    if i == 0 :
        wordcld = WordCloud(width=1000, height=1000, background_color = 'wh
ite',min_font_size=14).generate(str1)
        plt.figure(figsize=(16,16))
    else:
        wordcld = WordCloud(width=500, height=500, background_color = 'whit
e',min_font_size=8).generate(str1)
        plt.figure(figsize=(10,10))
    plt.imshow(wordcld)
```

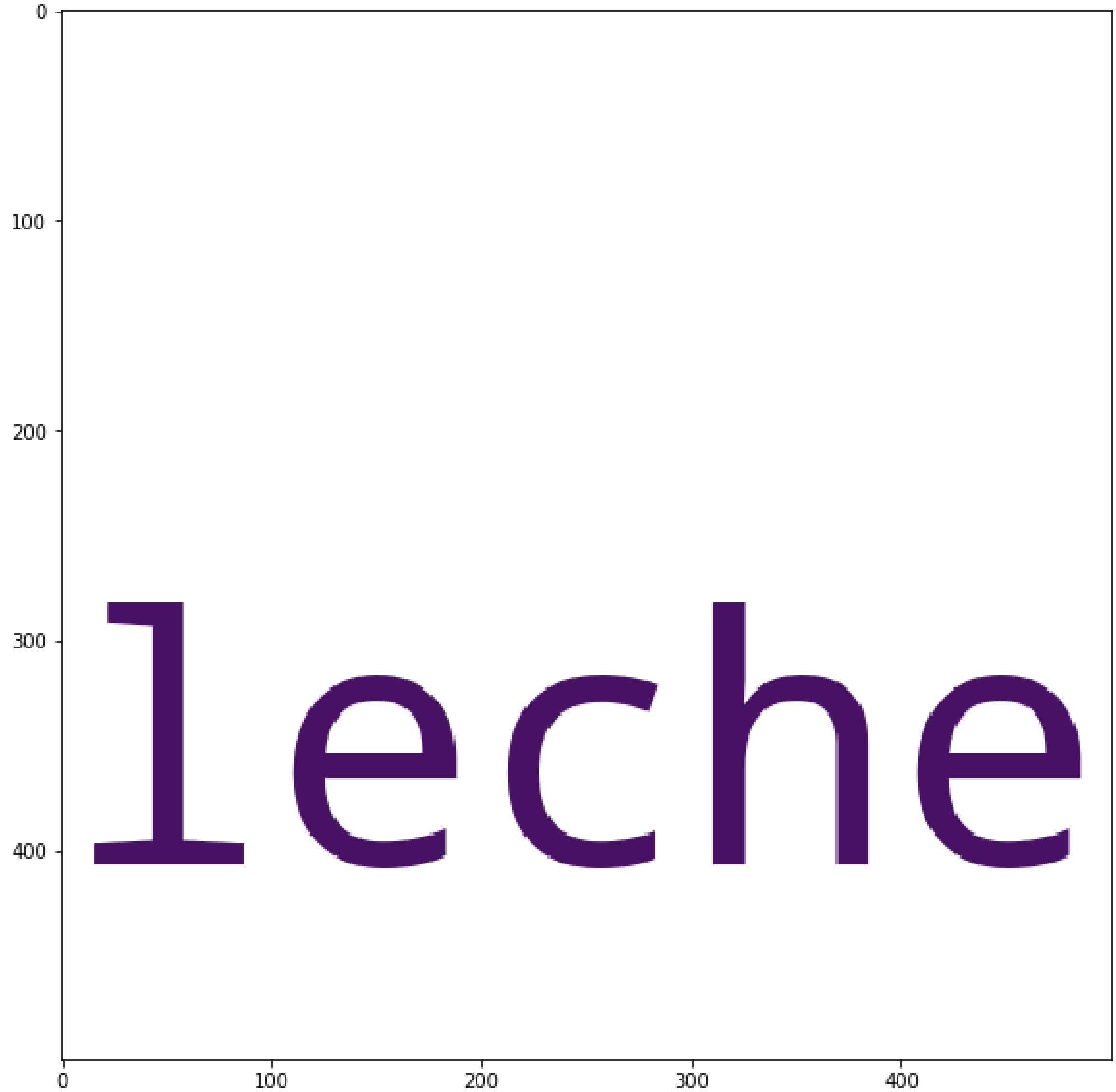

antioxidant
carbohydrate
allergen
cashew
coloring
concern
club
coupon
deliver
bug
bone
donut
component
create
con
deserve
enhance
hole
flaxseed
flavour
gobble
driver
essential
headache
flower
grocer
fortune
leftover
horse
filter
infection
meet
material
holiday
lentil
pesticide
oat
toy
0
200
400
600
800
1000

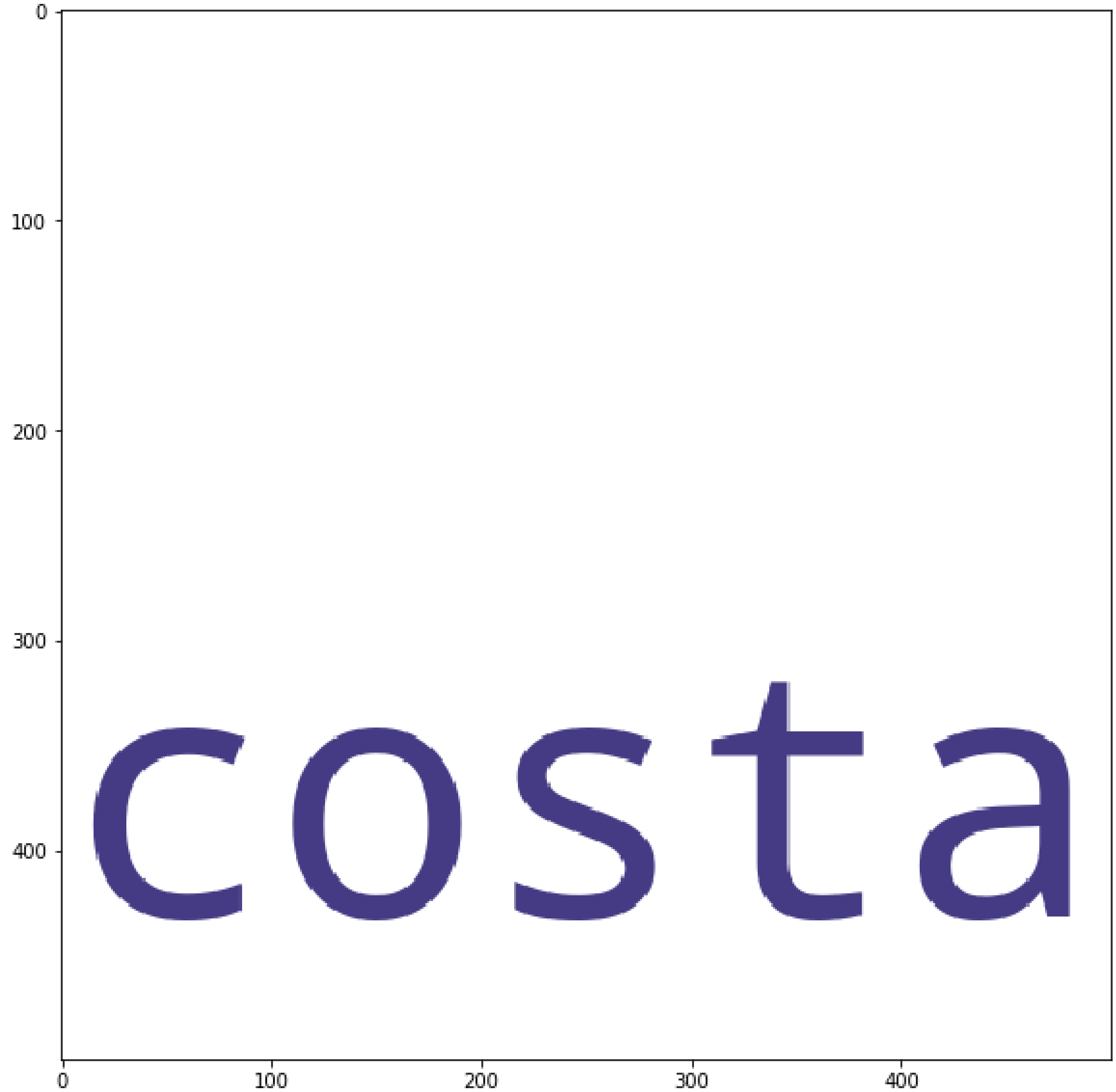

bears
0
100
200
300
400
0
100
200
300
400

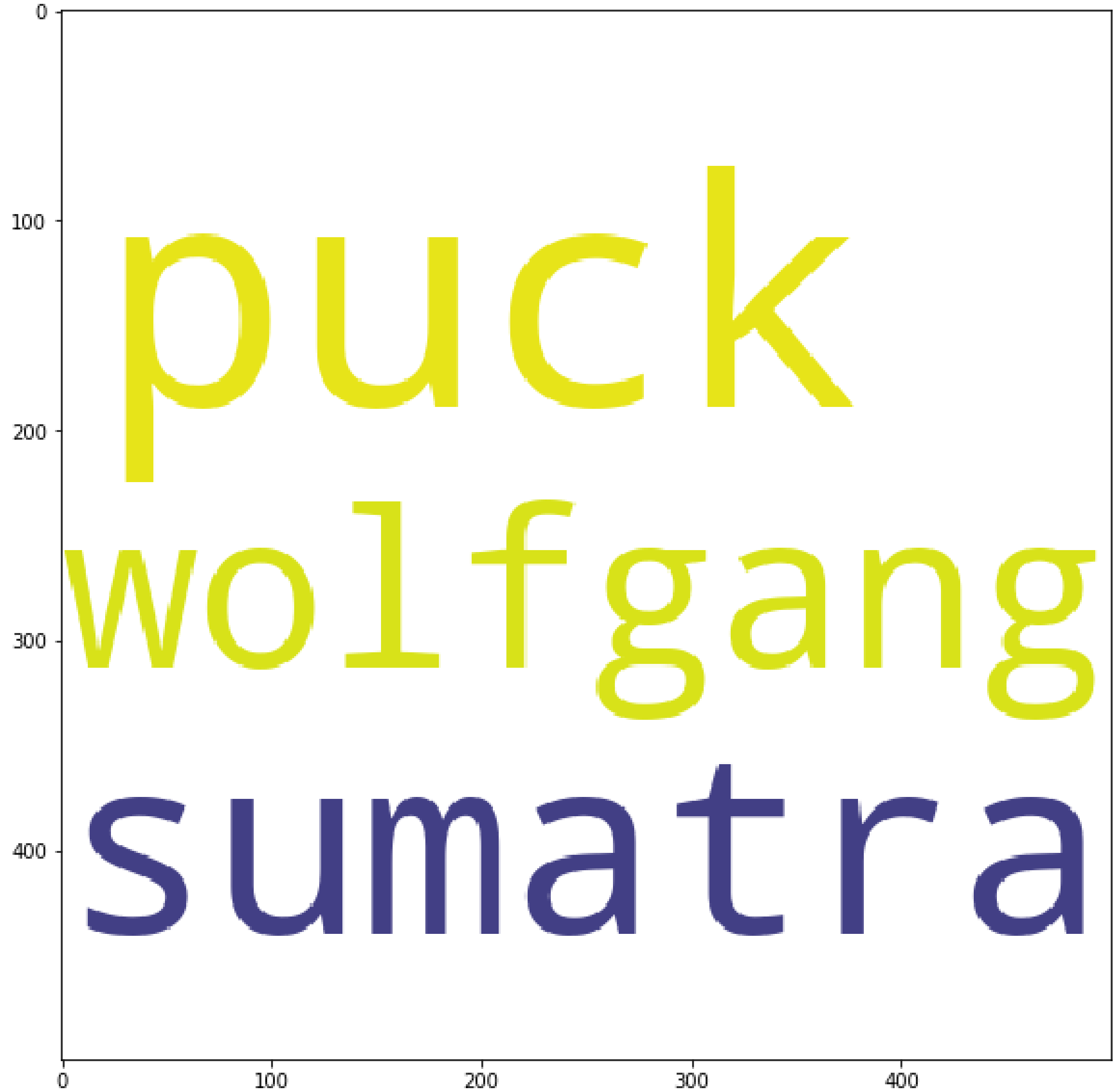

rica
0
100
200
300
400

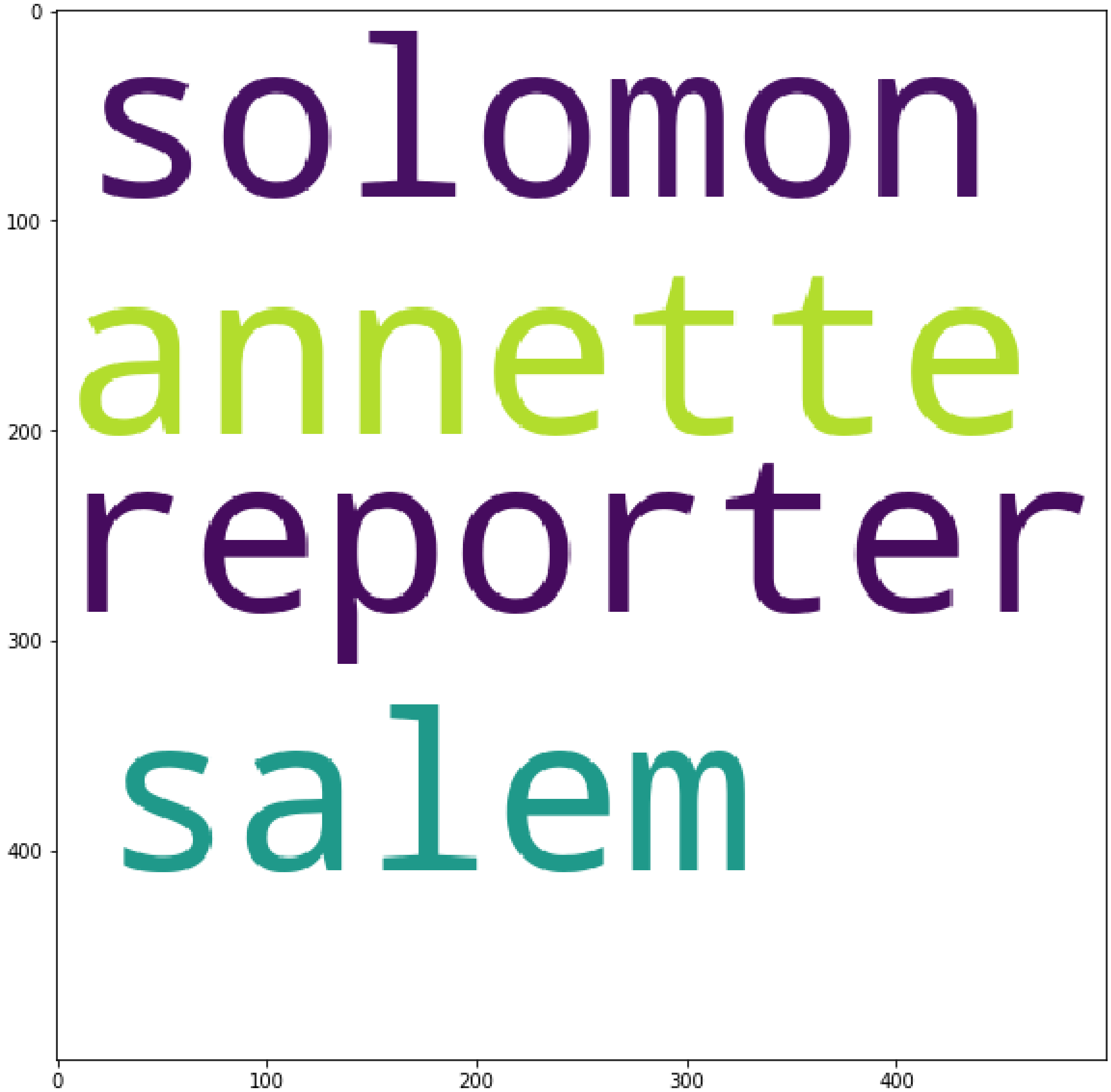

gummy
0
100
200
300
400
0
100
200
300
400

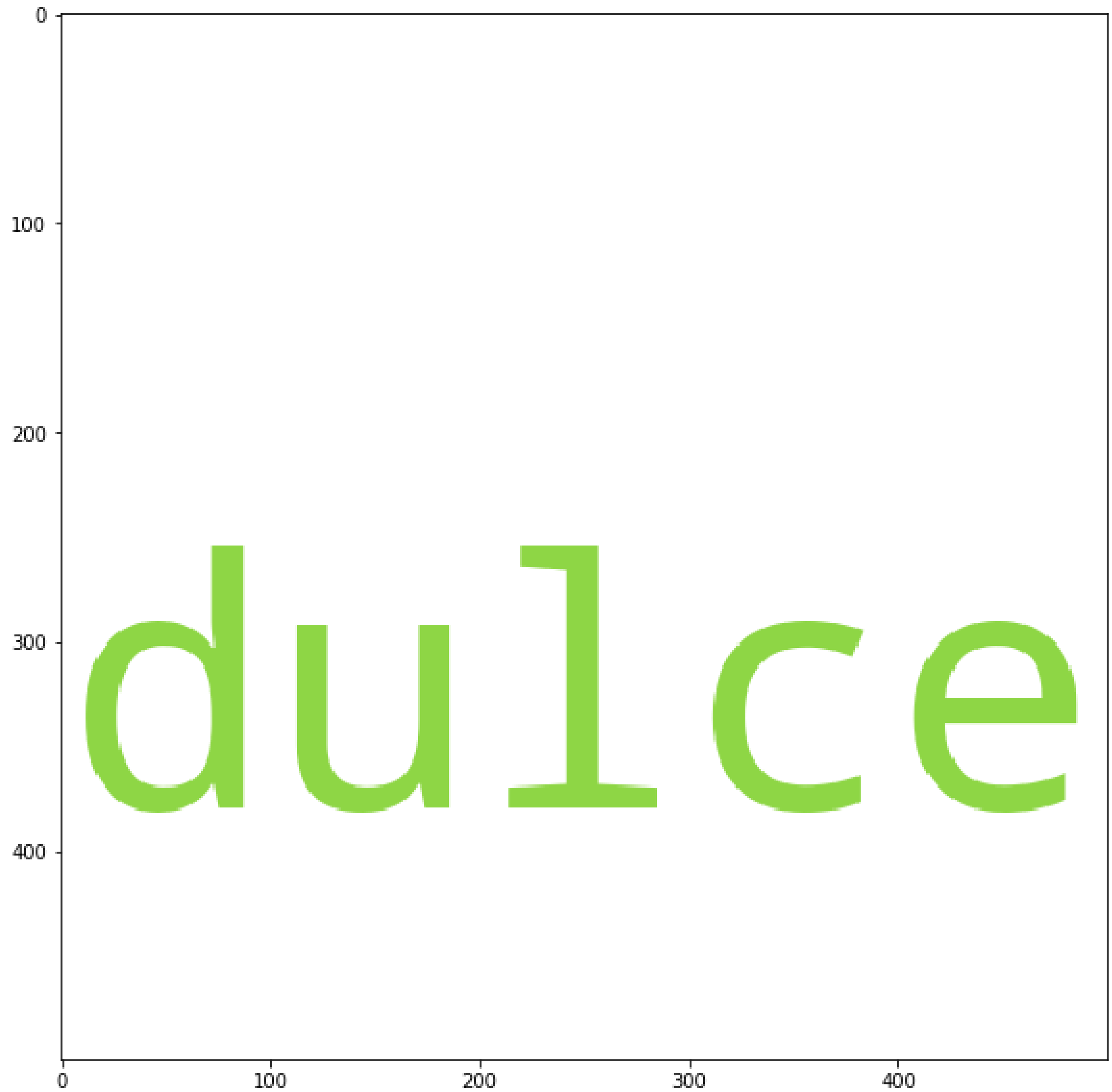

tacs
tic
0
100
200
300
400
0
100
200
300
400


leche


0
100
200
300
400
0
100
200
300
400
costa


puck
wolfgang
sumatra
0
100
200
300
400
0
100
200
300
400


solomon
annette
reporter
salem
0
100
200
300
400



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

In [0]:
```
# Please write all the code with proper documentation
```

In [6]:
```
print(new_mtx.shape)
```

```
(2000, 100)
```

In [42]:
```
#from sklearn.metrics.pairwise import cosine_similarity
def get_similar_words(given_word):
    cos_simil = []
    cos_simil_lib = []
    #given_word = 'crispbread'
    i = tfidfeat.index(given_word)
    #print(i)
    if i :
        for j in range(0,1999):
            dot_prod = np.dot(new_mtx[i],new_mtx[j])
            norm1 = np.linalg.norm(new_mtx[i])
            norm2 = np.linalg.norm(new_mtx[j])
            cos1 = dot_prod / (norm1 * norm2)
            if i != j:
                cos_simil.append(cos1)
                #cos2 = cosine_similarity(new_mtx[i].reshape(1,-1),new_mtx
[j].reshape(1,-1))
                #cos_simil_lib.append(cos2)
                #print(cos1, cos2)
        top_cosimil_fn = []
        top_cosimil_ft = []

        for i in cosimil_idx :
            if not(np.isnan(cos_simil[i])) and i !=0 :
                top_cosimil_fn.append(cos_simil[i])
                top_cosimil_ft.append(tfidfeat[i])
        if len(top_cosimil_fn) > 0 :
            for j in range(0,19):
                print(top_cosimil_fn[j],top_cosimil_ft[j])
        else:
            print("Not able to find similar words for the selected word:",g
iven_word,".")
    else:
        print(given_word,'Is not part of Top 2000. Only words present in To
p 2000 features can be used')
```

In [34]:
```
get_similar_words('crispbread')
```

```
0.9906464335557039 unsalted
0.9872056464738044 costly
0.9751241107573054 senses
0.9521259959121324 lobster
0.8366478760718714 disgusted
0.8184592135732645 reply
0.8149613106155542 grateful
0.81036352909496 recieved
0.7391010403985433 reminiscent
0.6295840089829084 updated
0.616240286128393 digestion
0.567608787849009 holiday
0.510126116693823 lactose
0.498219863032091 component
0.48331647709971576 settled
0.47052174232886296 regardless
0.4626171277787581 unnecessary
0.43851004067944516 farm
0.40226568271596463 grandchildren
```

In [43]:
```
get_similar_words('magnesium')
```

```
Not able to find similar words for the selected word: magnesium .
```

[6] Conclusions

In [ ]:
```
# 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 components & number of clusters.
```

Being an unsupervised learning oriented assignment not able to judge the quality of the results produced.

Depends heavily on the quality of the Vectorizer and the feature items produced by the vectorizer.

In this assignment I don't know how to improve the performance of the model .

Number of components

We had to use the elbow method to get the number of components .

Unfortunately the graph that I could generate had no clear elbow and graph was smoothly increasing.

Due to the absence of a clear elbow I have taken 100 as the number of components

Number of Clusters

I tried processing the clustering with different values but the algorithm was generating one big cluster with label 0

with a lot of data points and realtively smaller clusters with fewer data points .

I have used 10 as the value for n_clusters .

Find similar Words using Co-sine similarity

In [5]:
```
head_tab = [['Query Word','crispbread']]
print(tabulate.tabulate(head_tab,tablefmt='fancy_grid'))

res_tab =[["Cosine \nSimilarity","Feature \nname"],
[ 0.9906464335557039,"unsalted"],
[ 0.9872056464738044 ,"costly"],
[0.9751241107573054 ,"senses"],
[0.9521259959121324 ,"lobster"],
[0.8366478760718714 ,"disgusted"],
[0.8184592135732645 ,"reply"],
[0.8149613106155542 ,"grateful"],
[0.81036352909496 ,"recieved"],
[0.7391010403985433 ,"reminiscent"],
[0.6295840089829084 ,"updated"],
[0.616240286128393 ,"digestion"],
[0.567608787849009 ,"holiday"],
[0.510126116693823 ,"lactose"],
[0.498219863032091 ,"component"],
[0.48331647709971576 ,"settled"],
[0.47052174232886296 ,"regardless"],
[0.4626171277787581 ,"unnecessary"],
[0.43851004067944516 ,"farm"],
[0.40226568271596463 ,"grandchildren"]]

print(tabulate.tabulate(res_tab,tablefmt='fancy_grid'))
```

Query Word	crispbread

Cosine Similarity	Feature name
0.9906464335557039	unsalted
0.9872056464738044	costly
0.9751241107573054	senses
0.9521259959121324	lobster
0.8366478760718714	disgusted
0.8184592135732645	reply
0.8149613106155542	grateful
0.81036352909496	recieved
0.7391010403985433	reminiscent
0.6295840089829084	updated
0.616240286128393	digestion
0.567608787849009	holiday
0.510126116693823	lactose
0.498219863032091	component
0.48331647709971576	settled
0.47052174232886296	regardless
0.4626171277787581	unnecessary
0.43851004067944516	farm
0.40226568271596463	grandchildren