# Clustering on Amazon Fine FOod Reviews

In [1]:
```
#importing necessary packages
import sys
import warnings
if not sys.warnoptions:
    warnings.simplefilter("ignore")
import sqlite3
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
from sklearn.feature_extraction.text import CountVectorizer,TfidfVector
izer
import pickle
import sklearn.cross_validation
from sklearn.model_selection import train_test_split
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.metrics import precision_score,recall_score,f1_score,confu
sion_matrix,roc_auc_score,roc_curve
```

```
C:\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: Deprecat
ionWarning: This module was deprecated in version 0.18 in favor of the
model_selection module into which all the refactored classes and functi
ons are moved. Also note that the interface of the new CV iterators are
different from that of this module. This module will be removed in 0.2
0.
  "This module will be removed in 0.20.", DeprecationWarning)
```

## Reading already Cleaned, Preprocessed data from database

After removing stopwords, punctuations, meaningless characters, HTML tags from Text and done stemming. Using it directly as it was alredy done in prevoius assignment

In [2]:
```
#Reading
conn= sqlite3.connect('cleanedTextData.sqlite')
data= pd.read_sql_query('''
SELECT * FROM Reviews
''',conn)
data=data.drop('index',axis=1)
data.shape
```

Out[2]:
```
(364171, 11)
```

In [3]:
```
data.columns
```

Out[3]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
r',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'CleanedText'],
      dtype='object')
```

In [4]:
```
data['CleanedText'].head(3)
```

Out[4]:
```
0    witti littl book make son laugh loud recit car...
1    rememb see show air televis year ago child sis...
2    beetlejuic well written movi everyth act speci...
Name: CleanedText, dtype: object
```

In [ ]:
```
def wordCloud(clusterPerReview,reviewText,k):
    '''
    Prints  wordclouds of all the clusters given cluster number per rev
iew and review text
    '''
    clusterGroup={}
    i=0
```

```
    for c in clusterPerReview:
        if c in clusterGroup.keys():
            clusterGroup[c]+= reviewText[i]
        else:
            clusterGroup[c]=reviewText[i]
        i+=1
    print('So we have',k,'clusters here representing in wordcloud:')
    for i in list(set(cluster)):
        print('Cluster Number',i+1,':')
        plt.figure()
        plt.imshow(WordCloud().generate(clusterGroup[i]))
        plt.axis("off")
```

# Kmeans

## Sorting on the basis of 'Time' and taking top 50k pts

This data has time attribute so it will be reasonable to do time based splitting instead of random splitting.

So, before splitting we have to sort our data according to time and here we are taking 50k points from our dataset(population)

In [5]:
```
data["Time"] = pd.to_datetime(data["Time"], unit = "ms")
data = data.sort_values(by = "Time")
```

In [6]:
```
#latest 50k points according to time
Xdata1= data[:50000]['CleanedText']
len(Xdata1)
```

Out[6]:
```
50000
```

In [137]:
```
from sklearn.cluster import KMeans
from wordcloud import WordCloud
import matplotlib.pyplot as plt
```

```
%matplotlib inline

def optimalKmeans(Xdata):
    param_K = [2,3,4,5,6,7,8]
    inertia={}
    for K in param_K:
        model= KMeans(n_clusters=K, init= 'k-means++', precompute_dista
nces= True, n_jobs= -1)
        model.fit(Xdata)
        inertia[K]= model.inertia_
    plt.plot(list(inertia.keys()), list(inertia.values()))
    plt.xlabel("No. of cluster")
    plt.ylabel("Inertia")
    plt.show()
    bestK= min(inertia, key=inertia.get)
    print('The best K according to min inertia is ',bestK)
    return bestK
```

---

# Kmeans: BOW Vectorization

Bow vectorization is basic technique to convert a text into numerical vector.

- We will build a model on train text using fit-transform

In [8]:
```
# vectorizing X and transforming
bowModel1=CountVectorizer()
XdataBOWV1=bowModel1.fit_transform(Xdata1)
XdataBOWV1.shape
```

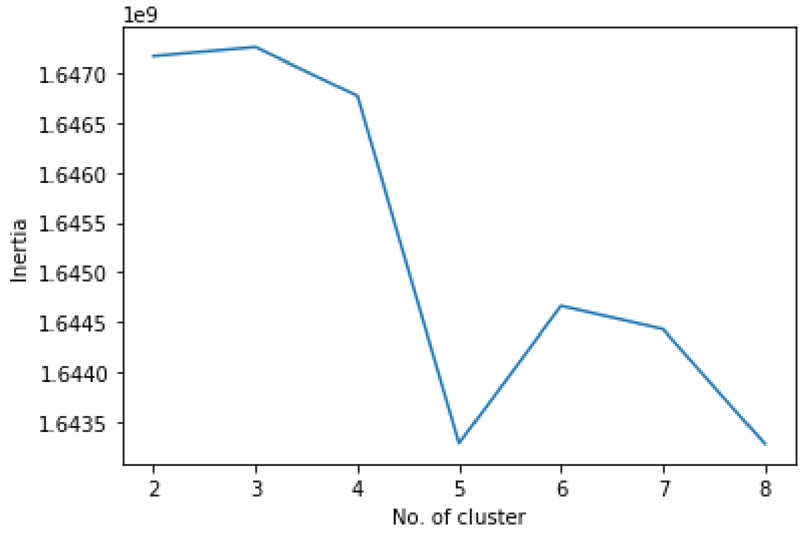
Out[8]:
```
(50000, 32970)
```

In [9]:
```
#Standardizing vectors
XdataBOWV1 = StandardScaler(with_mean=False).fit_transform(XdataBOWV1)
```

```
C:\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataCon
```

```
versionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataCon
versionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

In [10]:
```
k= optimalKmeans(XdataBOWV1)
```



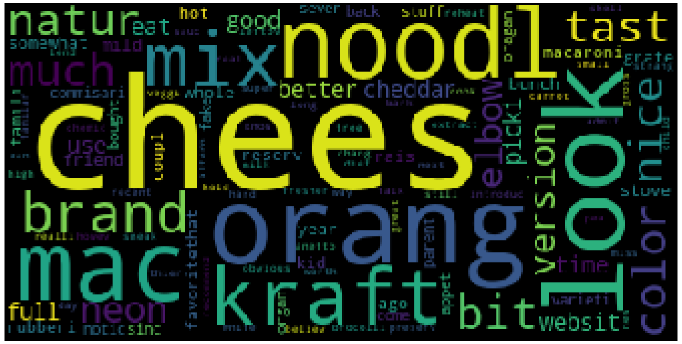

```
The best K according to min inertia is  8
```

In [199]:
```
BOWkm = KMeans(n_clusters=k, init= 'k-means++', precompute_distances= T
rue, n_jobs= -1)
cluster= list(BOWkm.fit_predict(XdataBOWV1))
```

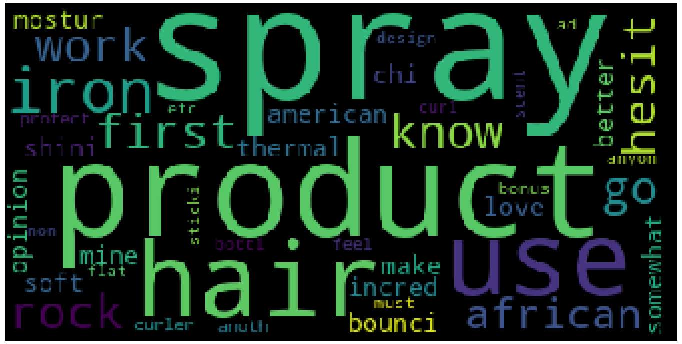
In [201]:
```
wordCloud(cluster,list(Xdata1),8)
```

```
So we have 8 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
```

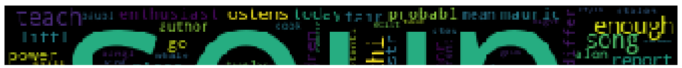
```
Cluster Number 4 :
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
Cluster Number 8 :
```

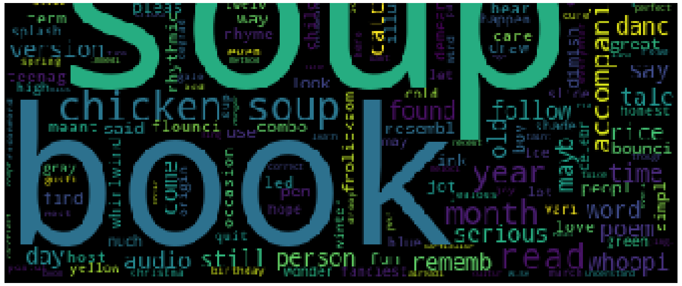




flavor
nutrit
steam
label
sugar
cane
ad
add
milk
come
recip
suggest
vanilla
mani
torani
sodium
south
torr
gram
san
compani
ice
hot
syrup
coffe
chocol
francisco
water
sweeten
twist
familiar
simpl
pure
strong
frothi


spray
product
hair
use
iron
work
mostur
first
know
hesit
american
thermal
go
love
rock
african
bounci
soft
mine
make
incred
opinion
better
somewhat
shini
protect
chi
design
feel
bonus
curler
sticki

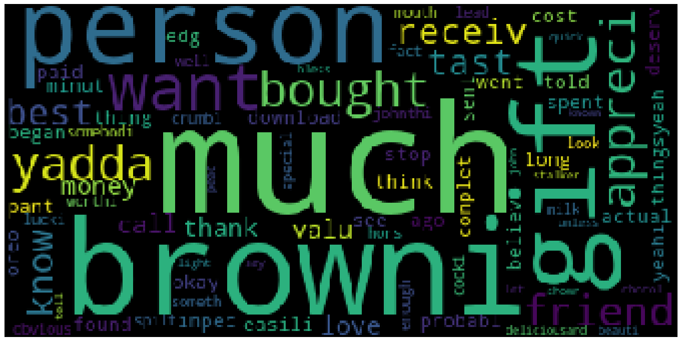

veggi
low
sodium
soup
serv
good
food
littl
pack
find
fat
doctor
thing
ad
adjust
someth
organ
healthi
quit
product
benefit
minestron
differ
homemad
well
buy
new
make
per


teach
enthusiast
probabl
enough
song
author
go
report


soup
book
chicken
soup
found
follow
accompani
danc
talc
rice
time
year
month
word
poem
serious
read
whoppi
rememb
person
still
audio
day
occasion
come



great
food
bag
save
keep
work
junk
healthi
alway
bad
vend
thees
eat
tube
gym
raw
home
way
anyth
someth
restaur
coupl
machin
product
snack
fast
visit
lunchpail
shouldnt



person
receiv
cost
tast
want
bought
told
gift
appreci
best
much
yadda
money
browni
friend
thank
valu
call
know
love
actual
spent
long
think
stop

## Observations:-

- **Cluster 1 :-** This cluster has major words as how poeple feel about food :- good, well, lot, little, love, tasty, wonderful, flavor etc
- **Cluster 2 :-** This cluster has major words as of chinease food:- noodle, macaroni, cheese etc
- **Cluster 3 :-** This cluster has major words from sweet and milk made products:- milk, chocolate, vanilla, sugar, coffee, syrup
- **Cluster 4 :-** This cluster has major words not so related to food stuffs like:- spray, hair, bouncy, iron, rock etc
- **Cluster 5 :-** This cluster has major words as nutrition like:- sodium, fat, veggi, homemade, high, low, little etc
- **Cluster 6 :-** This cluster has major words as liquid items:- chicken soup, hot etc
- **Cluster 7 :-** This cluster has no major distinction but has something to do with gym, fittness
- **Cluster 8 :-** This cluster has major words as dilevery:- want, bought, recived, gift

---

# Kmeans: TFIDF vectorization

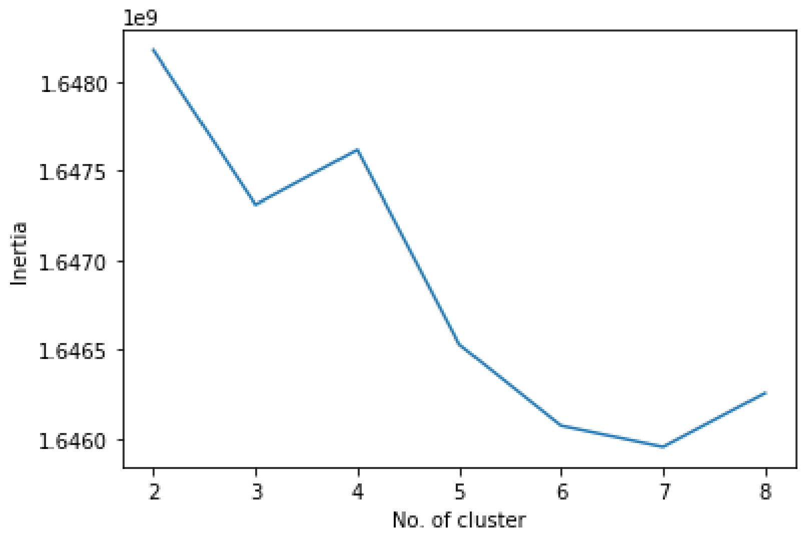
- We will build a model on train text using fit-transform
- Then transform (test) text on model build by train text
- Transformed data will be in the form of sparse matrix

In [12]:
```
# generating vetor out of text using tfidf
tfidfModel1=TfidfVectorizer()
XdataTFIDFV1= tfidfModel1.fit_transform(Xdata1)
```

In [13]:
```
#Standardizing vectors
```

```
XdataTFIDFV1 = StandardScaler(with_mean=False).fit_transform(XdataTFIDF
V1)
```

In [14]:
```
k= optimalKmeans(XdataTFIDFV1)
```




```
The best K according to min inertia is  7
```

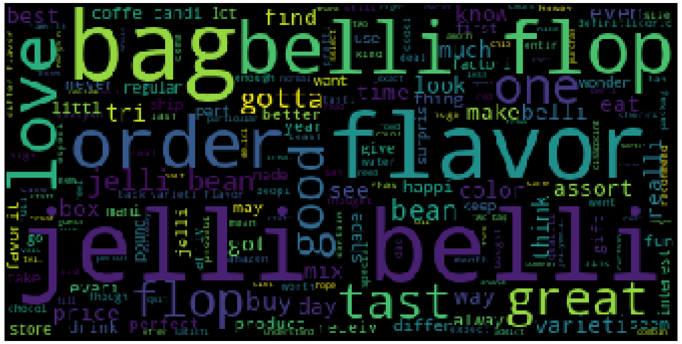
In [15]:
```
TFIDFkm = KMeans(n_clusters=k, init= 'k-means++', precompute_distances=
 True, n_jobs= -1)
cluster= list(TFIDFkm.fit_predict(XdataTFIDFV1))
```

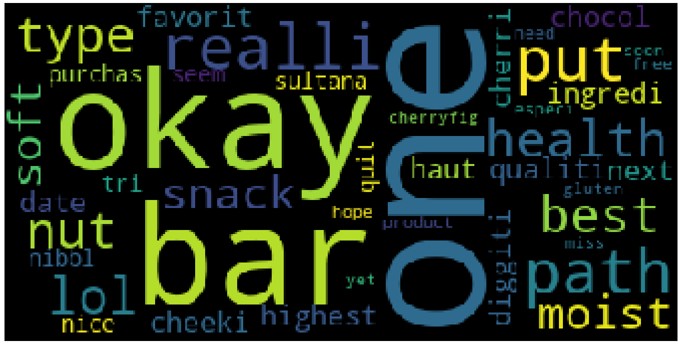
Out[15]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=7, n_init=10, n_jobs=-1, precompute_distances=True,
    random_state=None, tol=0.0001, verbose=0)
```

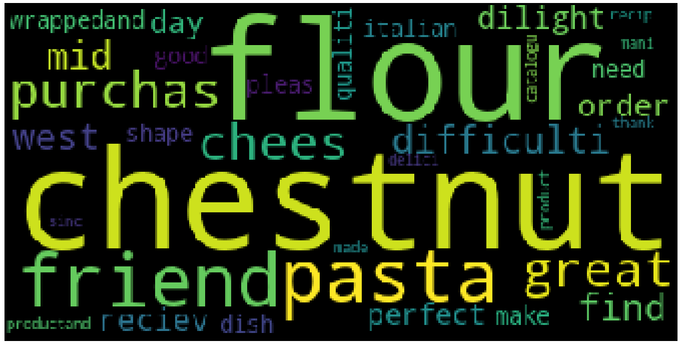
In [60]:
```
wordCloud(cluster,list(Xdata1),7)
```

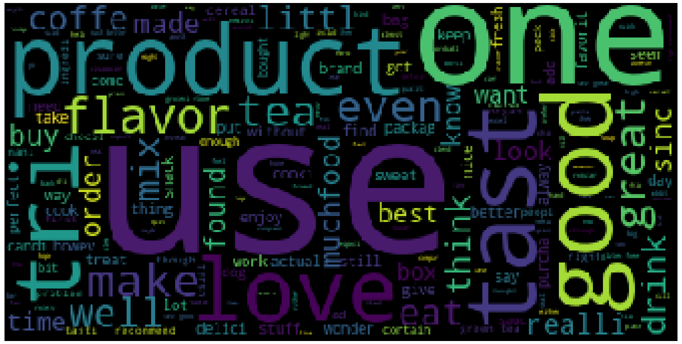
```
So we have 7 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
```

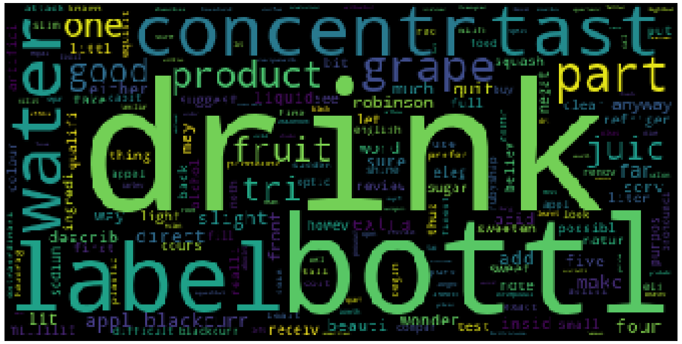
```
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
```

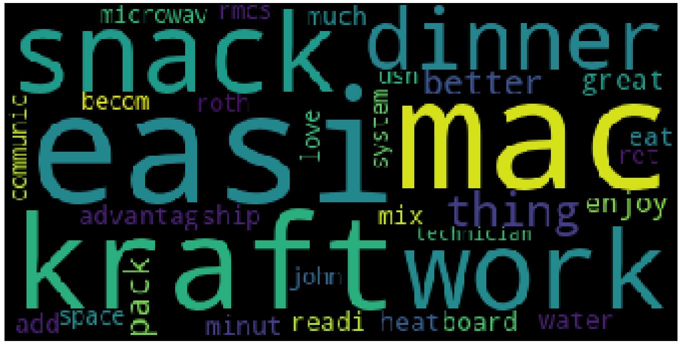


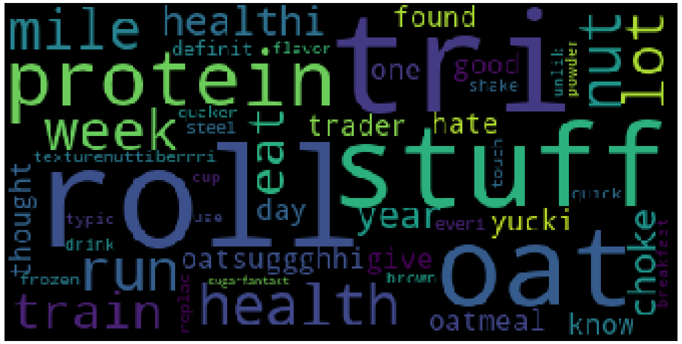




flour
chestnut
friend
pasta
great
find
purchas
chees
difficulti
west
shape
mid
good
pleas
qualiti
italian
dilight
need
order
day
wrappedand
perfect
make
reciev
dish
productand


product
one
use
love
good
tast
tri
flavor
tea
even
make
well
time
buy
coffe
made
littl
great
drink
think
best
muchfood
found
mix
order
realli
know
want
look
sinc
eat
box


drink
bottl
label
water
concentrtast
one
good
product
grape
part
fruit
juic
tri
slight
robinson
sugar
add
four




## Observations:-

- **Cluster 1 :-** This cluster has major words from candy:- jelly, jelly belly, jelly bean
- **Cluster 2 :-** This cluster has major words chocolate:- chocolate bar, with nut, snack etc
- **Cluster 3 :-** This cluster has major words from itallian:- pasta, cheese, italian, flour
- **Cluster 4 :-** This cluster has major words from coffee:- coffee, tea, hot, drink etc
- **Cluster 5 :-** This cluster has major words as juice:- grape, fruit, bottle, drink, water, concentration etc

- **Cluster 6 :-** This cluster has no major distinction but has something to do with snack and dinner
- **Cluster 7 :-** This cluster has major words from nutrition:- protein, oat, oatmeal, healthy, nuts etc

# Kmeans: Avg W2V vectorization

In [16]:

```
import gensim
# training our gensim model on our train text
import re
import string
def cleanhtml(sentance): #substitute expression contained in <> with '
 '
    cleaned= re.sub(re.compile('<.*?>'),' ',sentance)
    return cleaned
#function for removing punctuations chars
def cleanpunc(sentance):
    cleaned= re.sub(r'[?|!|\'|"|#]',r'',sentance)
    cleaned= re.sub(r'[.|,|)|(|\|/]',r'',sentance)
    return cleaned
i=0
lists=[]

for sent in Xdata1.values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    lists.append(filtered_sentence)
```

```
w2v_model= gensim.models.Word2Vec(lists,min_count=5,size=50,workers=4)
print(len(list(w2v_model.wv.vocab)))
```

```
C:\Anaconda3\lib\site-packages\gensim\utils.py:1209: UserWarning: detec
ted Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

```
8991
```

In [17]:

```
w2v_words = list(w2v_model.wv.vocab)
```

In [18]:

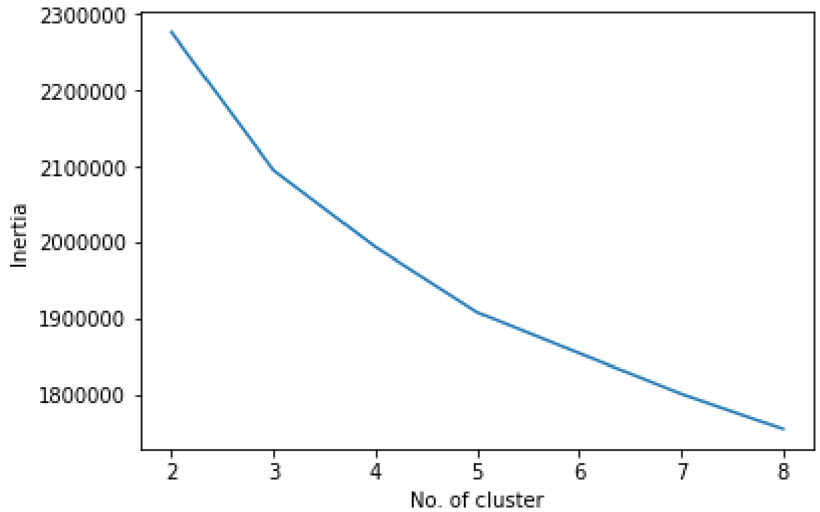
```
# converting list of sentance into list of list of words
# then to vector using avg w2v
# function to convert list of list of words to vect using avg w2v
def w2vVect(X):
    '''
    This function takes list of sentance as input (X) and convert it in
to
    list of list of words and then feed it into our gensim model to get
 vector
    and then take its average, finally returns sent_vectors(vector of s
entance)
    ************GENSIM MODEL WAS TRAINED ON TRAINDATA**************
    '''

    lists=[]
    for sent in X.values:
        filtered_sentence=[]
        sent=cleanhtml(sent)
        for w in sent.split():
            for cleaned_words in cleanpunc(w).split():
                if(cleaned_words.isalpha()):
                    filtered_sentence.append(cleaned_words.lower())
                else:
                    continue
        lists.append(filtered_sentence)

    sent_vectors = [];
```

```
    for sent in lists:
        sent_vec = np.zeros(50)
        cnt_words =0;
        for word in sent:
            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)
    return sent_vectors
```

In [19]:
```
# Vectorizing our data
XdataW2VV1= w2vVect(Xdata1)
```

In [20]:
```
#Standardizing vectors
XdataW2VV1 = StandardScaler(with_mean=False).fit_transform(XdataW2VV1)
```

In [21]:
```
k= optimalKmeans(XdataW2VV1)
```



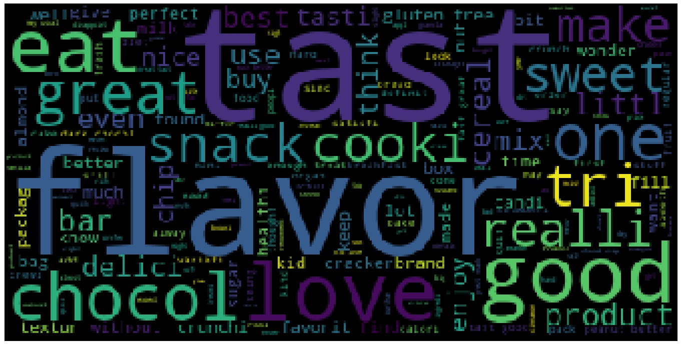

```
The best K according to min inertia is  8
```

```
In [63]: W2Vkm = KMeans(n_clusters=k, init= 'k-means++', precompute_distances= True, n_jobs= -1)
         cluster= list(W2Vkm.fit_predict(XdataW2VV1))
```

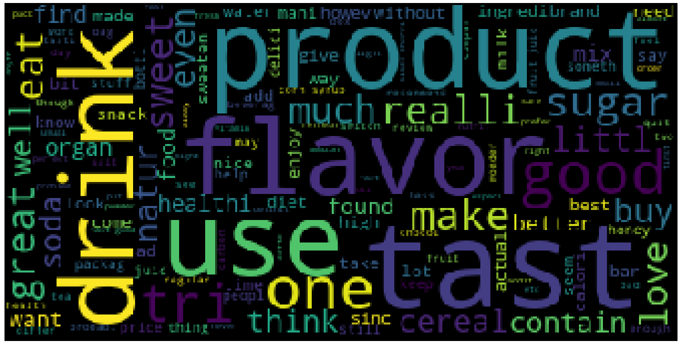
```
Out[63]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=8, n_init=10, n_jobs=-1, precompute_distances=True,
             random_state=None, tol=0.0001, verbose=0)
```

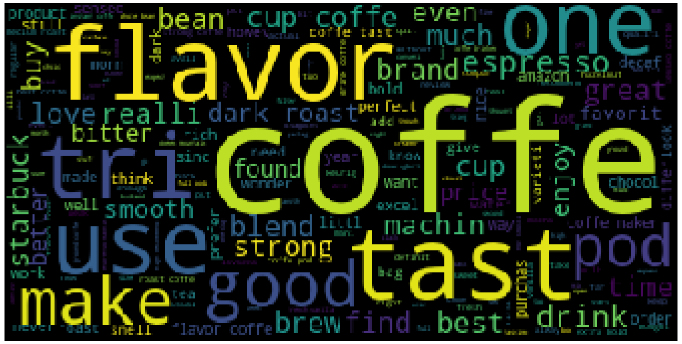
```
In [93]: wordCloud(cluster,list(Xdata1),8)
```

```
So we have 8 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
Cluster Number 8 :
```

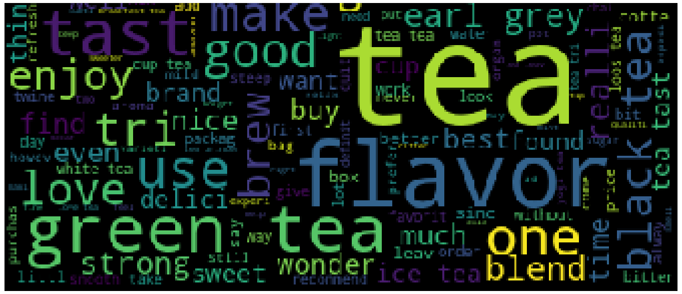


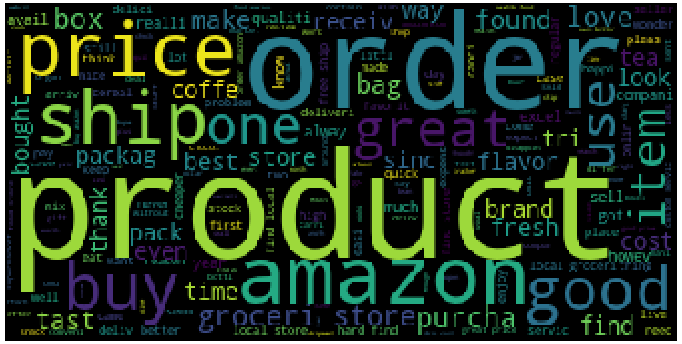

use
flavor
tast
make
good
mix
tri
sauc
cook
one
product
add
great
rice
best
pasta
salt
noodl
dish
soup
littl
chicken
oil
food
eat
love
even
well
spice
buy
made
find
put
bread
recip
realli
need
delici
top
hot
bit
nice
much
fresh
heat
lot
time
think
season

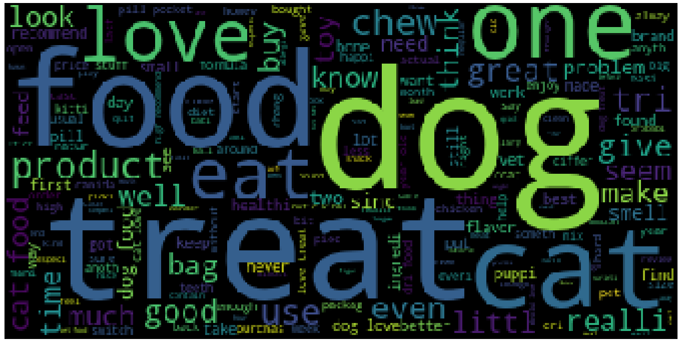

product
flavor
drink
use
tast
good
sugar
realli
much
littl
sweet
make
one
tri
great
eat
well
buy
love
cereal
contain
think
found
healthi
snack
organ
soda
find
made
natur
give
nice
mix
best
better
food
even
want

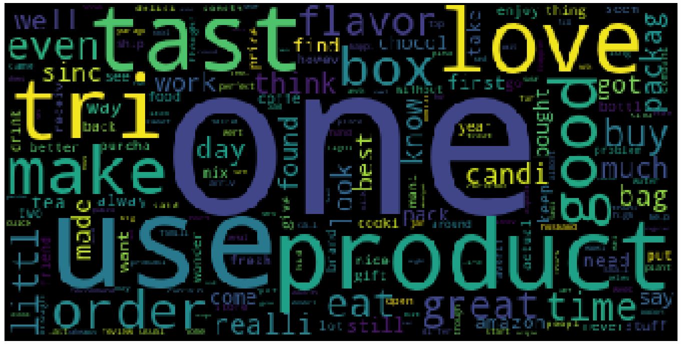

coffe
flavor
one
tri
use
tast
make
good
pod
cup
bean
brand
espresso
great
much
love
realli
dark
roast
bitter
found
blend
strong
smooth
starbuck
machin
enjoy
drink
best
find
brew
favorit
buy
even
chocol
price
time
think
well
made
bold


tea
bag
product
great
drink


tea
flavor
tast
make
good
earl grey
enjoy
green tea
love
use
tri
one
blend
black tea
brew
buy
best
found
strong
wonder
sweet
find
nice
brand
want
even
much
time
realli


product
order
price
amazon
ship
one
great
buy
good
use
item
coffe
bag
box
packag
best
store
flavor
brand
fresh
pack
time
tast
groceri store
purcha
find
found
love
look
receiv
way
thank
bought
cost


dog
treat
food
love
one
cat
eat
product
chew
know
great
look
well
bag
good
use
even
littl
realli
give
make
smell
seem
tri
buy
much
time
cat food




## Observations:-

- **Cluster 1 :-** This cluster has major words from sweet:- snack, cookie, chocolate, bar etc
- **Cluster 2 :-** This cluster has major words chinease:- sauce, noodle, pasta, salt
- **Cluster 3 :-** This cluster has major words from drinks
- **Cluster 4 :-** This cluster has major words from coffee:- tea bag, tea, hot, drink, green tea, blended etc
- **Cluster 5 :-** This cluster has major words from tea:- coffee, tea, hot, drink etc
- **Cluster 6 :-** This cluster has major words as dilevery:- amazon, order, shippment, delivery, bought, recived, gift
- **Cluster 7 :-** This cluster has major words from animal food:- dog, cat, chew etc
- **Cluster 8 :-** This cluster has major words as how poeple feel about food :- good, well, lot, little, love, tasty, wonderful, flavor etc

# Kmeans: TFIDF-weighted avg W2V vectorization

In [23]:
```
tfmodel=TfidfVectorizer(max_features=2000)
```

```
tf_idf_matrix = tfmodel.fit_transform(Xdata1.values)
tfidf_feat=tfmodel.get_feature_names()
dictionary = {k:v for (k,v) in zip(tfmodel.get_feature_names(), list(tf
model.idf_))}
```

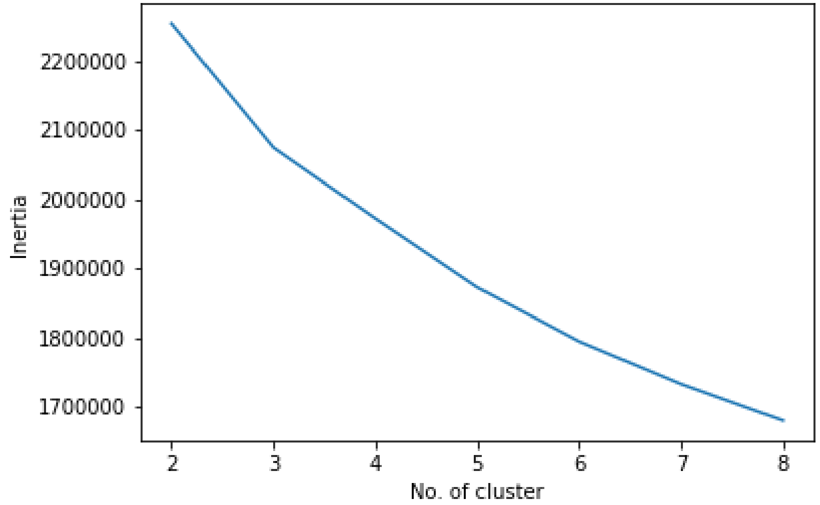
In [24]:
```
def tfidfw2vVect(X):
    '''
    This function converts list of sentance into list of list of words
 and then
    finally applies average-tfidf-w2w to get final sentance vector
    w2v model and w2v words already made during w2v vectorization part
    '''
    lists=[]
    for sent in X.values:
        filtered_sentence=[]
        sent=cleanhtml(sent)
        for w in sent.split():
            for cleaned_words in cleanpunc(w).split():
                if(cleaned_words.isalpha()):
                    filtered_sentence.append(cleaned_words.lower())
                else:
                    continue
        lists.append(filtered_sentence)

    tfidfw2v_sent_vectors = []; # the tfidf-w2v for each sentence/revie
w is stored in this list
    row=0;
    for sent in lists: # 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 senten
ce/review
        for word in sent: # for each word in a review/sentence
            try:
                if word in w2v_words:
                    vec = w2v_model.wv[word]
                    #tf_idf = tf_idf_matrix[row, tfidf_feat.index(wor
d)]
                    #to reduce the computation we are
                    #dictionary[word] = idf value of word in whole cour
```

```
pus
                    #sent.count(word) = tf valeus of word in this revie
w
                    tf_idf = (dictionary[word])*((sent.count(word))/len
(sent))
                    sent_vec += (vec * tf_idf)
                    weight_sum += tf_idf
            except:
                pass
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidfw2v_sent_vectors.append(sent_vec)
        row += 1
    # converting nan and infinte values in vect to digit
    tfidfw2v_sent_vectors= np.nan_to_num(tfidfw2v_sent_vectors)
    return tfidfw2v_sent_vectors
```

In [25]:
```
# feeding text data and recieving vectorized data
XdataTFIDFW2VV1= tfidfw2vVect(Xdata1)
```

In [26]:
```
#Standardizing vectors
XdataTFIDFW2VV1 = StandardScaler(with_mean=False).fit_transform(XdataTF
IDFW2VV1)
```

In [27]:
```
k= optimalKmeans(XdataTFIDFW2VV1)
```




```
The best K according to min inertia is  8
```

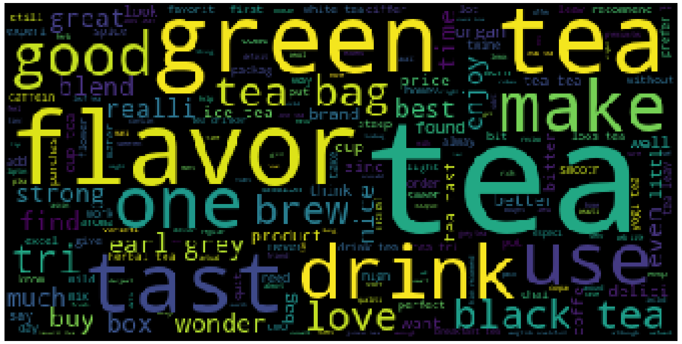
In [28]:
```python
TFIDFW2Vkm = KMeans(n_clusters=k, init= 'k-means++', precompute_distanc
es= True, n_jobs= -1)
cluster= list(TFIDFW2Vkm.fit_predict(XdataTFIDFW2VV1))
```

Out[28]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=8, n_init=10, n_jobs=-1, precompute_distances=True,
    random_state=None, tol=0.0001, verbose=0)
```

In [94]:
```python
wordCloud(cluster,list(Xdata1),8)
```

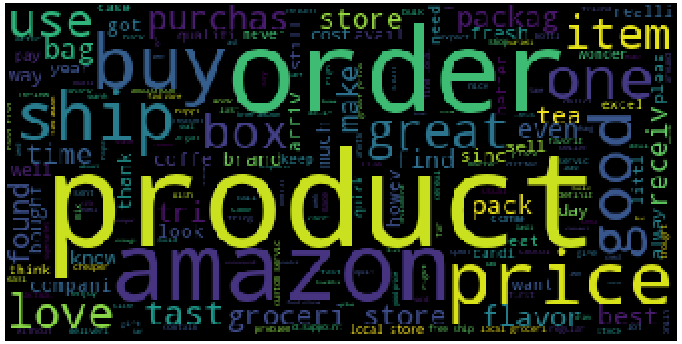
```
So we have 8 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
Cluster Number 8 :
```

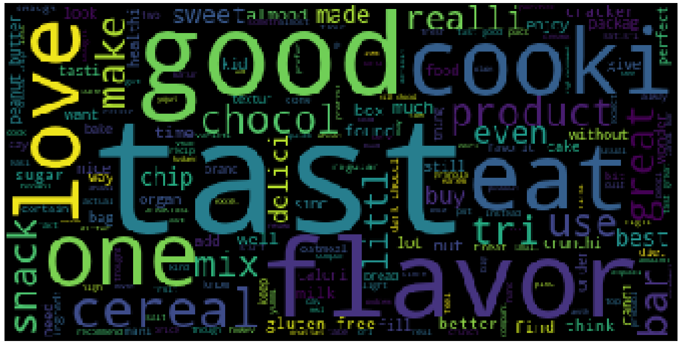

use
tast
flavor
make
cook
good
product
love
one
sauc
add
eat
mix
great



green tea
tea
flavor
good
make
drink
tast
one
use
brew
black tea
tea bag
love

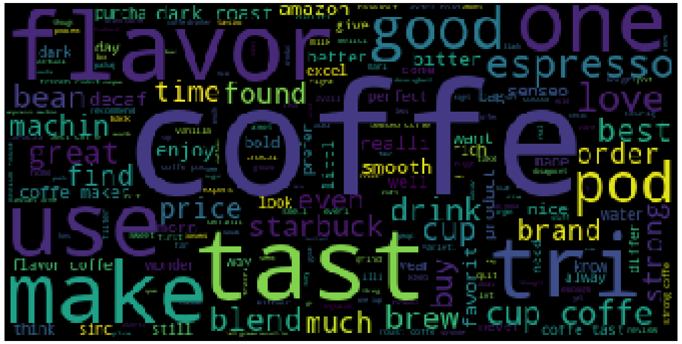


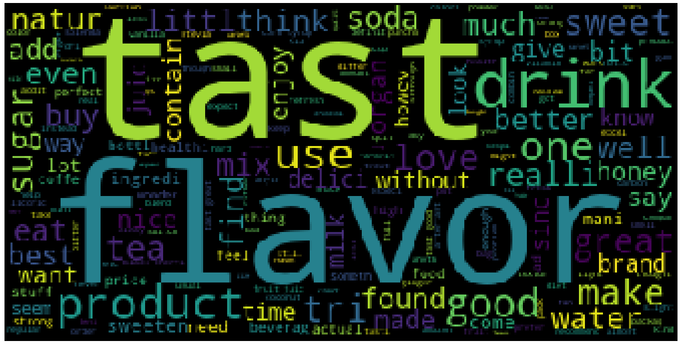
food
dog
treat
cat
love
one
product
eat
use
chew
realli
give


product
amazon
buyorder
price
ship
great
good
one
item
use
store
purchas
packag
box
love
tast
flavor
groceri store
pack
tea
receiv
best


tast
good
cooki
flavor
love
eat
one
cereal
product
chocol
mix
snack
make
great
even
tri
use
littl
realli
made
delici
chip
bar
best
gluten free


one
product
use
tast
good
love
tri
realli
make
great
littl
even
time
flavor
eat
buy
bag
order
packag
got
box
day
candi
found work look take
much know
best
sinc tea
keep
think




## Observations:-

- **Cluster 1 :-** This cluster has major words as liquid items:- chicken soup, hot, oil etc
- **Cluster 2 :-** This cluster has major words from tea:- coffee, tea, green tea, black tea, hot, drink etc
- **Cluster 3 :-** This cluster has major words from animal food:- dog, cat, chew etc

- **Cluster 4 :-** This cluster has major words as dilevery:- amazon, order, shippment, delivery, bought, recived, gift
- **Cluster 5 :-** This cluster has no distinction but have something to do with flavour
- **Cluster 6 :-** This cluster has no distinction but have something to do with product
- **Cluster 7 :-** This cluster has major words from coffee:- tea bag, tea, hot, drink, green tea, blended, brew, starbucks etc
- **Cluster 8 :-** This cluster has major words liquid:- honey, tea, soda, syrup etc

==========================================================================

# Agglomerative Clustering

In [95]:
```
from sklearn.cluster import AgglomerativeClustering
```

### Taking sample of 4000 pts from the corpus

In [29]:
```
#latest 4k points according to time
Xdata2= data[:4000]['CleanedText']
len(Xdata2)
```

Out[29]:
```
4000
```

## Agglomerative: W2V Vectorization

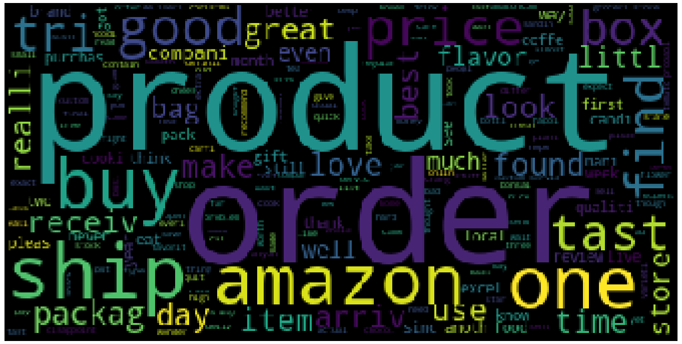
In [30]:
```
# Vectorizing our data
XdataW2VV2= w2vVect(Xdata2)
```

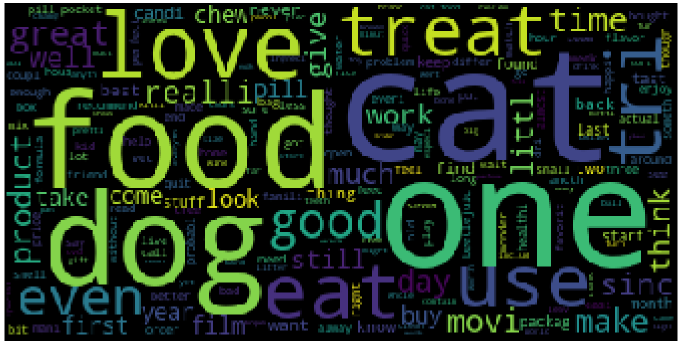
In [31]:
```
#Standardizing vectors
XdataW2VV2 = StandardScaler(with_mean=False).fit_transform(XdataW2VV2)
```

```
In [194]: W2V2aglo= AgglomerativeClustering(n_clusters=7)
          cluster= list(W2V2aglo.fit_predict(XdataW2VV2))
```

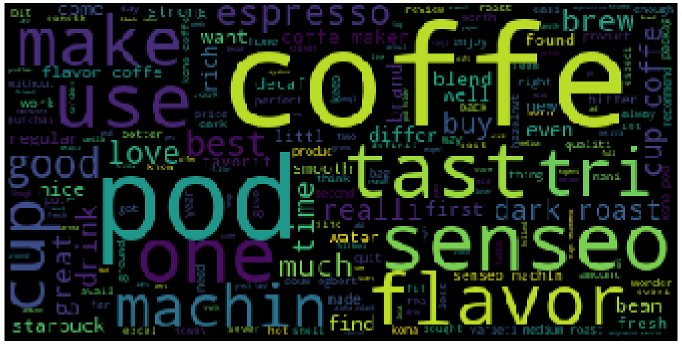
```
In [195]: wordCloud(cluster,list(Xdata2), 7)
```

```
So we have 5 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
```



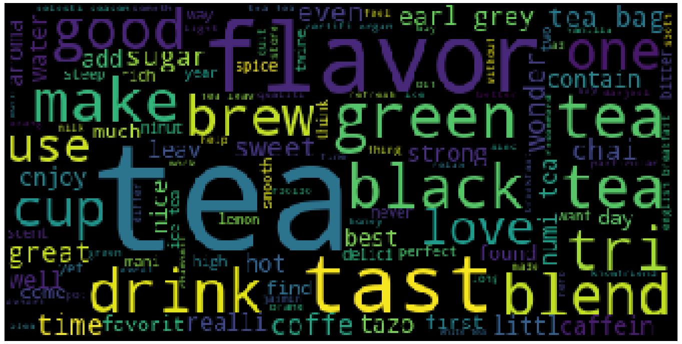



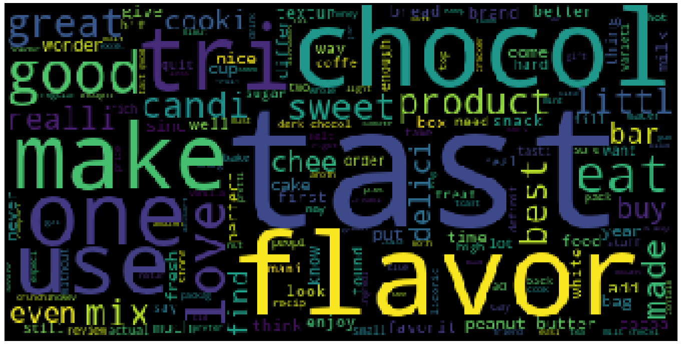

tast
product
one
flavor
sugar
bar
use
good
great
drink
find
snack
food
sweet
make
even
realli
cereal
love
buy
natur
healthi
littl
best
water
calori
contain
chocol
tri



coffe
pod
tast
tri
senseo
flavor
machin
make
use
one
espresso
cup
good
love
best
brew
much
time
dark
roast
realli
great
drink
blend
buy
even
starbuck
found
find
bean
fresh



sauc
use
tast
flavor
make
good
one
eat
tri
product
great
food
noodl
cook
love
well
add
chicken
pasta
best
hot
realli
chees
littl
water
find
even
put
soup
mix




## Observations:-

- **Cluster 1 :-** This cluster has major words as dilevery:- amazon, order, shippment, delivery, bought, recived, gift
- **Cluster 2 :-** This cluster has major words from animal food:- dog, cat, chew etc
- **Cluster 3 :-** This cluster has major words as sweet item:- bar, cocolate, cereal, sugar etc
- **Cluster 4 :-** This cluster has major words from coffee:- hot, drink, espresso, cup, blended, brew etc

- **Cluster 5 :-** This cluster has major words chinease:- sauce, noodle, pasta, salt, chicken etc
- **Cluster 6 :-** This cluster has major words from tea:- tea, green tea, black tea, hot, drink, blend, tea bag etc
- **Cluster 7 :-** This cluster has major words from chocolate:- chocolate, bar, candy, sweet, nut etc

## Agglomerative: TFIDF Weighted W2V Vectorization

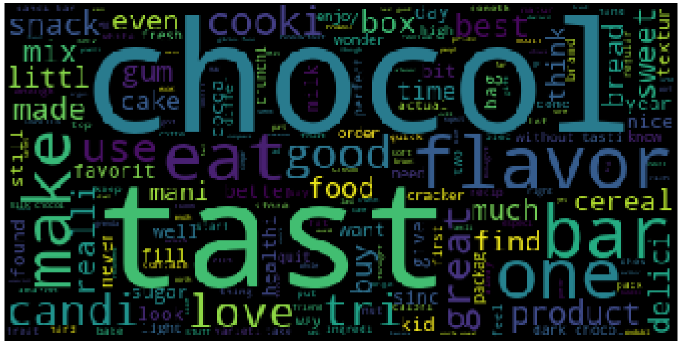
In [32]:
```
# feeding text data and recieving vectorized data
XdataTFIDFW2VV2= tfidfw2vVect(Xdata2)
```

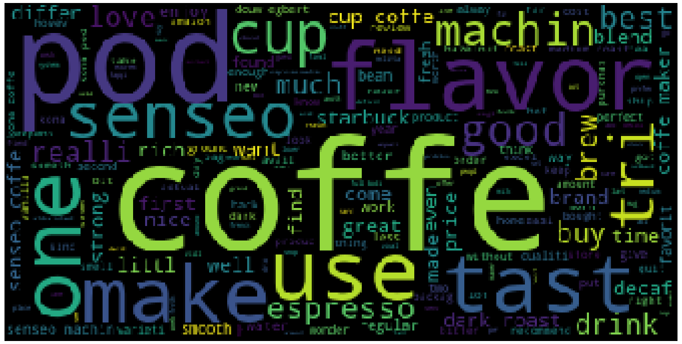
In [33]:
```
#Standardizing vectors
XdataTFIDFW2VV2 = StandardScaler(with_mean=False).fit_transform(XdataTF
IDFW2VV2)
```

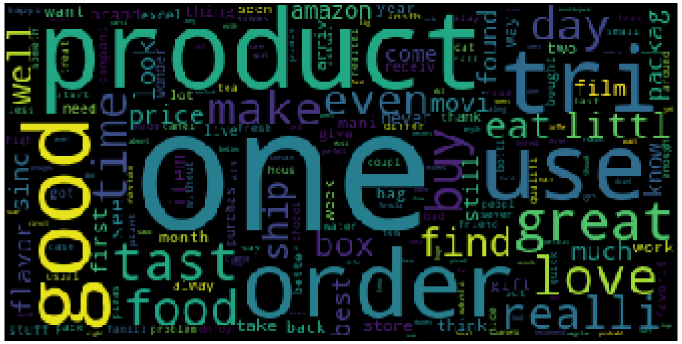
In [196]:
```
TFIDFW2VV2aglo= AgglomerativeClustering(n_clusters=7)
cluster= list(TFIDFW2VV2aglo.fit_predict(XdataTFIDFW2VV2))
```

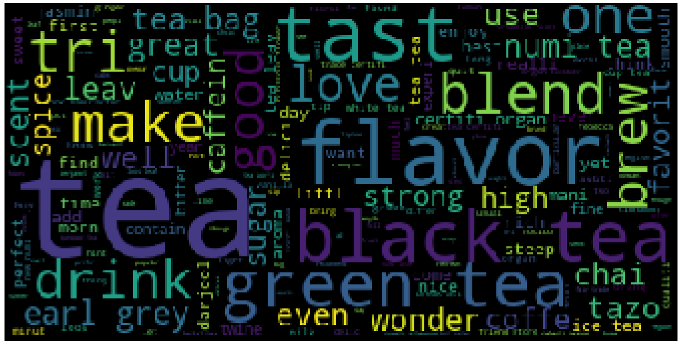
In [197]:
```
wordCloud(cluster,list(Xdata2),7)
```

```
So we have 7 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
```

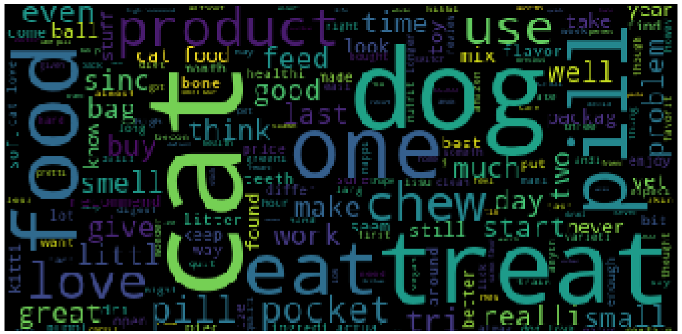

chocol
tast
flavor
make
eat
good
bar
one
love
candi
cooki
snack
even
box
best
mix
littl
made
use
food
great
product
cereal
much
find
sweet
bread
gum
cake
time
favorit
well
want
buy
realli
think
delici

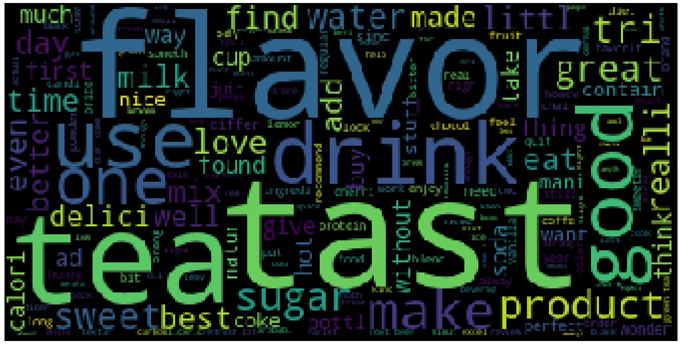

coffe
pod
flavor
senseo
cup
machin
make
use
tast
one
good
tri
brew
espresso
drink
much
love
best
blend
starbuck
realli
great
buy
time
decaf
dark roast
price
strong
brand


product
one
good
order
tri
use
great
tast
food
love
realli
find
time
day
make
even
box
ship
buy
amazon
price
littl
eat
well
film
month
flavor
much
store
packag


tea
tast
flavor
black tea
green tea
blend
make
love
tri
drink
good
brew
one
use
tea bag
great
earl grey
strong
high
chai
tazo
wonder
even


use
sauc
make
flavor
tast
one
good
tri
great
chee
product
cook
noodl
eat
love
chicken
pasta
reall
food
add
salt
mix


cat
dog
food
one
treat
eat
product
pill
love
chew
use
well
time
feed
good
smell
pocket
bag




## Observations:-

- **Cluster 1 :-** This cluster has major words from chocolate:- chocolate, bar, candy, sweet, nut etc
- **Cluster 2 :-** This cluster has major words from coffee:- hot, drink, espresso, cup, blended, brew etc
- **Cluster 3 :-** This cluster has major words as dilevery:- amazon, order, shippment, delivery, bought, recived, gift
- **Cluster 4 :-** This cluster has major words from tea:- tea, green tea, black tea, hot, drink, blend, tea bag etc
- **Cluster 5 :-** This cluster has major words chinease:- sauce, noodle, pasta, salt, chicken etc
- **Cluster 6 :-** This cluster has major words from animal food:- dog, cat, chew etc
- **Cluster 7 :-** This cluster has major words as drinks:- milk, coke, soda, mix etc

==========================================================================

# DBSCAN

In [161]:
```
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import DBSCAN
def NNforEPS(XdataVec,nn):
    '''
    performs elbow method and plots the curve after calculating nearest
 neighbors in vectors
    '''
    knn = NearestNeighbors(n_neighbors = nn, n_jobs= -1)
    knn.fit(XdataVec)
    dist , _ = knn.kneighbors(XdataVec)
    sort = sorted(dist[:,nn-1])
    plt.plot(list(range(1,len(XdataVec)+1)),sort,'r-')
    plt.xlabel('n_samples')
    plt.ylabel('Distance')
    plt.title('elbow method for finding eps')
    plt.grid()
    plt.show()
```

### Getting 4000 data from data corpus

In [34]:
```
#latest 4k points according to time
Xdata3= data[:4000]['CleanedText']
len(Xdata3)
```

Out[34]: 4000

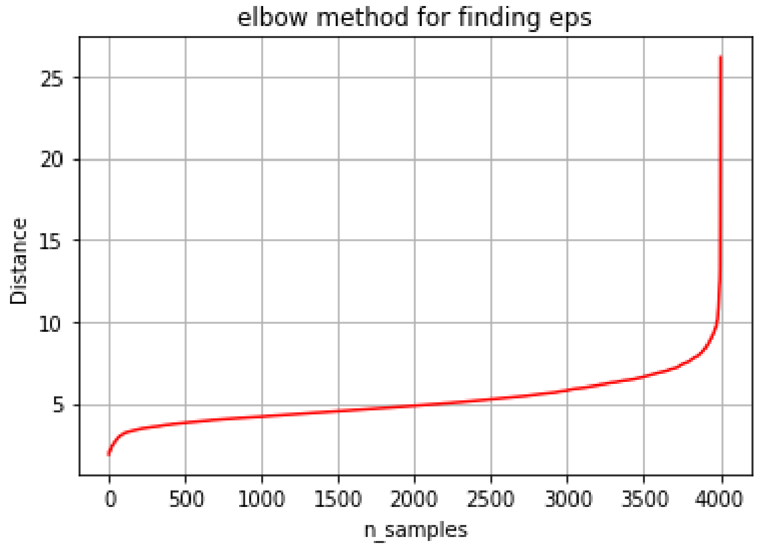
## DBSCAN: W2V Vectorization

```
In [35]: # Vectorizing our data
XdataW2VV3= w2vVect(Xdata3)
```

```
In [36]: #Standardizing vectors
XdataW2VV3 = StandardScaler(with_mean=False).fit_transform(XdataW2VV3)
```

**Elbow method**

```
In [193]: NNforEPS(XdataW2VV3,10)
```

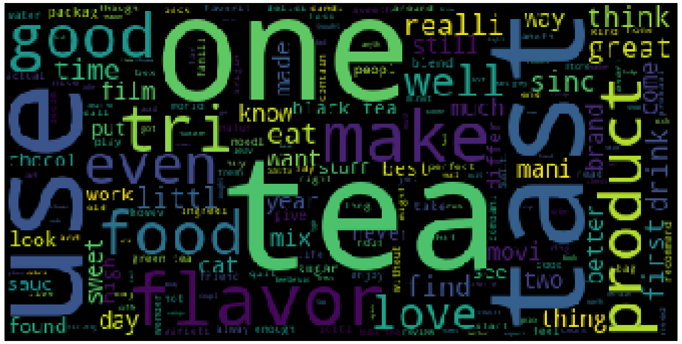


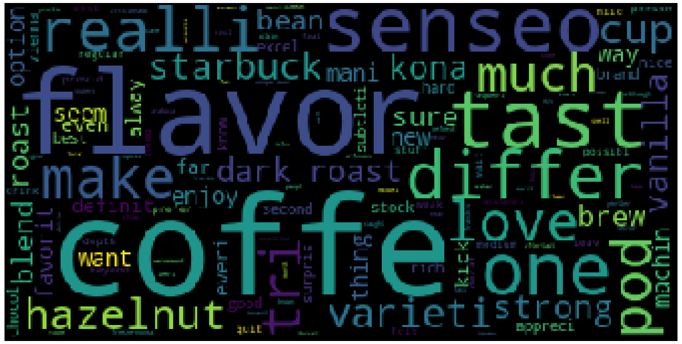

```
In [191]: W2Vdbscan= DBSCAN(eps=3.5, min_samples=10, n_jobs=-1)
cluster= list(W2Vdbscan.fit_predict(XdataW2VV3))
```

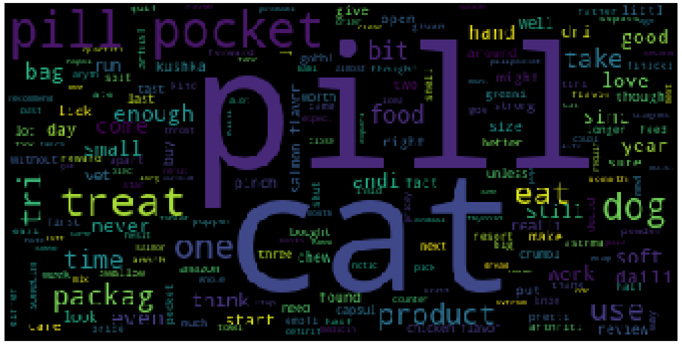
```
In [192]: wordCloud(cluster,list(Xdata3),len(set(cluster)))
```

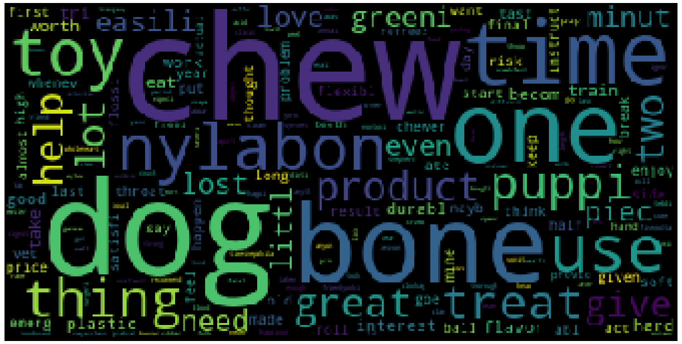
```
So we have 7 clusters here representing in wordcloud:
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
```

```
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 0 :
```

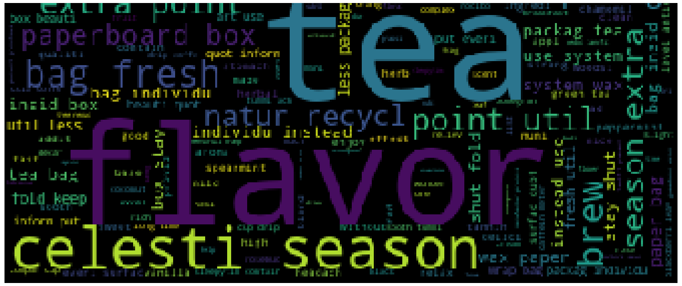




coffe
flavor
tast
senseo
realli
differ
make
cup
starbuck
much
one
love
pod
hazelnut
varieti
strong
brew
dark roast
kona
sure
new
vanilla
roast
blend
enjoy
want
tri
thing
kick
machin
bean
way


pill
cat
pill pocket
treat
dog
bit
eat
food
enough
one
time
packag
product
use
good
take
love
hand
tri
small
year
soft
think
bag
day


chew
dog
bone
time
one
nylabon
toy
puppi
product
use
thing
treat
great
give
help
lot
two
lost
littl
love
greeni
easili
minut
even
piec
need


recycl paperboard individu wrap
util natur box packag





## Observations:-

- **Cluster 1 :-** This cluster has major words from tea:- tea, green tea, black tea, hot
- **Cluster 2 :-** & **Cluster 3 :-** This cluster has major words from coffee:- hot, drink, espresso, cup, blended, brew etc
- **Cluster 4 :-** & **Cluster 5 :-** This cluster has major words from animal food:- dog, cat, chew etc
- **Cluster 6 :-** This cluster has major words from tea:- tea, green tea, black tea, hot, drink, blend, tea bag etc
- **Cluster 7 :-** This cluster has major words as drinks:- milk, chocolate, soda, tea, coffe etc

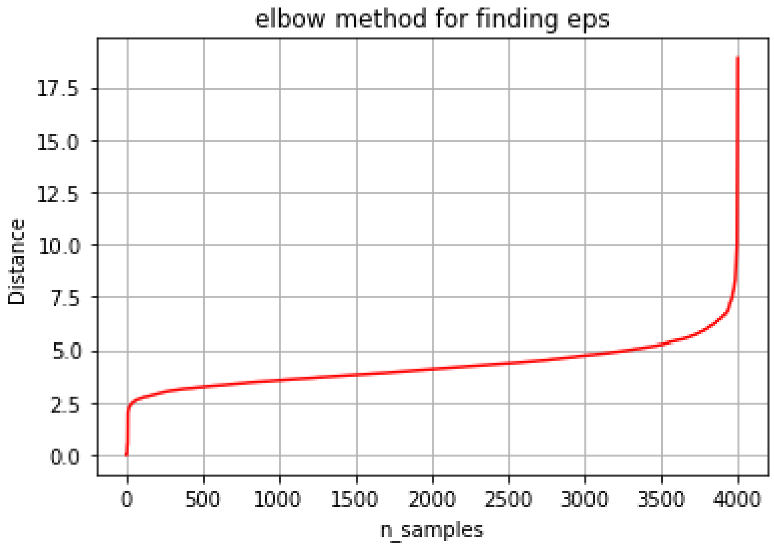
# DBSCAN: TFIDF Weighted W2V Vectorization

In [37]:
```
# feeding text data and recieving vectorized data
XdataTFIDFW2VV3= tfidfw2vVect(Xdata3)
```

In [38]:
```
#Standardizing vectors
XdataTFIDFW2VV3 = StandardScaler(with_mean=False).fit_transform(XdataTF
IDFW2VV3)
```

#### Elbow method

In [167]:
```
NNforEPS(XdataTFIDFW2VV3,5)
```

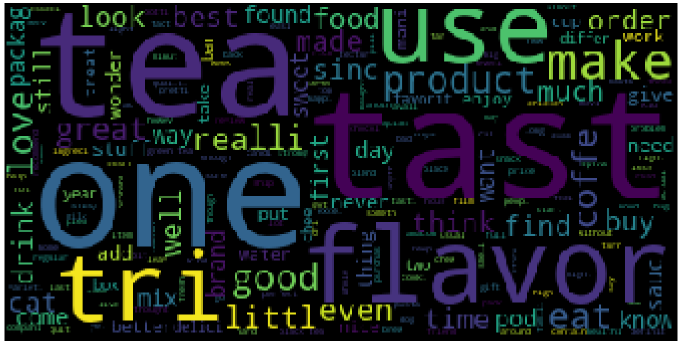


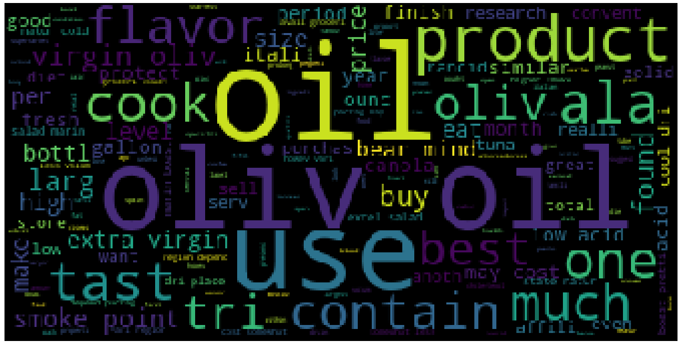

In [168]:
```
TFIDFW2Vdbscan= DBSCAN(eps=4, min_samples=5, n_jobs=-1)
cluster= list(TFIDFW2Vdbscan.fit_predict(XdataTFIDFW2VV3))
```

In [169]:
```
wordCloud(cluster,list(Xdata3),len(set(cluster)))
```

```
So we have 12 clusters here representing in wordcloud:
```

```
Cluster Number 1 :
Cluster Number 2 :
Cluster Number 3 :
Cluster Number 4 :
Cluster Number 5 :
Cluster Number 6 :
Cluster Number 7 :
Cluster Number 8 :
Cluster Number 9 :
Cluster Number 10 :
Cluster Number 11 :
Cluster Number 0 :
```

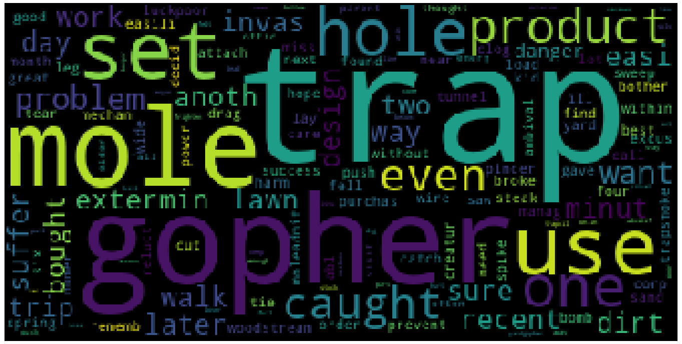


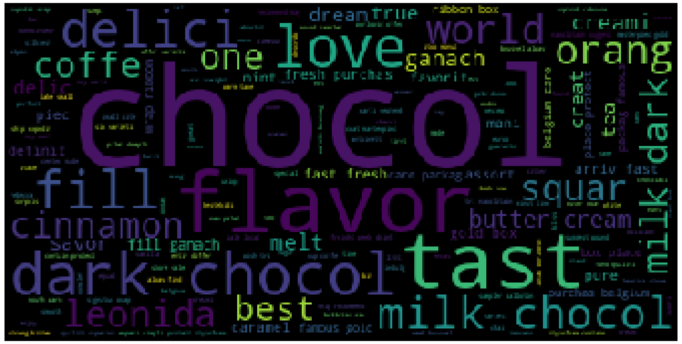




jerki
beef
make
flavor
tast
meat
spici
sweet
well
great
good
habanero



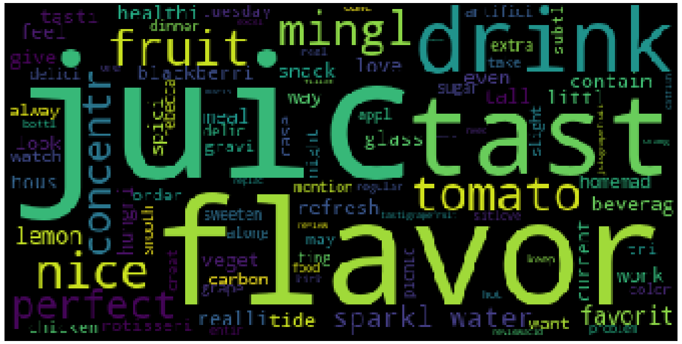
tea
name
blend
breakfast
english breakfast

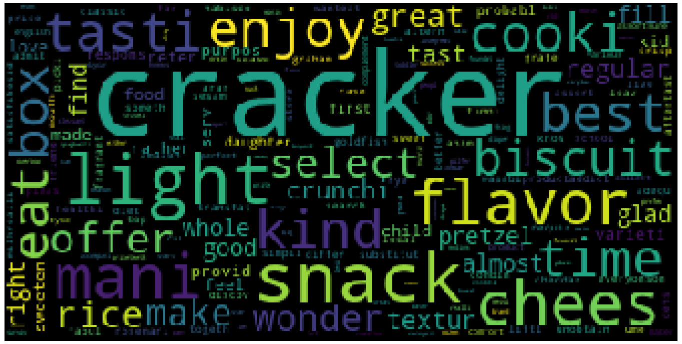


trap
gopher
mole
hole
product
set
use
one
caught
even

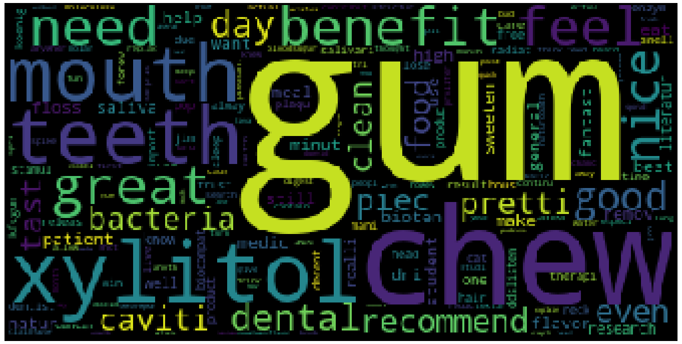

chocol
flavor
tast
dark chocol
milk chocol
delici
love
world
orang
coffe
one
fill
squar
cinnamon
leonida
best
milk
dark
butter
cream
melt
ganach
dream
true
creami

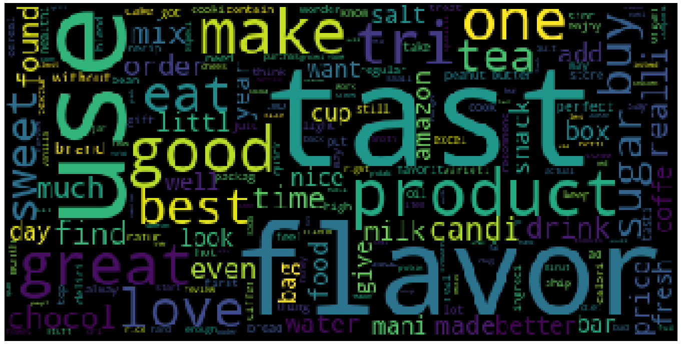

chocol
cocoa
tast
make
made
flavor
box
candi
use
dark
hot cocoa
rich
buy
famili
assort
sinc
year
one
asbach
product
time
order


salt
product
iodiz
morton
use
littl
eat
thing
good
peanut
great
peopl
make
year
food
know
everi
even
ad
much
lot
well
need
best
test
give
must
store brand
sinc


juic
flavor
tast
drink
fruit
mingl
tomato
nice
perfect
concentr
lemon
sparkl
water
favorit
beverag
refresh
carbon
homemad
contain
extra
sugar
glass
snack
blackberri
healthi


cracker
light
tasti
enjoy
great
cooki
best
biscuit
flavor
select
eat
box
offer
kind
mani
snack
time
chees
rice
make
wonder
textur
pretzel
crunchi
whole
good
regular
almost
glad
tast
food
find
child


gum
chew
mouth
teeth
xylitol
need
day
benefit
feel
nice
great
bacteria
clean
food
pretti
good
piec
dental
caviti
recommend
even
tast
saliva
floss
patient
want
high




## Observations:-

- **Cluster 1 :-** & **Cluster 4 :-** This cluster has major words from tea:- tea, green tea, black tea, hot, drink, blend, tea bag etc
- **Cluster 2 :-** This cluster has major words from oil:- olive oil, extravrgin oil, smoke point etc
- **Cluster 3 :-** This cluster has major words from meat:- jerky, meat, beef etc
- **Cluster 5 :-** This cluster has major words from trap :- food to get animal from lawn in trap etc
- **Cluster 6 :-** & **Cluster 7 :-** This cluster has major words from chocolate
- **Cluster 8 :-** This cluster has major words as salted peanuts
- **Cluster 9 :-** This cluster has major words as juice and drinks
- **Cluster 10 :-** This cluster has major words snacks:- biscuits, cookies, snacks, crunchy cracker etc
- **Cluster 11 :-** This cluster has major words as chewing gums
- **Cluster 12 :-** This cluster has no major distinction but something related to flavour of candy, drinks etc

----------------------------------------------------------------------
--------------------------------

### Observations

- Kmeans works well if time complexity is considered, otherwise DBSCAN does better
- DBSCAN is very slow for large data sets, in otherwise case we csn use Kmeans
- We got our best results in form of cluster in DBSCAN Clustering with TFIDF Weighted W2V Vectorization

In [39]:
```
print('end\n\n\n\n\n')
```

```
end
```