Assignment 10

November 12, 2018

0.1 Assignment 10: Apply K-Means clustering, Hierarchical Clustering, and DB-SCAN to Amazon food reviews dataset [M]

Given Dataset consists of reviews of fine foods from amazon. Reviews describe (1)product and user information, (2)ratings, and (3) a plain text review.Here, Clustering algorithm is applied on amazon reviews datasets to cluster the reviews.

Types of clustering :

```
1.K-Means clustering
2.Hierarchical Clustering
3.DBSCAN(Density Based spital clustering of application with noise).
```

Procedure to execute the above task is as follows:

1.K-Means clustering

- **Step1: Take Reviews data of amazon reviews data-set. And Ignore polarity column**
- **Step2: Apply K-means++ cluster and K-medoids cluster algorithm.**
- **Step3: Apply Feature generation techniques(Bow,tfidf,avg w2v,tfidfw2v)**
- **Step4: Apply K-Means clustering algorithm using each technique.**
- **Step5: To find Best k using Elbow method**
- **Step6: Read the cluster reviews**

2.Hierarchical Clustering

- **Step1: Take 5k Reviews sample of amazon reviews data-set. And Ignore polarity column**
- **Step2: Apply Feature generation techniques(Bow,tfidf,avg w2v,tfidfw2v)**
- **Step3: Apply Hierarchical Clustering algorithm using each technique.**
- **Step4: To find Best k using Elbow method**
- **Step5: Read the cluster reviews**

3.DBSCAN

- **Step1: Take sample of Reviews data of amazon reviews data-set. And Ignore polarity column**
- **Step2:consider min_pts = 2* dimension(consider 100 dimensions of data).**
- **Step3: Apply Feature generation techniques(avg w2v,tfidfw2v) BOW & TFIDF is high dimesional thus DBSCAn does not work properly**
- **Step4: Apply DBSCAN algorithm using avg w2v & tfidfw2v technique.**
- **Step5: To find Best k using Elbow method**
- **Step6: Read the cluster reviews**
- **Step7: As DBSCAN is sensible towards eps value,check the sensitives for different value of eps**

0.2 Objective:

- To cluster Amazon reviews using K-Means clustering, Hierarchical Clustering, and DB-SCAN algorithm.Read & display the random reviews in given set of clusters using word-cloud.

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# All necessary module
%matplotlib inline

#import  sys
import re
import math
import random
import pandas as pd
import numpy as np
import pickle
# modules for text processing
import nltk
import string
from tqdm import tqdm
from sklearn.externals import joblib

from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
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

import pytablewriter
from sklearn.feature_extraction.text import CountVectorizer


from nltk.stem.porter import PorterStemmer

from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing

from sklearn import linear_model
from scipy.stats import uniform
import os
# Importing k-Means class from sklearn
from sklearn.cluster import KMeans


from sklearn.metrics import pairwise_distances
```

In [3]:
```
from kmedoids import kMedoids
# Importing Agglomerative Clustering
from sklearn.cluster import AgglomerativeClustering
# DBSCAN
from sklearn.cluster import DBSCAN
```

In [4]:
```
import zipfile
archive = zipfile.ZipFile('/floyd/input/pri/Reviews.zip', 'r')
csvfile = archive.open('Reviews.csv')
```

In [5]:
```
# Reading CSV file and printing first five rows
amz = pd.read_csv(csvfile ) # reviews.csv is  dataset file
print(amz.head(2))
```

```
   Id   ProductId          UserId ProfileName  HelpfulnessNumerator  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                     1
1   2  B00813GRG4  A1D87F6ZCVE5NK      dll pa                     0

   HelpfulnessDenominator  Score        Time                Summary  \
0                       1      5  1303862400  Good Quality Dog Food
1                       0      1  1346976000      Not as Advertised

                                                Text
0  I have bought several of the Vitality canned d...
1  Product arrived labeled as Jumbo Salted Peanut...
```

In [6]:
```
# dimensions of dataset and columns name
print(amz.shape)
```

```
#print(amz1.shape)
print(amz.columns)
```

```
(568454, 10)
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

```
In [7]: print(amz.shape)
        amz.head(2)
```

```
(568454, 10)
```

```
Out[7]:    Id   ProductId          UserId ProfileName  HelpfulnessNumerator  \
        0   1  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                     1
        1   2  B00813GRG4  A1D87F6ZCVE5NK      dll pa                     0

           HelpfulnessDenominator  Score        Time                Summary  \
        0                       1      5  1303862400  Good Quality Dog Food
        1                       0      1  1346976000      Not as Advertised

                                                        Text
        0  I have bought several of the Vitality canned d...
        1  Product arrived labeled as Jumbo Salted Peanut...
```

Data Pre-processing on raw data: Every datasets contains some unwanted data.Raw data is preprocessed by removing duplication.

```
In [8]: #Processing of ProductId
        #Sorting data according to ProductId in ascending order
        sorted_data=amz.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='qu
        #sorted_data.head() # printing sorted data
        # To check the duplications in raw data
        dupli=sorted_data[sorted_data.duplicated(["UserId","ProfileName","Time","Text"])]
        print(dupli.head(5))
        # Remove Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='f
        final.shape
        #Checking to see how much % of data still remains
        (final['Id'].size*1.0)/(amz['Id'].size*1.0)*100
        final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
        #Before starting the next phase of preprocessing lets see the number of entries left
        print(final.shape)
```

```
            Id   ProductId          UserId  \
171222  171223  7310172001   AJD41FBJD9010
171153  171154  7310172001   AJD41FBJD9010
```

```
171151  171152  7310172001   AJD41FBJD9010
217443  217444  7310172101  A22FICU3LCG2J1
217444  217445  7310172101  A1LQV0PSM04DWI

                                         ProfileName  HelpfulnessNumerator  \
171222  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     1
171153  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
171151  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
217443                                     C. Knapp                     1
217444                               B. Feuerstein                     1

        HelpfulnessDenominator  Score        Time  \
171222                       1      5  1233360000
171153                       0      5  1233360000
171151                       0      5  1233360000
217443                       1      4  1275523200
217444                       1      4  1274313600

                                                  Summary  \
171222  best dog treat-- great for training---  all do...
171153  best dog treat-- great for training---  all do...
171151  dogs LOVE it--  best treat for rewards and tra...
217443                               Can't resist this !
217444                      Freeze dried liver as dog treats

                                                     Text
171222  Freeze dried liver has a hypnotic effect on do...
171153  Freeze dried liver has a hypnotic effect on do...
171151  Freeze dried liver has a hypnotic effect on do...
217443  My dog can't resist these treats - I can get h...
217444  My little pupster loves these things. She is n...
(393931, 10)
```

1 Text Preprocessing:

In [9]:
```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Out[9]: True

In [10]:
```
 stop = set(stopwords.words('english')) #set of stopwords
 sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer
```

```python
def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>$< /><')
    #cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special char
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

cleaning html tags like" <.*?>" and punctuations like " r'[?|!|'|"|#]',r''" from senetences

In [ ]:
```python
#Code for implementing step-by-step the checks mentioned in the pre-processing phase.

'''Pre processing of text data:It is cleaning and flitering text'''
i=0
str1=' '
global final_string
final_string=[]
all_positive_words=[]
all_negative_words=[]
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describe
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

    final_string.append(str1)
    i+=1
```

Dumping and loading Pre processing of text data in pickle file

```
In [11]: pickle_path_final_string='final_string.pkl'
         final_string_file=open(pickle_path_final_string,'wb')
         pickle.dump(final_string,final_string_file)
         final_string_file.close()
```

```
In [11]: pickle_path_final_string='final_string.pkl'
         final_string_unpkl=open(pickle_path_final_string,'rb')
         final_string=pickle.load(final_string_unpkl)
```

```
In [12]: final['CleanedText']=final_string
         #adding a column of CleanedText which displays the data after pre-processing of the rev
         Pre_Process_Data = final[['CleanedText','Time']]
```

1.0.1 Splitting dataset based on Time

```
In [13]: X1 = Pre_Process_Data[['CleanedText','Time']].sort_values('Time',axis=0).drop('Time',ax
         #40k data sample
         X_Text=X1[:40000]
         print(X_Text.shape)
```

```
(40000, 1)
```

2 WordCloud function

```
In [14]: from wordcloud import WordCloud, STOPWORDS

         def word_cloud_form(text_value):
             comment_words = ' '
             stopwords = set(STOPWORDS)
             for words in text_value.decode("utf-8").split():
                 comment_words =comment_words + words + ' '



             wordcloud = WordCloud(width = 800, height = 800,
                             background_color ='black',
                             stopwords = stopwords,
                             min_font_size = 10).generate(comment_words)

             # plot the WordCloud image
             plt.figure(figsize = (8, 8), facecolor='y', edgecolor='w')
             plt.imshow(wordcloud)
             plt.axis("off")
             plt.tight_layout(pad = 0)

             plt.show()
```

In [15]:
```
# result_display  is function to convert dataframe into table format in Markdown
def result_display(df):
    writer = pytablewriter.MarkdownTableWriter()
    writer.header_list = list(df.columns.values)
    writer.value_matrix = df.values.tolist()
    writer.write_table()
```

3 Methods to convert text into vector

Methods: * Bag of Words * Avg word2vec * Tf-idf * tf-idf weighted Word2Vec
Using above four method is used to convert text to numeric vector.

4 1. Bag of Words (BoW)

In [16]:
```
# truncated SVD for dimesionality reduction for 100 dimensions
svd = TruncatedSVD(n_components=100,n_iter=7)
```

In [17]:
```
def BOW(X_text_data):

    count_vect = CountVectorizer() #in scikit-learn
    vect_Data = count_vect.fit_transform(X_text_data.values.ravel())
    print(vect_Data .shape)


    global final_data
    Data=svd.fit_transform(vect_Data )

    # StandardScaler
    final_data= StandardScaler(with_mean=False).fit_transform(Data )
    print("TruncatedSVD :",final_data.shape)
```

In [18]:
```
BOW(X_Text)
```

```
(40000, 24155)
TruncatedSVD : (40000, 100)
```

Dumping & Loading Pickle file for data (BOW)

In [19]:
```
#Pickle file for training data

pickle_path_BOW='X_data_BOW.pkl'
X_data_BOW=open(pickle_path_BOW,'wb')
pickle.dump(final_data ,X_data_BOW)
X_data_BOW.close()
```

In [20]:
```
pickle_path_BOW='X_data_BOW.pkl'
unpickle_path1=open(pickle_path_BOW,'rb')
final_data=pickle.load(unpickle_path1)
```

```
In [21]: joblib.dump(final_data, 'final_data.joblib')
```

```
Out[21]: ['final_data.joblib']
```

```
In [22]: final_data = joblib.load('final_data.joblib')
```

5 2. Avg word2vec

Firstly, word2vec model is designed for amazon reviews using gensim module.

```
In [23]: import gensim

         def avgword2vec(X_text_data):

             list_sent=[]
             for text in tqdm(X_text_data.values.ravel()):
                 filter_text=[]
                 for i in text.split():
                     if(i.isalpha()):
                         filter_text.append(i.lower().decode("utf-8"))
                     else:
                         continue
                 list_sent.append(filter_text)

             global w2v_model
             w2v_model=gensim.models.Word2Vec(list_sent,min_count=5,size=100, workers=4)
             #this model is used in avg word2vec
             words = list(w2v_model.wv.vocab)

             sent_vectors = []
             for sent in  tqdm(list_sent): # for each review/sentence
                 sent_vec = np.zeros(100)
                 cnt_words =0 # num of words with a valid vector in the sentence/review
                 for word in sent:
                     try:
                         vec = w2v_model.wv[word]
                         sent_vec += vec
                         cnt_words += 1
                     except:
                         pass
                 sent_vec /= cnt_words
                 sent_vectors.append(sent_vec)


             # Converting Nan value to zero in sent vectors.
             Sent_Nan = np.where(np.isnan(sent_vectors), 0, sent_vectors)
             # converting sent list to nd array
             global  Sent_final_vector
```

```
        Sent_final_vector = np.asarray(Sent_Nan )
        print(type(Sent_final_vector))
```

```
In [24]: avgword2vec(X_Text)
```

```
100%|??????????| 40000/40000 [00:01<00:00, 39150.27it/s]
100%|??????????| 40000/40000 [00:06<00:00, 5816.25it/s]


<class 'numpy.ndarray'>
```

Dumping & Loading Pickle file for Avg word2vec

```
In [25]: pickle_path_AW2V='X_data_AW2V.pkl'
         X_data_AW2V=open(pickle_path_AW2V,'wb')
         pickle.dump(Sent_final_vector,X_data_AW2V)
         X_data_AW2V.close()

In [26]: pickle_path_AW2V='X_data_AW2V.pkl'
         unpickle_path3=open(pickle_path_AW2V,'rb')
         final_w2v_count=pickle.load(unpickle_path3)

In [27]: joblib.dump(final_w2v_count, 'final_w2v_count.joblib')

Out[27]: ['final_w2v_count.joblib']

In [23]: final_w2v_count = joblib.load('final_w2v_count.joblib')
```

5.0.1 3.TF-IDF

```
In [29]: def tfidf(X_text_data):

             tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
             final_tf_idf11 = tf_idf_vect.fit_transform(X_text_data.values.ravel())
             final_tf_idf11.get_shape()

             global tfidf_feat
             tfidf_feat = tf_idf_vect.get_feature_names()

             global final_tfidf_np
             final_tf_idf=svd.fit_transform(final_tf_idf11 )
             print("TruncatedSVD :",final_tf_idf.shape)
```

```
            #StandardScaleing and normalizing for Tf-IDF
            final_tfidf_np= StandardScaler(with_mean=False).fit_transform(final_tf_idf)

            print("Train Data: ",final_tfidf_np.shape)

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

            global dictionary
            dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))
```

```
In [30]: tfidf(X_Text)
```

```
TruncatedSVD : (40000, 100)
Train Data:  (40000, 100)
```

Dumping & Loading Pickle file for data (TF-IDF)

```
In [31]: pickle_path_tfidf='X_data_tfidf.pkl'
         X_data_tfidf=open(pickle_path_tfidf,'wb')
         pickle.dump(final_tfidf_np ,X_data_tfidf)
         X_data_tfidf.close()
```

```
In [32]: pickle_path_tfidf='X_data_tfidf.pkl'
         unpickle_path5=open(pickle_path_tfidf,'rb')
         final_tfidf_np=pickle.load(unpickle_path5)
```

```
In [33]: joblib.dump(final_tfidf_np, 'final_tfidf_np.joblib')
```

```
Out[33]: ['final_tfidf_np.joblib']
```

```
In [24]: final_tfidf_np= joblib.load('final_tfidf_np.joblib')
```

6 4.TF-IDF weighted Word2Vec

```
In [35]: # TF-IDF weighted Word2Vec
         # Train  Word2Vec model for given  text corpus
         i=0
         list_of_sent=[]
         for sent in tqdm(X_Text.values.ravel()):
             list_of_sent.append(sent.decode("utf-8").split())

         def tfidfword2vec(X_text_data):

             sent_vectors = []
             for sent in tqdm(list_of_sent): # for each review/sentence
                 sent_vec = np.zeros(100) # as word vectors are of zero length
```

```
                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)


            tfidf_sent_vectors1  = np.where(np.isnan(sent_vectors), 0, sent_vectors)
            global tfidf_sent_vector_data
            tfidf_sent_vector_data  = np.asarray(tfidf_sent_vectors1 )
```

```
100%|??????????| 40000/40000 [00:00<00:00, 124916.26it/s]
```

In [36]:
```
tfidfword2vec(X_Text)
```

```
100%|??????????| 40000/40000 [00:54<00:00, 740.32it/s]
```

Dumping & Loading Pickle file forText data (TF-IDF weighted word2vec)

In [37]:
```
pickle_path_tfidf_weighted='X_data_tfidf_weighted.pkl'
X_data_tfidf_weighted=open(pickle_path_tfidf_weighted,'wb')
pickle.dump(tfidf_sent_vector_data  ,X_data_tfidf_weighted)
X_data_tfidf_weighted.close()
```

In [25]:
```
pickle_path_tfidf_weighted='X_data_tfidf_weighted.pkl'
unpickle_path7=open(pickle_path_tfidf_weighted,'rb')
tfidf_sent_vectors =pickle.load(unpickle_path7)
```

7 1.K-Means clustering

In [26]:
```
# Cluster range
cluster_range=list(range(2,12))
```

7.1 Optimal Cluster using Elbow Method

In [27]:
```
# Optimal_cluster_kmeans is function to find best k values

def Optimal_cluster_kmeans(vectorization_output,vect_name):

    optimal_score = []

    for i in tqdm(range(len(cluster_range))):
```

```
            kmeans = KMeans(n_clusters = cluster_range[i], n_jobs = -1).fit(vectorization_o
            optimal_score.append(kmeans.inertia_)

        global Optimal_cluster

        Optimal_cluster = np.argmin(optimal_score) + 2 # As argmin return the index of mini
        print ("The optimal number of clusters == ", Optimal_cluster)
        print ("The loss for optimal cluster is ==  ", min(optimal_score))

        #plot the graph

        fig4 = plt.figure( facecolor='c', edgecolor='k')
        fig4.suptitle('Optimal Cluster using Elbow method '+str(vect_name), fontsize=12)
        plt.plot(cluster_range, optimal_score,'m*',linestyle='dashed')
        plt.xlabel("Number of clusters")
        plt.ylabel("Squared Loss")
        xy = (Optimal_cluster, min(optimal_score))
        plt.annotate('(%s, %s)' % xy, xy = xy, textcoords='data')
        plt.grid()
        plt.show()
```

7.1.1 Optimal cluster for Each Vectorization Techniques

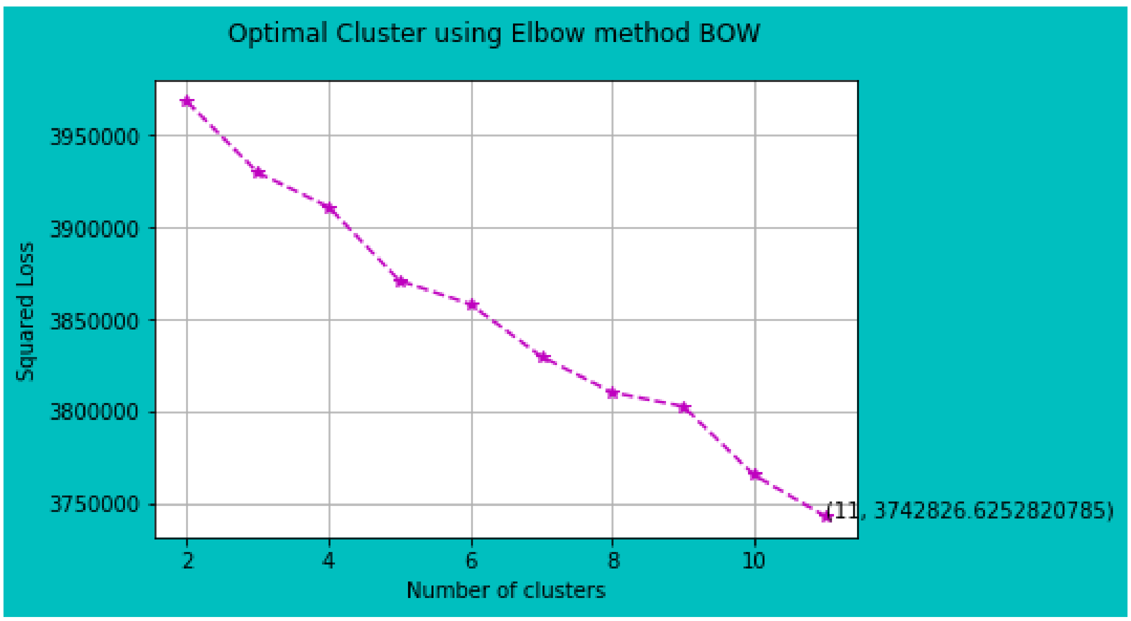
Graph to get Optimal Cluster using Elbow Method for Each Vectorization Techniques.

```
In [28]: # All vectorization_output using BOW,avg word2vec , TFIDF and TFIDf weighted word2vec
         vectorization_output=[final_data,final_w2v_count,
                               final_tfidf_np,tfidf_sent_vectors]

         vect_name=['BOW','Avgword2vec','TFIDF','TFIDFweightedword2vec']
```

```
In [25]: Optimal_cluster_vect=[]

         for y in range(len(vect_name)):
                     print("*" * 60)
                     print("\n")
                     print(vect_name[y])
                     print("\n")
                     print("*" * 60)
                     Optimal_cluster_kmeans(vectorization_output[y],vect_name[y])
                     Optimal_cluster_vect.append(Optimal_cluster)
```

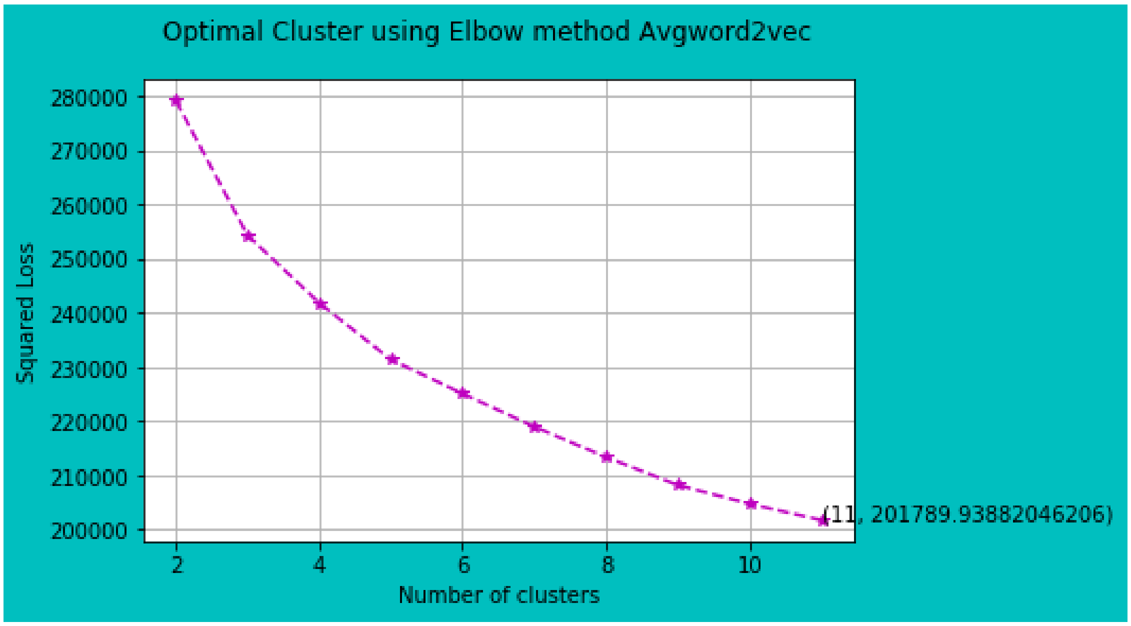
```
  0%|          | 0/10 [00:00<?, ?it/s]
```

```
************************************************************

BOW

************************************************************

100%|??????????| 10/10 [00:30<00:00,  3.01s/it]

The optimal number of clusters ==  11
The loss for optimal cluster is ==   3742826.6252820785
```

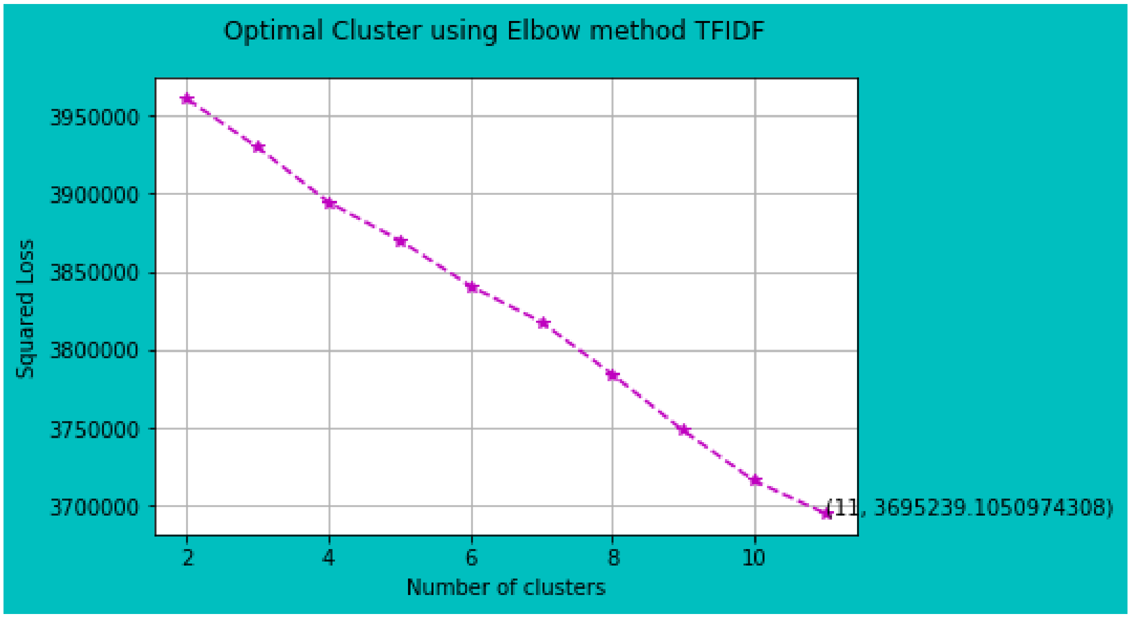



```
  0%|          | 0/10 [00:00<?, ?it/s]

************************************************************

Avgword2vec

************************************************************
```

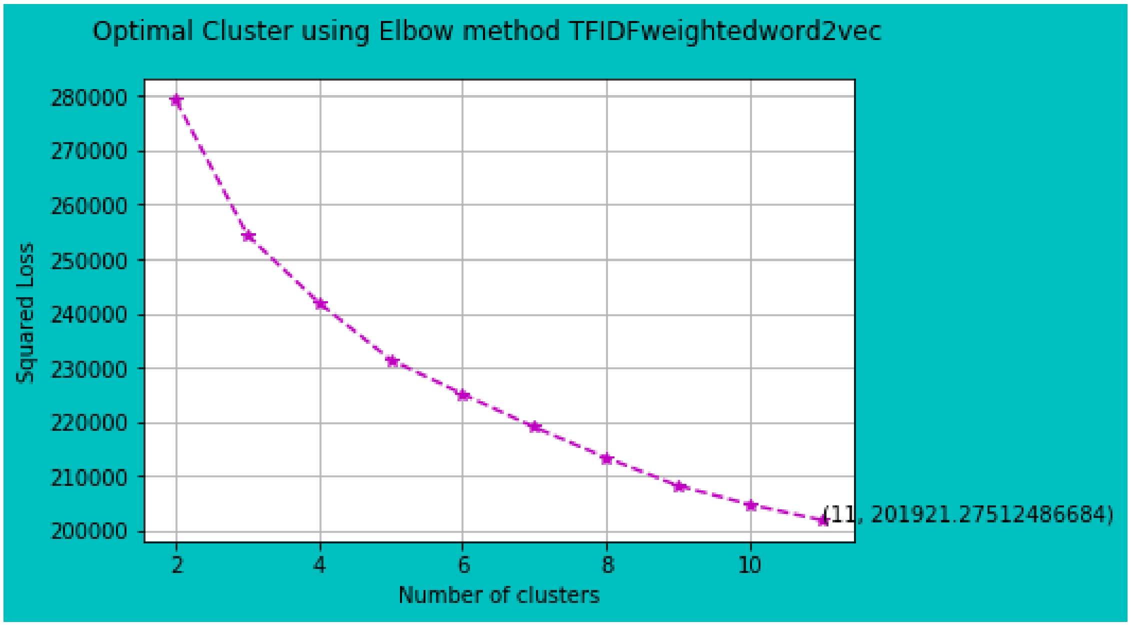
```
100%|??????????| 10/10 [00:31<00:00,  3.10s/it]

The optimal number of clusters ==  11
The loss for optimal cluster is ==   201789.93882046206
```




```
  0%|          | 0/10 [00:00<?, ?it/s]

************************************************************


TFIDF


************************************************************


100%|??????????| 10/10 [00:32<00:00,  3.27s/it]

The optimal number of clusters ==  11
The loss for optimal cluster is ==   3695239.1050974308
```




```
  0%|          | 0/10 [00:00<?, ?it/s]

***********************************************************


TFIDFweightedword2vec


***********************************************************


100%|??????????| 10/10 [00:32<00:00,  3.23s/it]

The optimal number of clusters ==  11
The loss for optimal cluster is ==   201921.27512486684
```




```
In [26]: Optimal_cluster_vect

Out[26]: [11, 11, 11, 11]
```

7.1.2 Best model with Optimal cluster Using Kmeans++ for Each vectorization techniques

```
In [27]: # Training the best model
         model_kmeans=[]
         for i in tqdm(range(len(Optimal_cluster_vect))):
                 print("$__$__" * 10)

                 print('\n')

                 model = KMeans(n_clusters = Optimal_cluster_vect[i], n_jobs = -1)
                 model.fit(vectorization_output[i])
                 model_kmeans.append(model)
                 print(str(vect_name[i])+'==',model)
```

```
  0%|          | 0/4 [00:00<?, ?it/s]

$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__



 25%|???       | 1/4 [00:03<00:11,  3.86s/it]
```

```
BOW== KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=11, n_init=10, n_jobs=-1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__



 50%|?????     | 2/4 [00:08<00:08,  4.31s/it]

Avgword2vec== KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=11, n_init=10, n_jobs=-1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__



 75%|????????  | 3/4 [00:13<00:04,  4.46s/it]

TFIDF== KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=11, n_init=10, n_jobs=-1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__$__



100%|??????????| 4/4 [00:17<00:00,  4.45s/it]

TFIDFweightedword2vec== KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=11, n_init=10, n_jobs=-1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
```

'model_kmeans' is calualted with optimal k value for each vectorization. Optimal cluster size =11 for each vectorizied technique.

7.1.3 Labels a cluster to Each Review

Giving Labels a cluster to each text Review.

```
In [28]: # Giving Labels a cluster to each text Review
         model_col_nam=['BOW_Label','Avgword2vec','TFIDF','TFIDFword2vec']
         df = X_Text
         for k in tqdm(range(len(model_kmeans))):
```

```
            name=model_col_nam[k]
            df[name] = model_kmeans[k].labels_
    df.head()
```

```
100%|??????????| 4/4 [00:00<00:00, 18.57it/s]
```

```
Out[28]:                                           CleanedText  BOW_Label  \
         150523  b'witti littl book make son laugh loud recit c...          0
         150500  b'rememb see show air televis year ago child s...          0
         451855  b'beetlejuic well written movi everyth excel a...          0
         374358  b'twist rumplestiskin captur film star michael...          0
         451854  b'beetlejuic excel funni movi keaton hilari wa...          0

                 Avgword2vec  TFIDF  TFIDFword2vec
         150523            2      9              5
         150500            2      9              5
         451855            2      9              5
         374358            2      9              5
         451854            2      9              5
```

How many points belong to each cluster

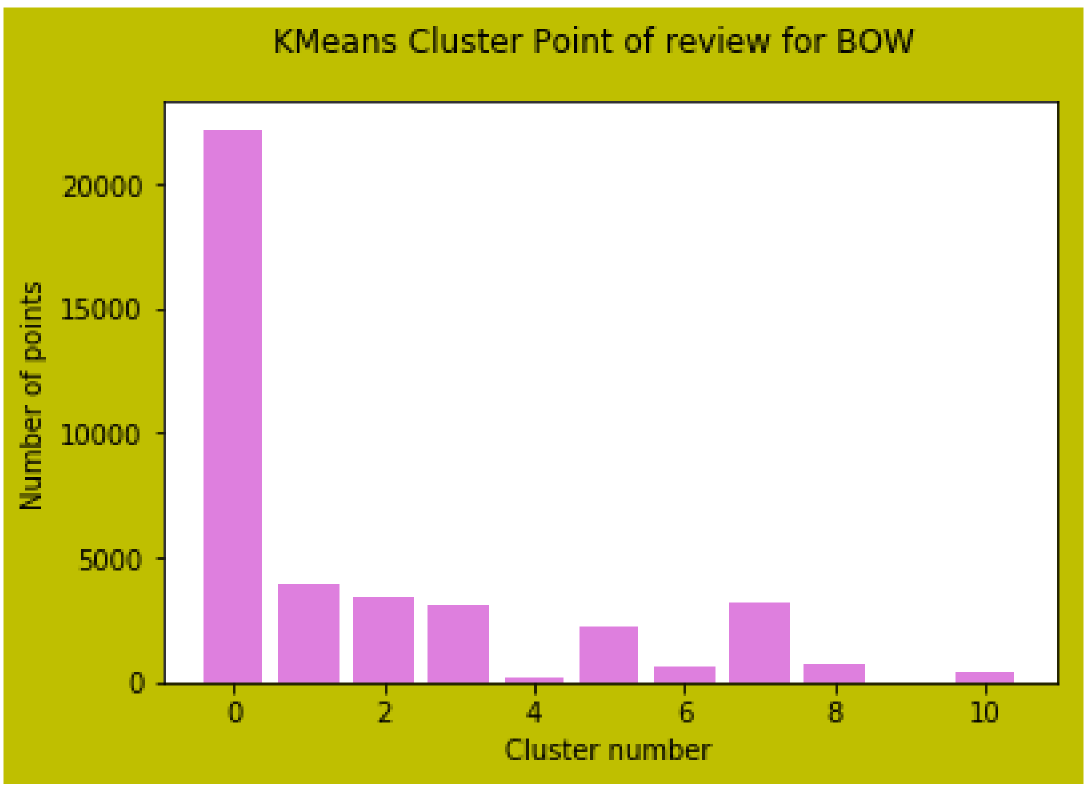
```
In [29]: df1=df.groupby(['BOW_Label'])['CleanedText'].count()
         df2=df.groupby(['Avgword2vec'])['CleanedText'].count()
         df3=df.groupby(['TFIDF'])['CleanedText'].count()
         df4=df.groupby(['TFIDFword2vec'])['CleanedText'].count()
         df5=pd.concat([df1, df2,df3,df4], axis=1).replace(np.nan, 0)
         df5.columns=model_col_nam

         #print(df5)
```

```
In [30]: result_display(df5)
```

BOW_Label	Avgword2vec	TFIDF	TFIDFword2vec
22164	2842	1790	3111
3907	4028	1767	4428
3405	5303	900	2545
3072	2329	871	4740
245	5213	4426	3544
2275	3048	200	7461
596	4942	2740	2355
3216	2446	597	3036
708	2934	677	3368
1	3968	25391	3053
411	2947	641	2359

7.2 KMeans Cluster Bar Graph and Displaying Reviews text assigned to Random cluster for BOW vectorization

```
In [31]: fig4 = plt.figure( facecolor='y', edgecolor='k')
         fig4.suptitle('KMeans Cluster Point of review for BOW', fontsize=12)

         plt.bar([x for x in range(Optimal_cluster_vect[0])],
                 df.groupby(['BOW_Label'])['CleanedText'].count(),
                 color='m',alpha = 0.5)
         plt.xlabel("Cluster number")
         plt.ylabel("Number of points")
         plt.show()

         random_cluster=random.randint(0, Optimal_cluster_vect[0])
         #for i in range(Optimal_cluster_vect[0]):
         print("A review  cleaned text  assigned to cluster ", random_cluster)
         print("*" * 60)
         text_data=df.loc[df.groupby(['BOW_Label']).groups[random_cluster][0]]['CleanedText']
         print(text_data)
         print('\n')
         print("*" * 60)
```

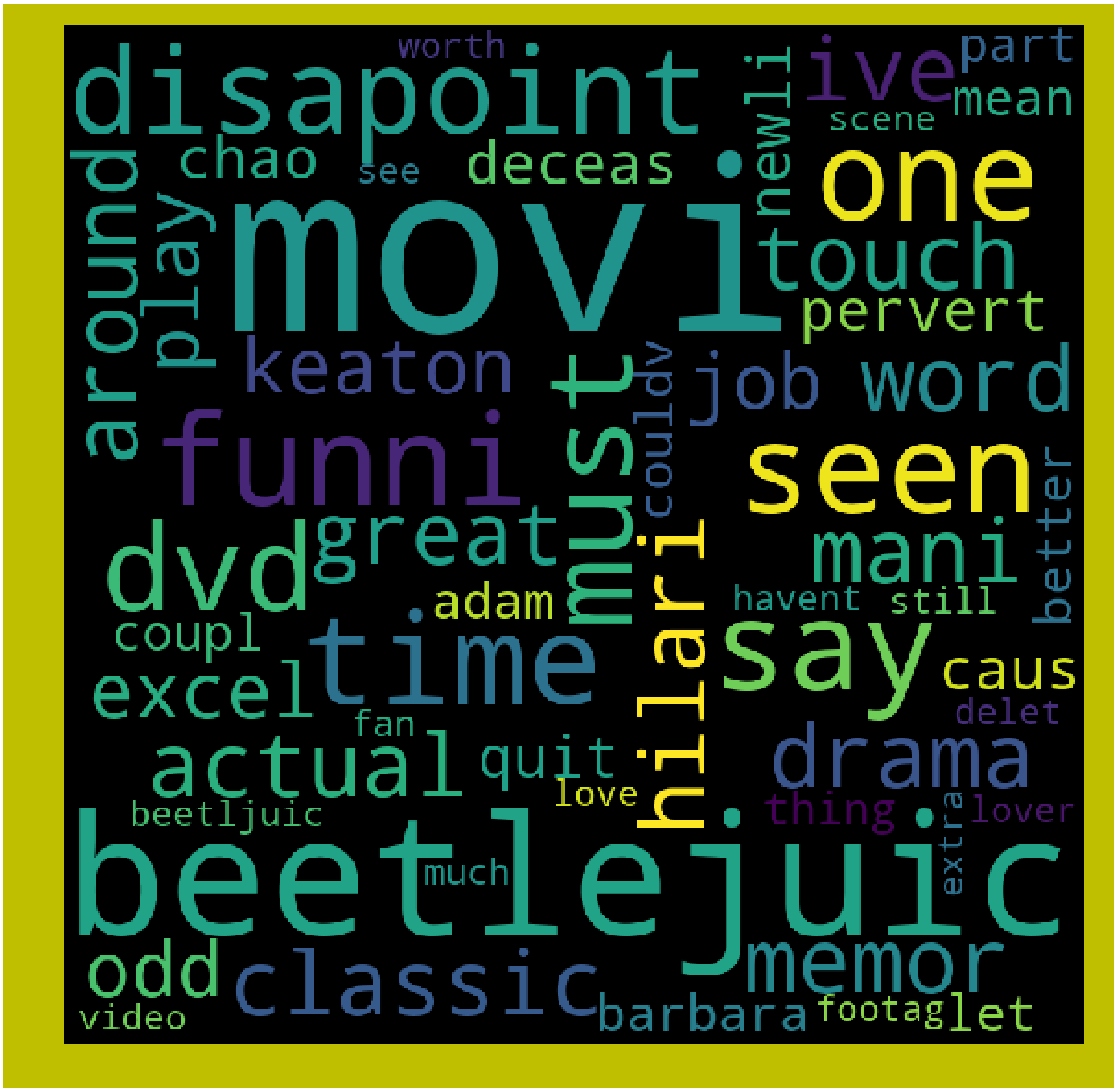



```
A review  cleaned text  assigned to cluster  7
************************************************************
```

```
b'say classic ive seen movi mani time actual word memor movi hilari funni time touch drama aroun
```

```
************************************************************
```

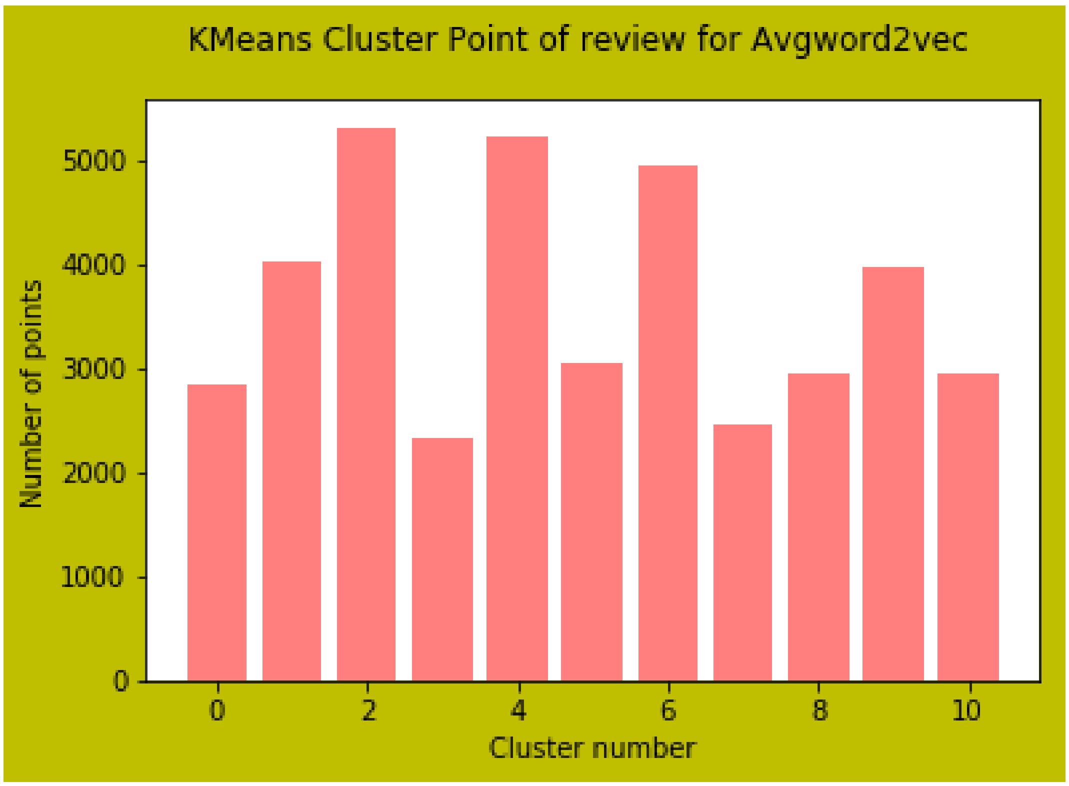
In [32]:
```
word_cloud_form(text_data)
```



- Random Cluster = 7 is about reviews which contained movie reviews which can be seen in wordcloud.

7.3 KMeans Cluster Bar Graph and Displaying Reviews text assigned to Random cluster for Avgword2vec vectorization

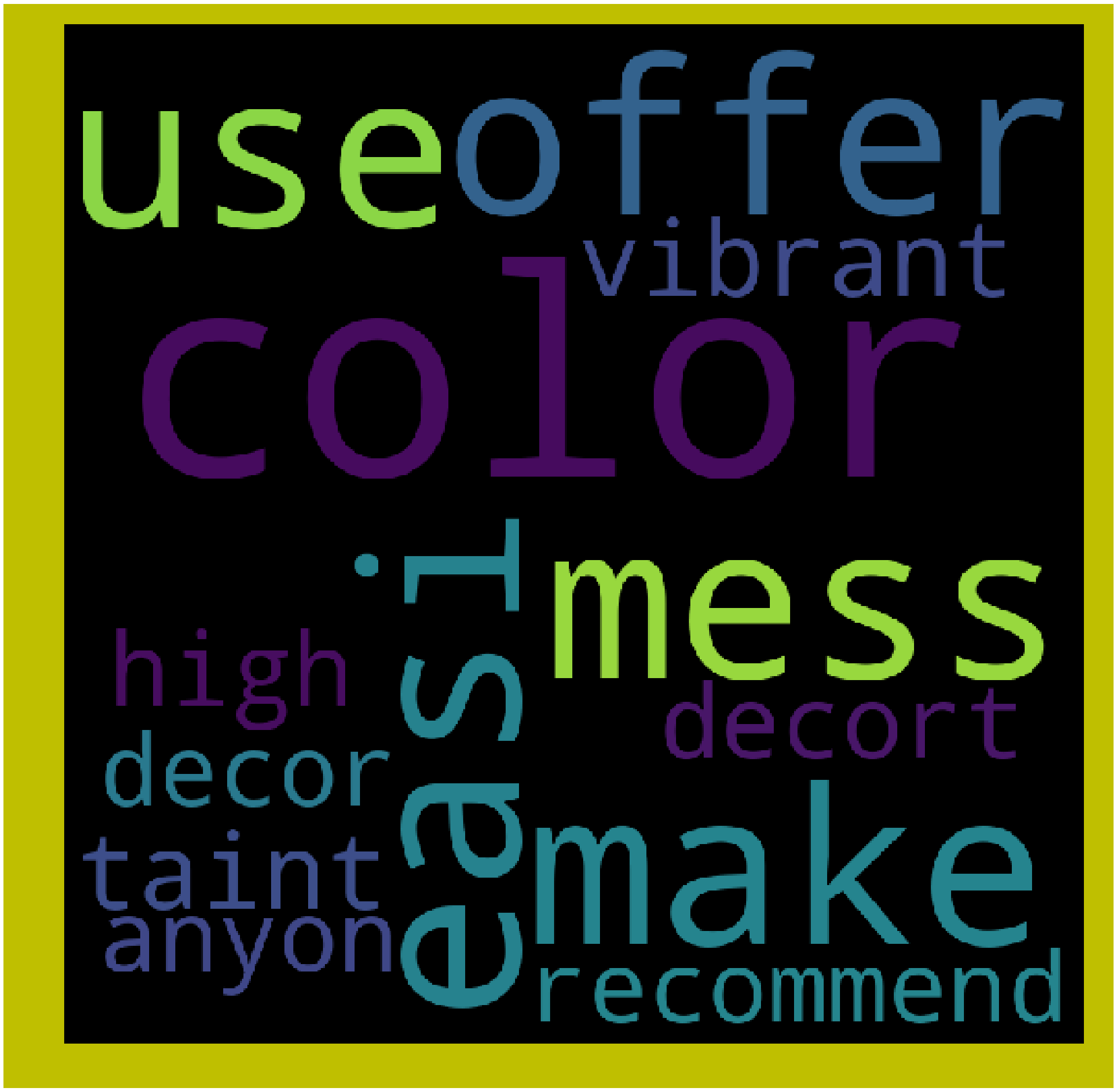
```
In [33]: fig6 = plt.figure( facecolor='y', edgecolor='k')
         fig6.suptitle('KMeans Cluster Point of review for Avgword2vec', fontsize=12)
         plt.bar([x for x in range(Optimal_cluster_vect[1])], df.groupby(['Avgword2vec'])['Clean
         plt.xlabel("Cluster number")
         plt.ylabel("Number of points")
         plt.show()

         #for i in range(Optimal_cluster):
         random_cluster=random.randint(0, Optimal_cluster_vect[1])
         print("A review  cleaned text  assigned to cluster ", random_cluster)
         print("*" * 60)
         text_data1=df.loc[df.groupby(['Avgword2vec']).groups[random_cluster][0]]['CleanedText']
         print(text_data1)
         print('\n')
         print("*" * 60)
```




```
A review  cleaned text  assigned to cluster  10
************************************************************
b'easi use make mess offer vibrant color taint decort color would high recommend anyon like deco
```

****

```
In [34]: word_cloud_form(text_data1)
```

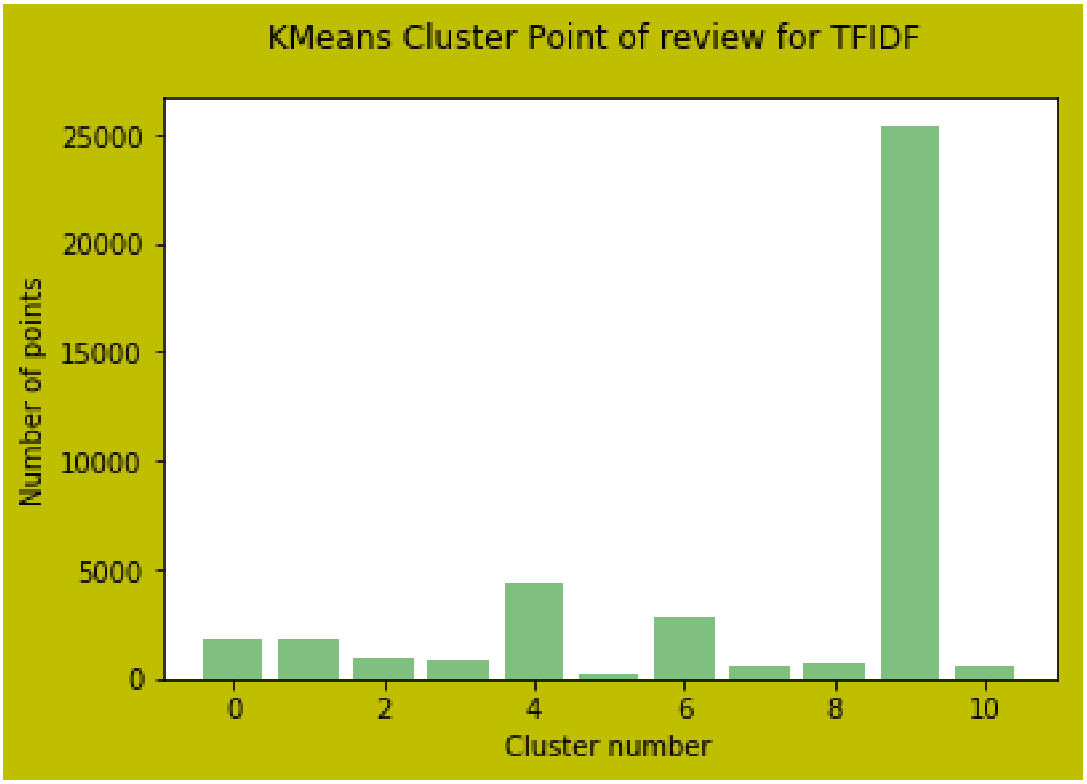


- Bar graph represents the cluster which shows counts of labelled reviews.
- Random Cluster = 10 is about reviews which contained color product (color realted reviews) reviews which can be seen in wordcloud.

7.4 KMeans Cluster Bar Graph and Displaying Reviews text assigned to Random cluster for TFIDF vectorization

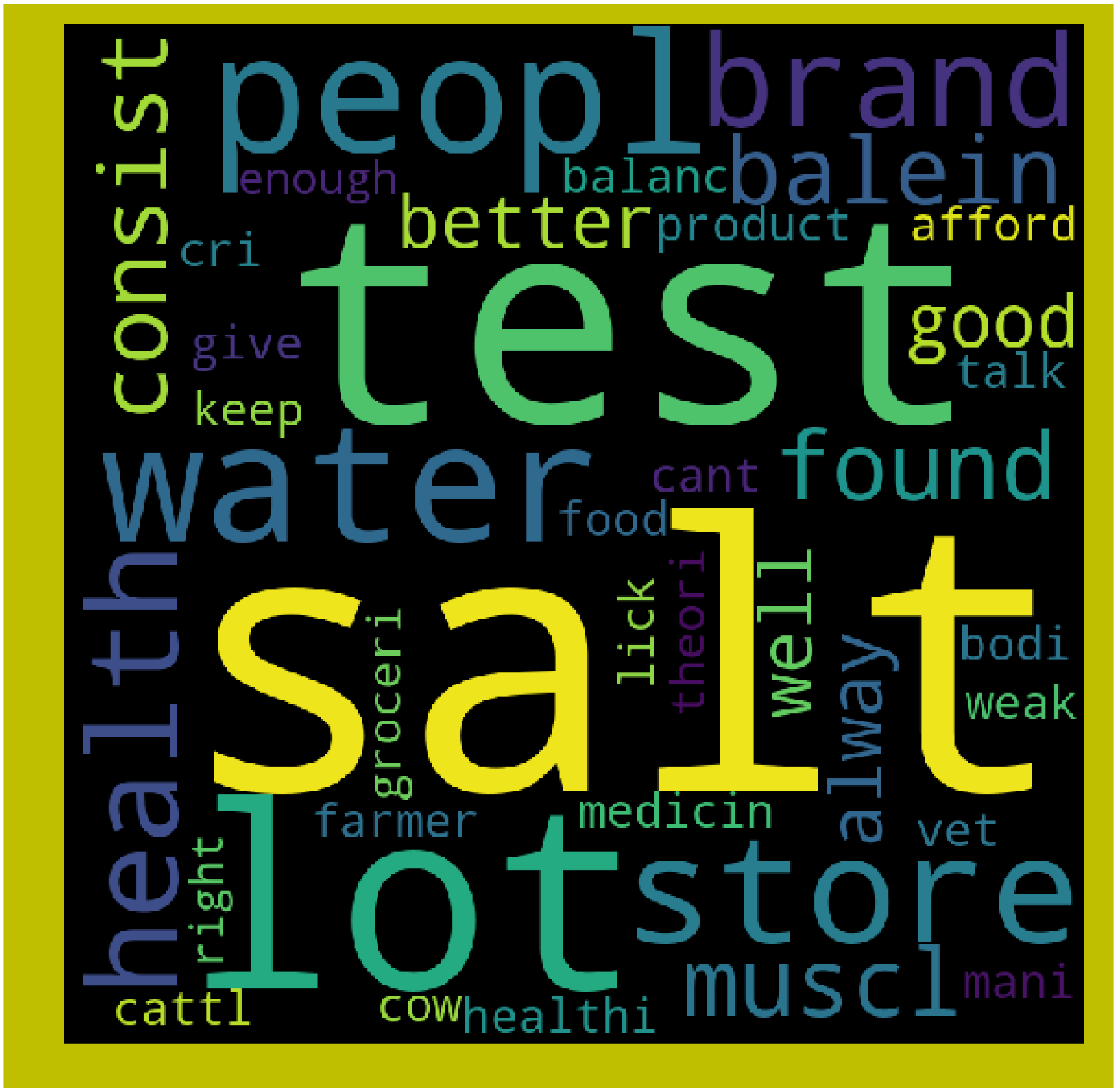
```
In [35]: fig7 = plt.figure( facecolor='y', edgecolor='k')
         fig7.suptitle('KMeans Cluster Point of review for TFIDF', fontsize=12)
```

```
plt.bar([x for x in range(Optimal_cluster_vect[2])], df.groupby(['TFIDF'])['CleanedText
plt.xlabel("Cluster number")
plt.ylabel("Number of points")
plt.show()

#for i in range(Optimal_cluster):
random_cluster=random.randint(0, Optimal_cluster_vect[2])
print("A review  cleaned text  assigned to cluster ", random_cluster)
print("*" * 60)
text_data2=df.loc[df.groupby(['TFIDF']).groups[random_cluster][0]]['CleanedText']
print(text_data2)
print('\n')
print("*" * 60)
```




```
A review  cleaned text  assigned to cluster  7
************************************************************
b'lot muscl test found balein salt consist test better peopl salt salt test well alway good prod


************************************************************
```

In [36]: word_cloud_form(text_data2)

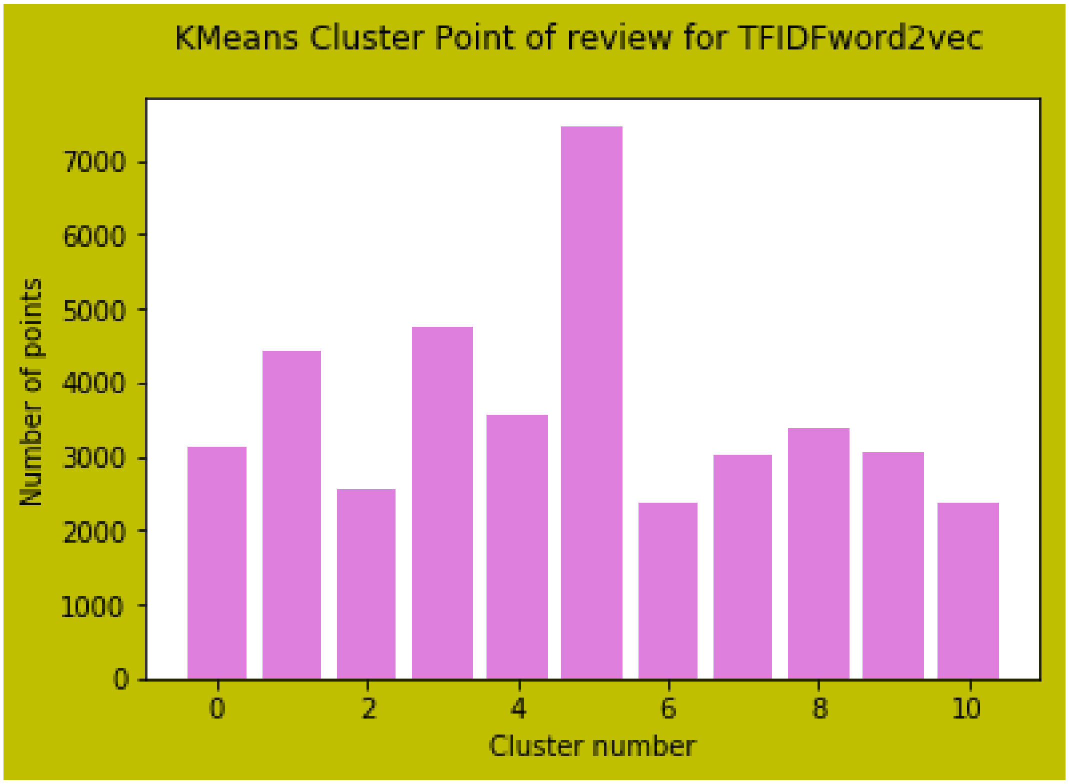


- Bar graph represents the cluster which shows counts of labelled reviews.
- Random Cluster = 7 is about reviews which contained food product (food taste realted things) reviews which can be seen in wordcloud.

7.5 KMeans Cluster Bar Graph and Displaying Reviews text assigned to each cluster for TFIDF weighted word2vec vectorization

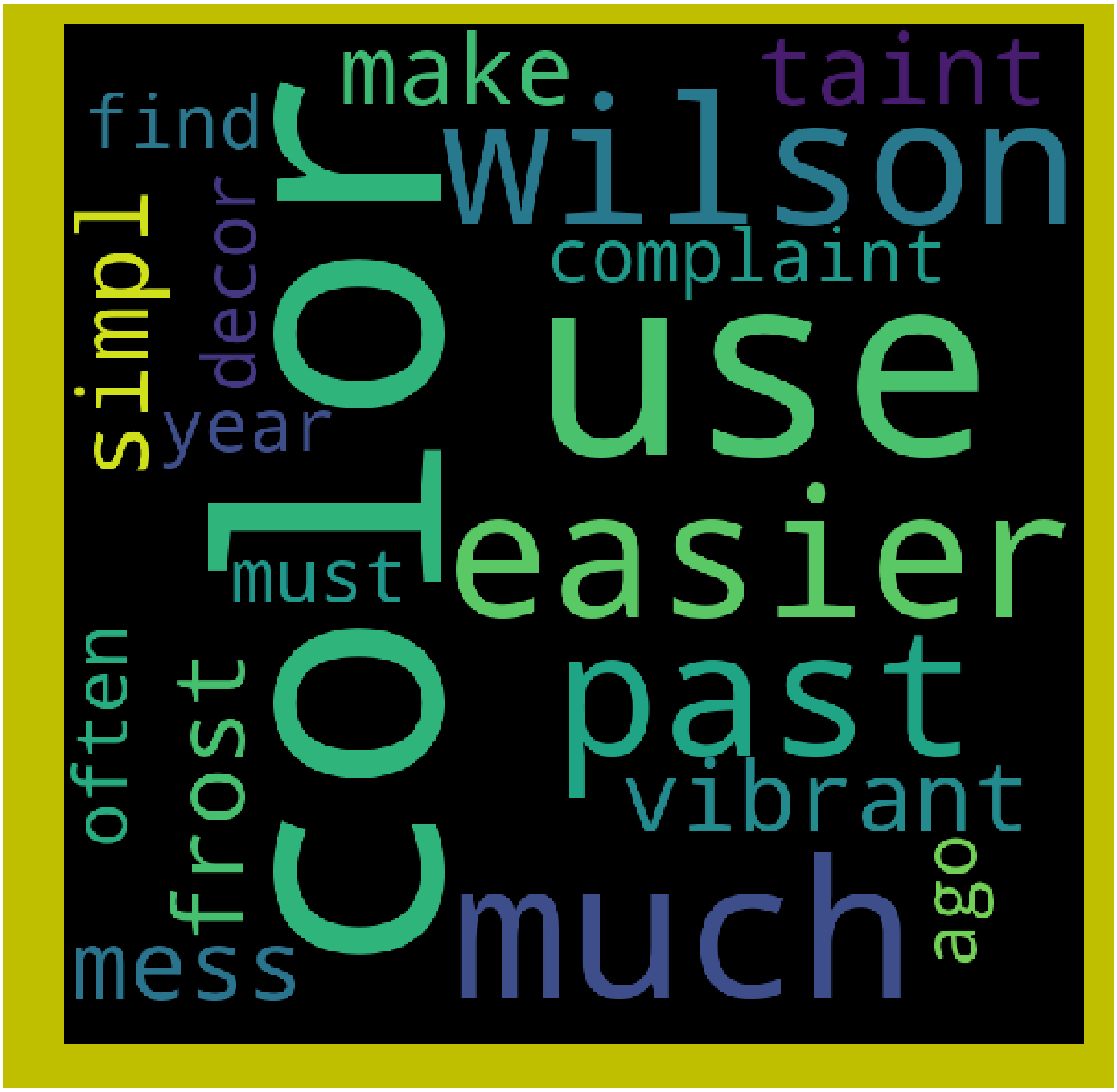
```
In [37]: fig7 = plt.figure( facecolor='y', edgecolor='k')
         fig7.suptitle('KMeans Cluster Point of review for TFIDFword2vec', fontsize=12)
         plt.bar([x for x in range(Optimal_cluster_vect[3])], df.groupby(['TFIDFword2vec'])['Cle
         plt.xlabel("Cluster number")
         plt.ylabel("Number of points")
         plt.show()
```

```
#for i in range(Optimal_cluster):
random_cluster=random.randint(0, Optimal_cluster_vect[2])
print("A review  cleaned text  assigned to cluster ", i)
print("*" * 60)
text_data3=df.loc[df.groupby(['TFIDFword2vec']).groups[i][0]]['CleanedText']
print(text_data3)
print('\n')
print("*" * 60)
```




```
A review  cleaned text  assigned to cluster  3
************************************************************
b'much easier use wilson past color color vibrant taint frost like color simpl use make mess com


************************************************************
```

In [38]: word_cloud_form(text_data3)



- Bar graph represents the cluster which shows counts of labelled reviews.
- Random Cluster = 3 is about reviews which is realted to supermarket praising .

7.5.1 Observations for kmeans++

BOW_Label	Avgword2vec	TFIDF	TFIDFword2vec
22164	2842	1790	3111
3907	4028	1767	4428
3405	5303	900	2545
3072	2329	871	4740
245	5213	4426	3544
2275	3048	200	7461

BOW_Label	Avgword2vec	TFIDF	TFIDFword2vec
596	4942	2740	2355
3216	2446	597	3036
708	2934	677	3368
1	3968	25391	3053
411	2947	641	2359

- Reviews which are preprocessed(cleaned Text) is clustered .And reviews in each set with given cluster number is viewd as above for each vectorization .
- Avg word2vec & tfIDF weighted word2vec are distributed review's word with equal probably manners.Each cluster contains equally distributed words for given cluster number.
- In case of BOW & TFIDF,Words distribution is unequal .For some clusters, words allocation is high while for other extremely low.
- Reviews are clustered with kmeans++ algorithm.

8 KMedoids

```
In [39]: # This KMedoids file is obtained from -> https://github.com/letiantian/kmedoids
```

KMedoids file provided in above link is useful for python 2.7 users. For python3.6 users, some modification is need to be done. KMedoids file is rewritten with little modification.

```
In [29]: vectorization_output=[final_data,final_w2v_count,final_tfidf_np,tfidf_sent_vectors]
```

8.0.1 Computing pairwise distances.

Computing pairwise distances for each Vectorization_output and saving the results in 'D_results' .

```
In [30]: # Vectorization_output

         D_results=[]
         vect_result=[]
         for i in range(len(vectorization_output)):
             #5k reviews
             vectorization_output[i]=vectorization_output[i][:5000]
             vect_result.append(vectorization_output[i])
             D = pairwise_distances(vectorization_output[i], metric='euclidean')
             D_results.append(D)
```

For finding optimal value of number of clusters.

```
In [31]: # For finding optimal value of number of clusters.
         def compute_loss(M, C, data): # Squared Loss
             loss = 0.0
             for key, arr in C.items():
                 for pos in arr:
                     loss = loss + ((data[M[key]] - data[pos]).sum()) ** 2

             return loss
```

8.1 kmedoids algorithm

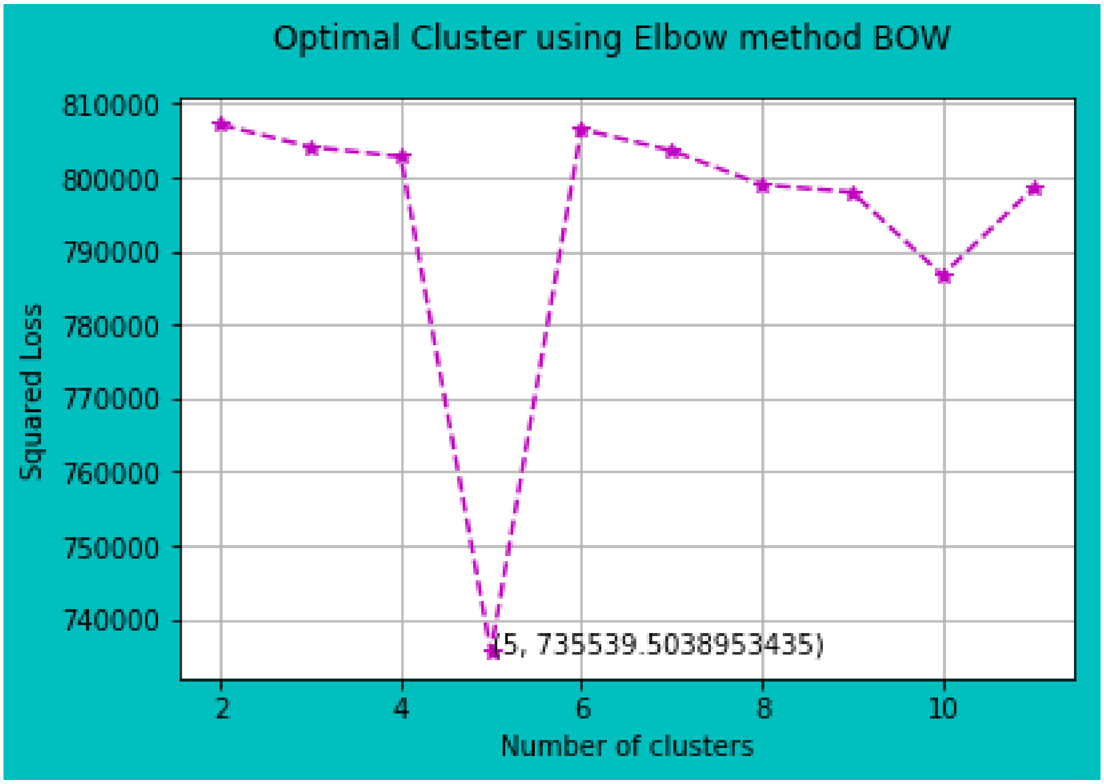
```
In [32]: # Optimal_cluster_kmedoids is function to calucalte
         # optimal k value using kmedoids algorithm
         def Optimal_cluster_kmedoids(vectorization_output,D_value,vect_name):


             optimal_score = []

             for i in tqdm(range(len(cluster_range))):

                 cluster=cluster_range[i]
                 M, C = kMedoids(D_value, cluster) # Training Clustering.
                 loss=compute_loss(M, C, vectorization_output)
                 optimal_score.append(loss) # Appending the squared loss obtained in the list

             global Optimal_cluster
             Optimal_cluster = np.argmin(optimal_score) + 2 # As argmin return the index of mini
             print ("The optimal number of clusters == ", Optimal_cluster)
             print ("The loss for optimal cluster is ==  ", min(optimal_score))

             fig4 = plt.figure( facecolor='c', edgecolor='k')
             fig4.suptitle('Optimal Cluster using Elbow method '+str(vect_name), fontsize=12)
             plt.plot(cluster_range, optimal_score,'m*',linestyle='dashed')
             plt.xlabel("Number of clusters")
             plt.ylabel("Squared Loss")
             xy = (Optimal_cluster, min(optimal_score))
             plt.annotate('(%s, %s)' % xy, xy = xy, textcoords='data')
             plt.grid()
             plt.show()
```

vect_result: all vector witk 5k reviews for each vectorization Techniques

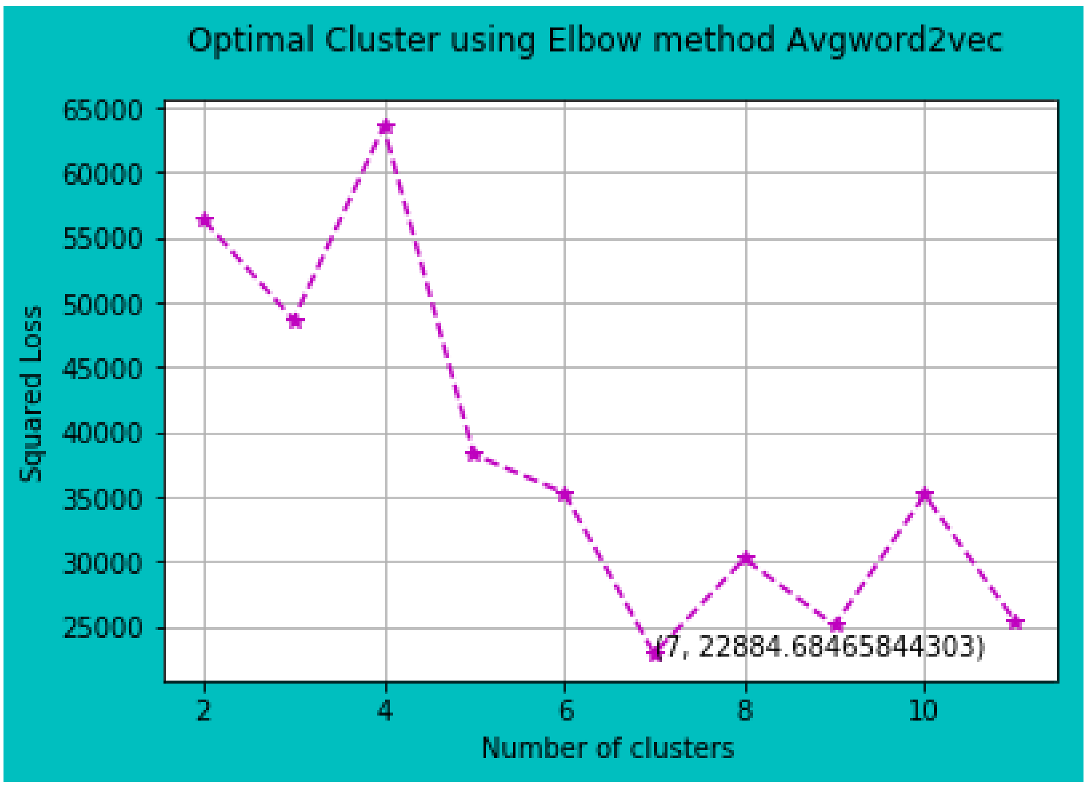
D_results : Computed pariwise distances for each vectorization Techniques

```
In [35]: vect_name=['BOW','Avgword2vec','TFIDF','TFIDFweightedword2vec']

         Optimal_cluster_vect=[]

         for y in range(len(vect_name)):
                     print("*" * 60)
                     print(vect_name[y])
                     print("*" * 60)
                     Optimal_cluster_kmedoids(vect_result[y],D_results[y],vect_name[y])
                     Optimal_cluster_vect.append(Optimal_cluster)
```

```
  0%|          | 0/10 [00:00<?, ?it/s]

************************************************************
BOW
************************************************************


100%|??????????| 10/10 [01:17<00:00,  7.79s/it]


The optimal number of clusters ==  5
The loss for optimal cluster is ==   735539.5038953435
```

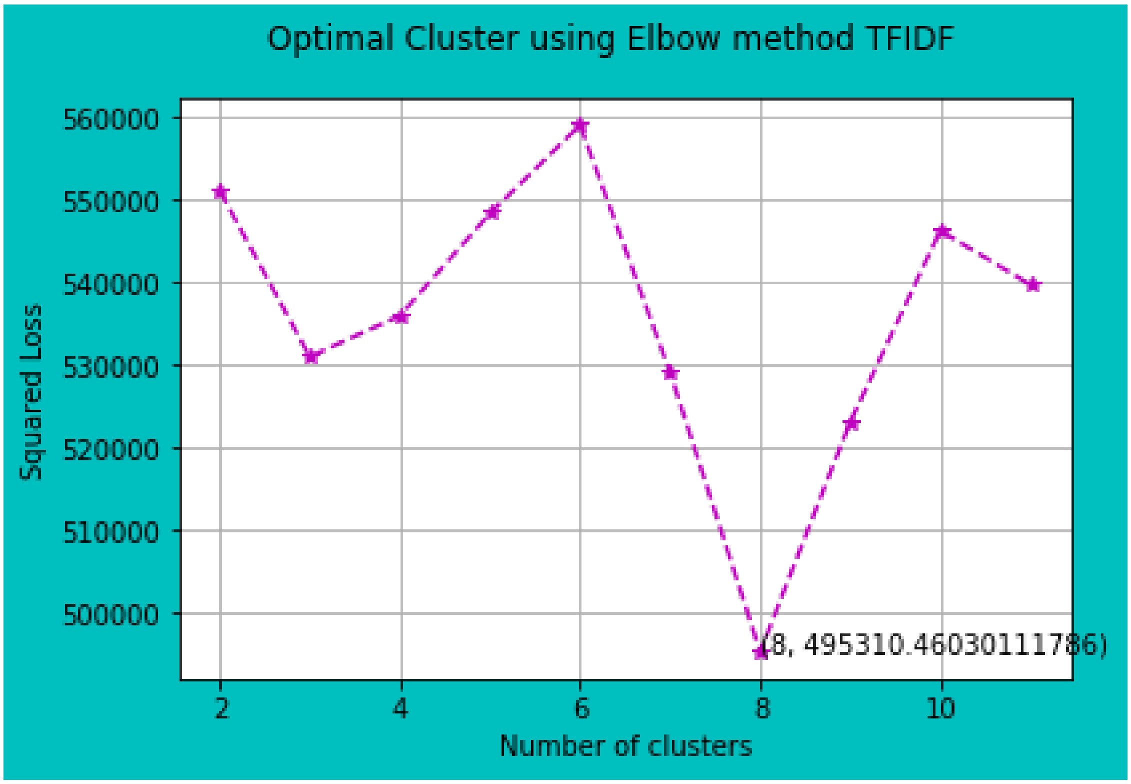


```
  0%|          | 0/10 [00:00<?, ?it/s]

************************************************************
Avgword2vec
************************************************************


100%|??????????| 10/10 [00:59<00:00,  5.96s/it]


The optimal number of clusters ==  7
The loss for optimal cluster is ==   22884.68465844303
```

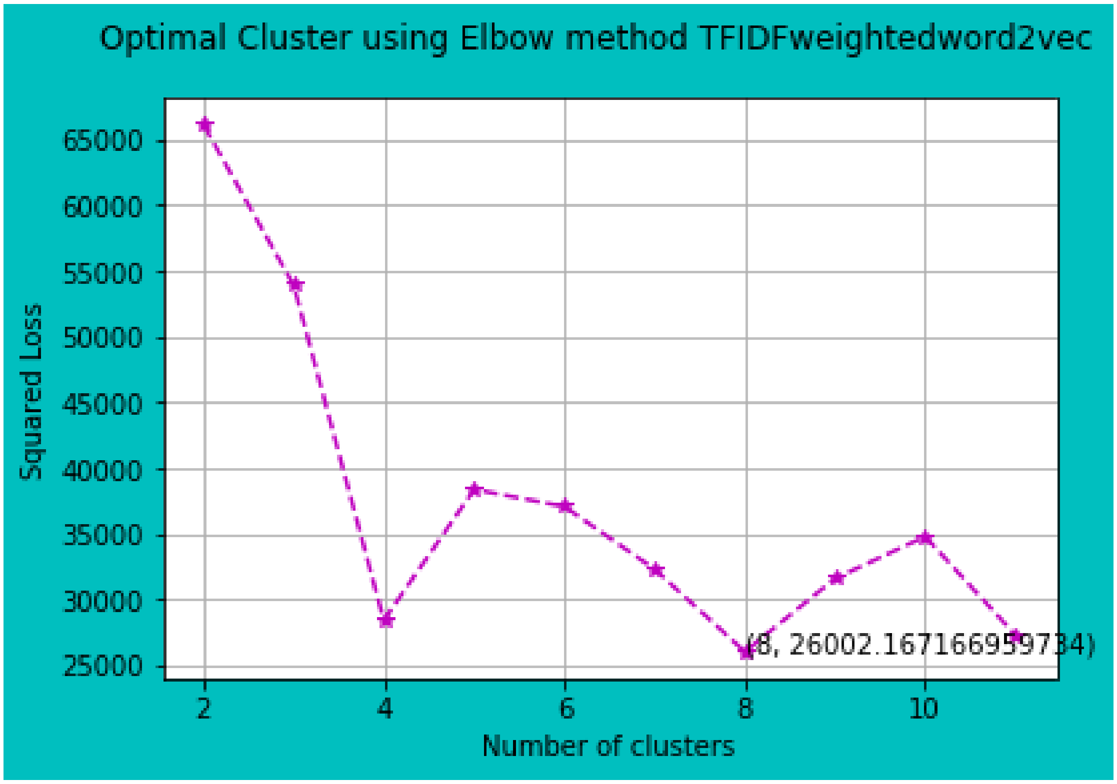



```
  0%|          | 0/10 [00:00<?, ?it/s]

************************************************************
TFIDF
************************************************************
```

```
100%|??????????| 10/10 [01:03<00:00,  6.33s/it]


The optimal number of clusters ==  8
The loss for optimal cluster is ==   495310.46030111786
```




```
  0%|          | 0/10 [00:00<?, ?it/s]

************************************************************
TFIDFweightedword2vec
************************************************************


100%|??????????| 10/10 [00:57<00:00,  5.78s/it]


The optimal number of clusters ==  8
The loss for optimal cluster is ==   26002.167166959734
```




```
In [36]: print(Optimal_cluster)
```

```
8
```

```
In [37]: # Using optimal_cluster to best kmedoid.

         M, C = kMedoids(D, k =  Optimal_cluster)

In [38]: # Training the best model

         M_result=[]
         C_result=[]
         for i in tqdm(range(len(Optimal_cluster_vect))):
                 M, C = kMedoids(D_results[i], k = Optimal_cluster_vect[i]) # Using optimal_clus

                 M_result.append(M)
                 C_result.append(C)
```

```
100%|??????????| 4/4 [00:25<00:00,  6.28s/it]
```

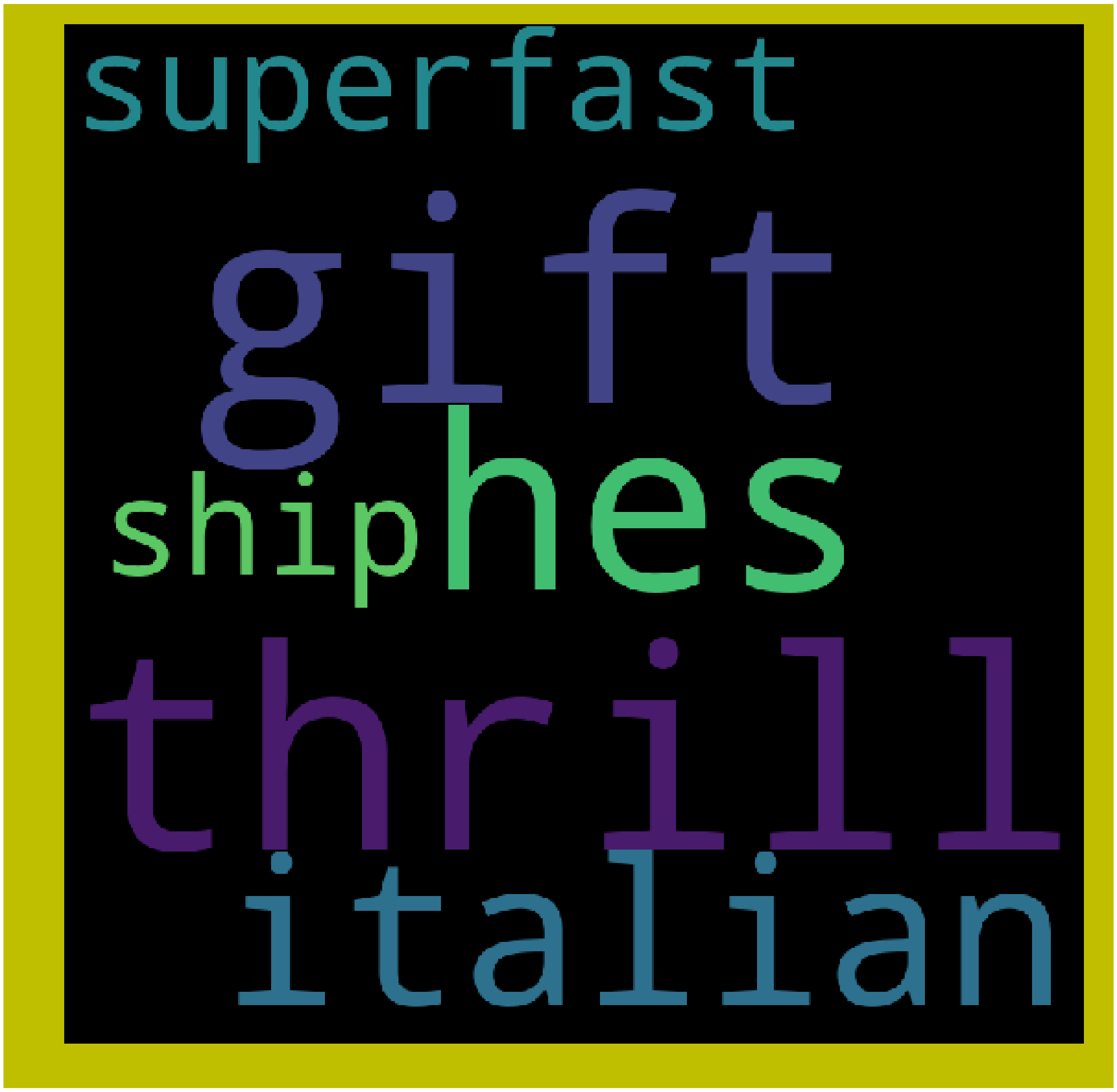
"wordcloud_km" function for printing & displaying wordcloud

```
In [39]: def  wordcloud_km(vect_no):

             random_cluster_k=random.randint(0, (Optimal_cluster-1))
             #print(random_cluster_k)
             counts=M_result[vect_no][random_cluster_k]
             print ("Cluster ",random_cluster_k)
             print (" ")
             text_data4=X_Text.iloc[counts]['CleanedText']
             print (text_data4)
             word_cloud_form(text_data4)
             print ("\nA Review belonging to this cluster. -> \n")
             C1=C_result[vect_no][random_cluster_k]
             #C1_count=[i for i in range(len(C1)) if C1[i]==counts][0]
             text_data41=X_Text.iloc[C1[0]]['CleanedText']

             print ( text_data41)
             word_cloud_form(text_data41)
             print ("\n")
             print ("*" * 90)
```

8.1.1 Kmedoids algorithm using BOW

```
In [49]: wordcloud_km(0)
```

```
Cluster  2

b'thrill gift hes italian superfast ship'
```



A Review belonging to this cluster. ->

b'discov oil year ago bought one flavor thunderstruck qualiti use place veget oliv oil whenev di

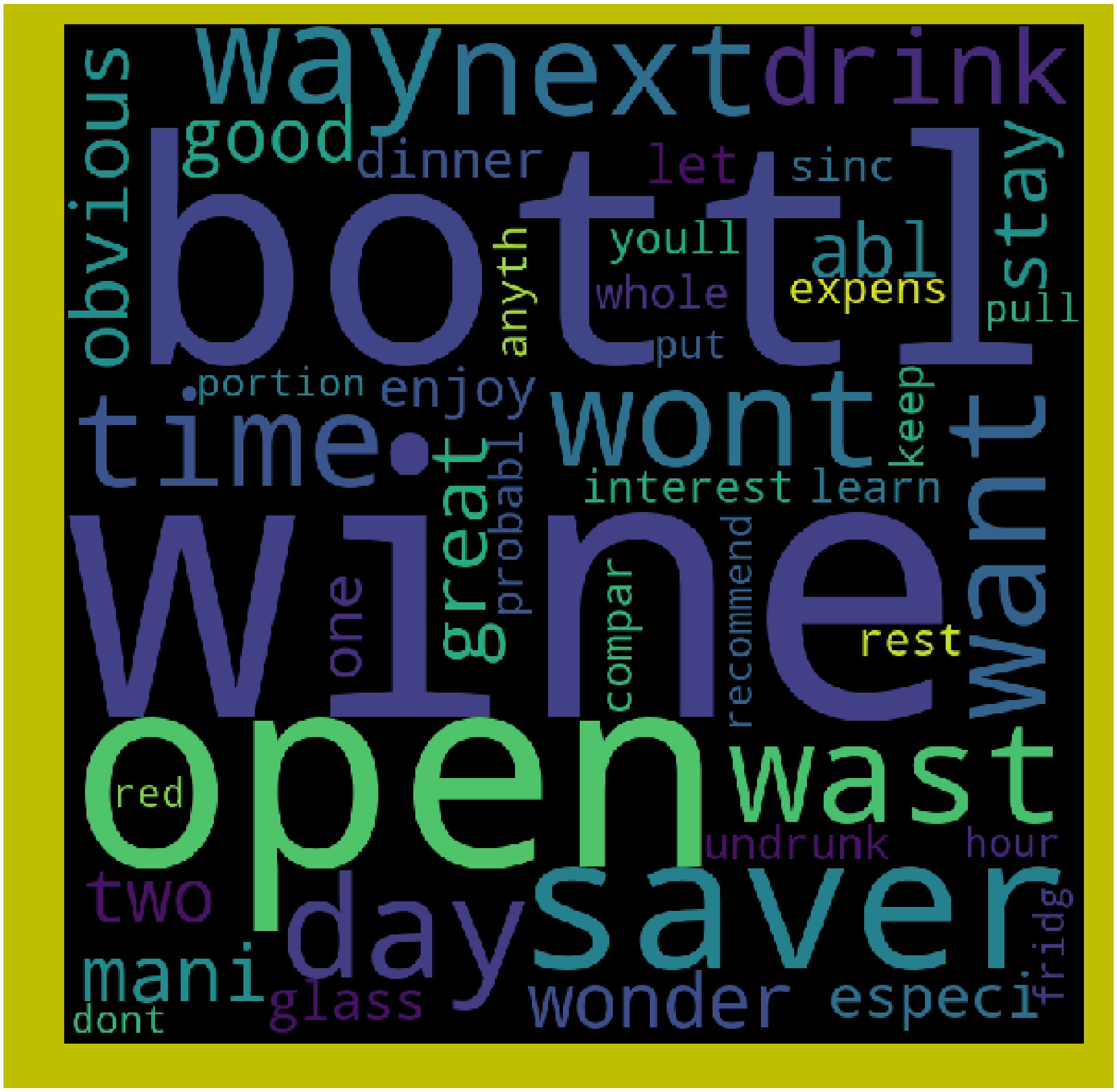
****

8.1.2 Kmedoids algorithm using Avgword2vec

```
In [50]: wordcloud_km(1)
```

```
Cluster  0

b'stuff perfect camp trip your lazi cut tofu green onion mix proper miso past son love nice salt
```


```
A Review belonging to this cluster. ->

b'wine saver great mani way obvious wonder abl open bottl wine stay good day two especi like one
```



****

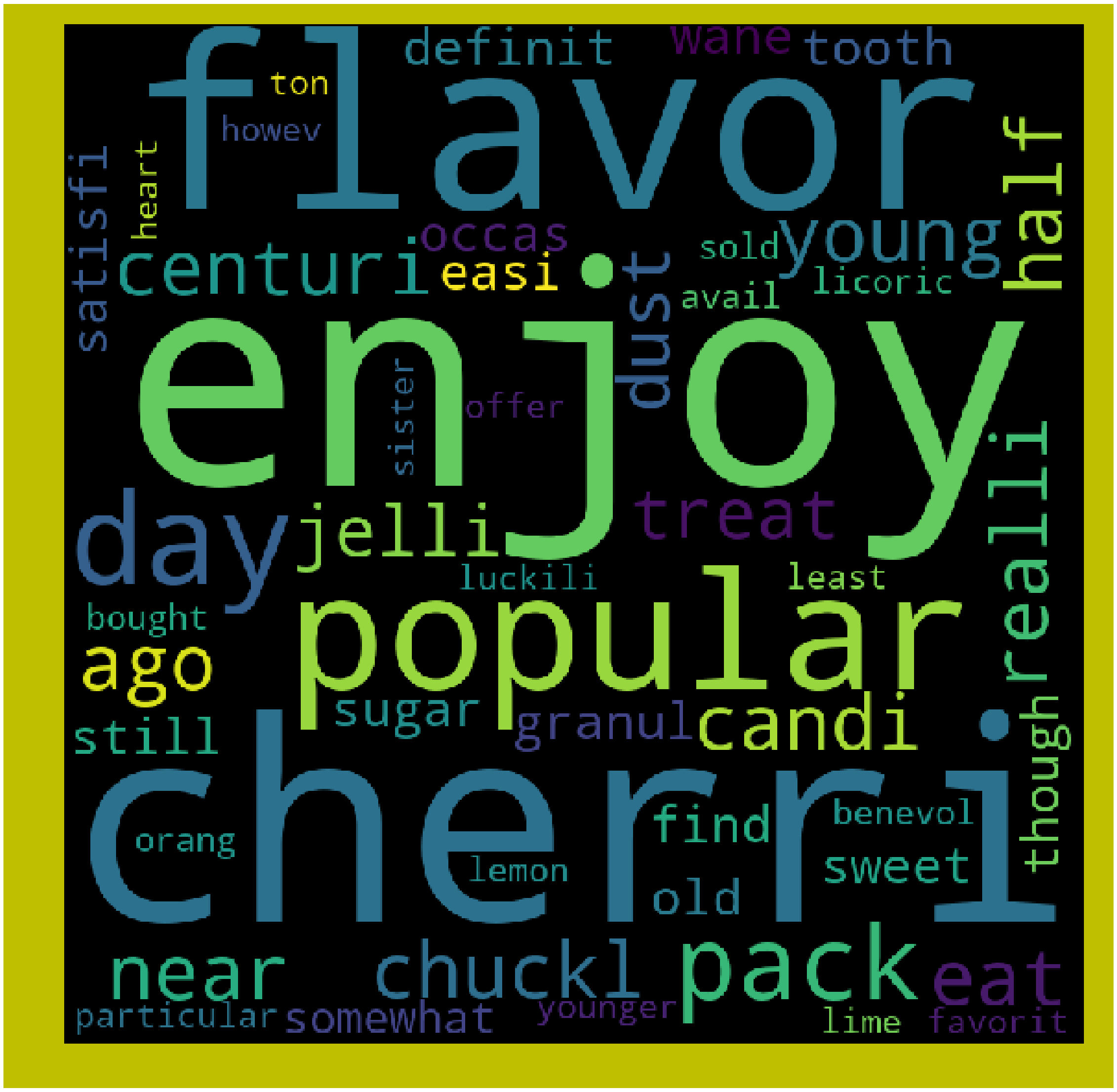
8.1.3 Kmedoids algorithm using TFIDF

```
In [51]: wordcloud_km(2)
```

```
Cluster  2

b'tea good flavor power enjoy without sweeten'
```

A Review belonging to this cluster. ->

b'young near half centuri ago chuckl popular candi realli enjoy eat jelli treat dust granul suga

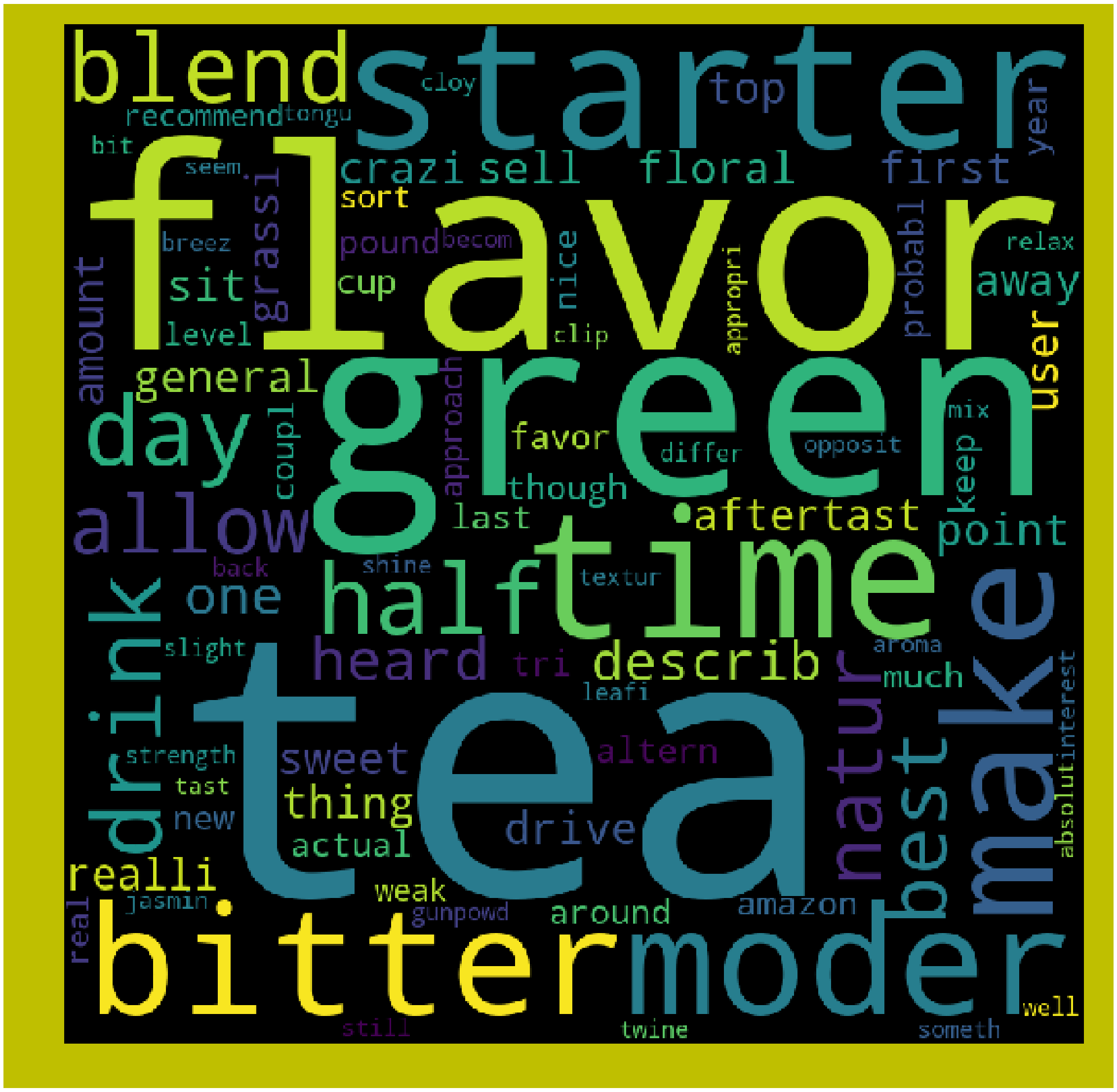


****

8.1.4 Kmedoids algorithm using TFIDF weighted word2vec

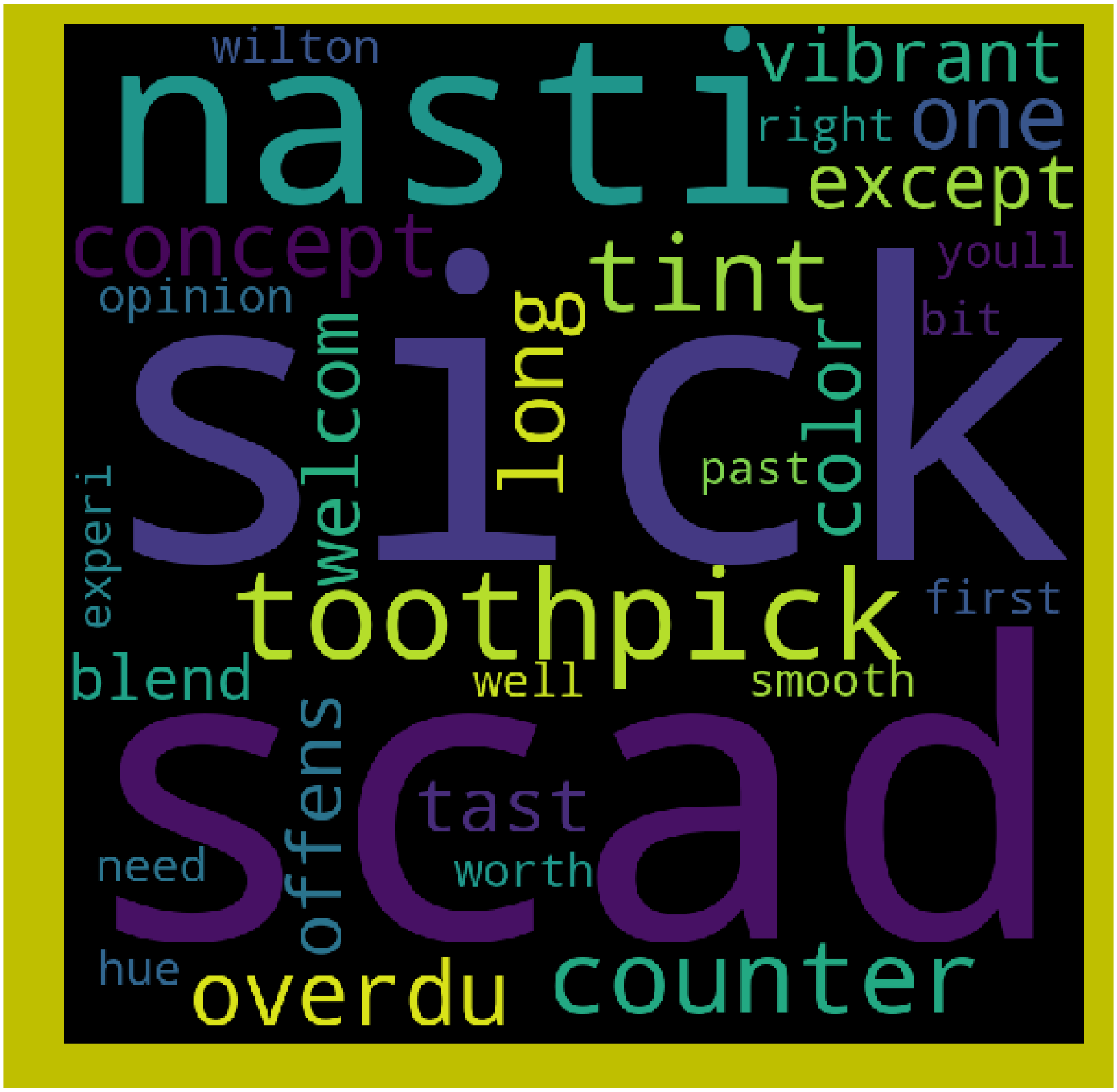
```
In [52]: wordcloud_km(3)
```

```
Cluster  1

b'heard describ starter green tea one general sell point sweet floral flavor sit top away thing
```



A Review belonging to this cluster. ->

b'sick scad nasti toothpick counter tint concept one long overdu except welcom color vibrant off



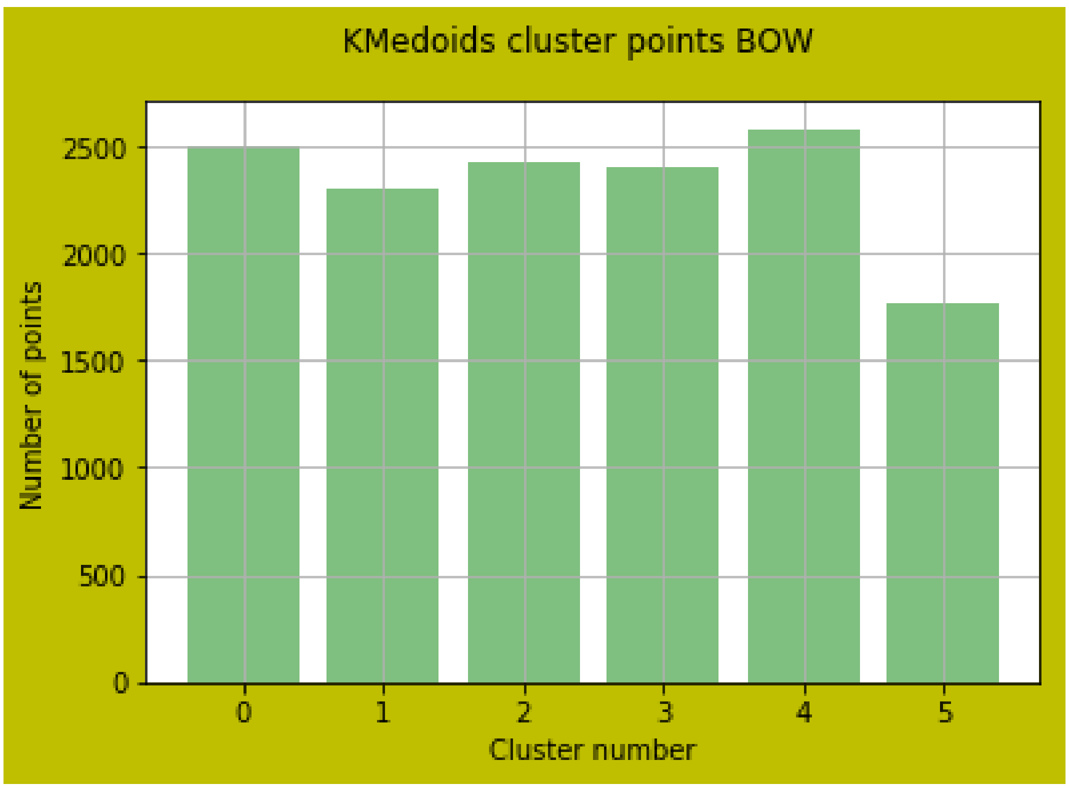
****

8.1.5 Plots for Number of points in each cluster with all vectorization method

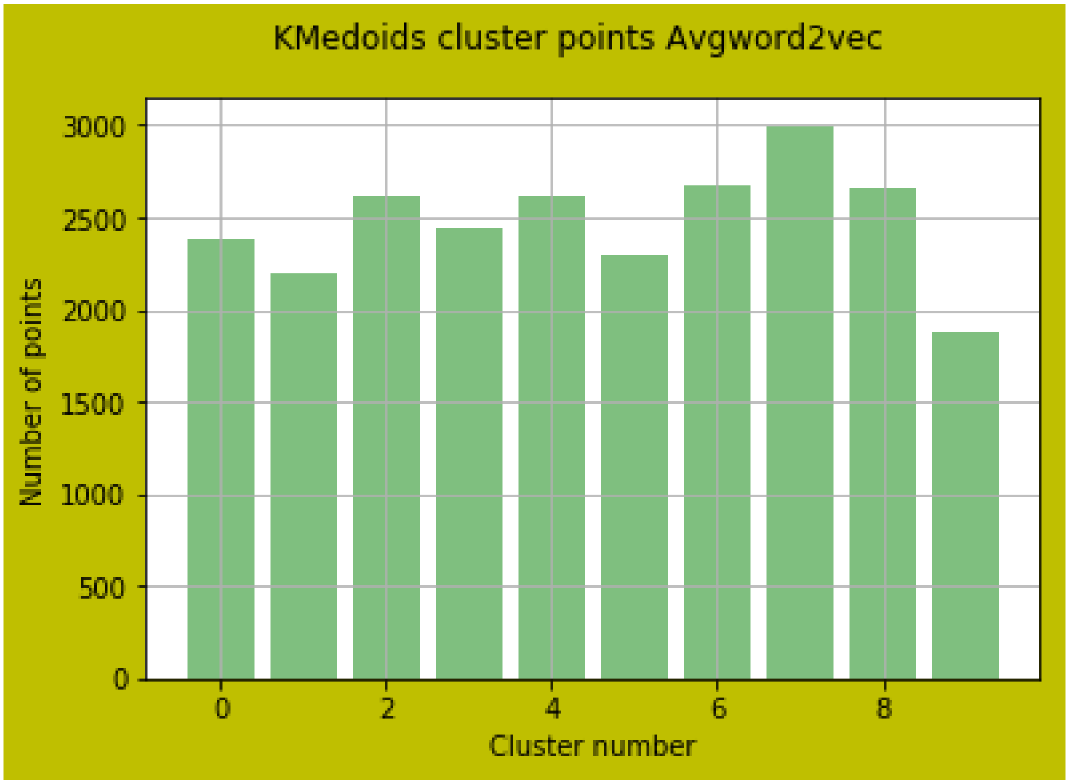
```
In [53]: # Plotting Number of points in each cluster .
         for i in range(len(Optimal_cluster_vect)):
             counts = []
             cc=C_result[i]
             #print(cc.items())
             for key, arr in cc.items():
                 counts.append(round(arr.mean()))
```

```
print("counts for  "+str(vect_name[i])+"==",counts)
fig4 = plt.figure( facecolor='y', edgecolor='k')
fig4.suptitle('KMedoids cluster points '+str(vect_name[i]), fontsize=12)
plt.bar([x for x in range(Optimal_cluster_vect[i])], counts,color='g', alpha = 0.5)
plt.xlabel("Cluster number")
plt.ylabel("Number of points")
plt.grid()
plt.show()
```

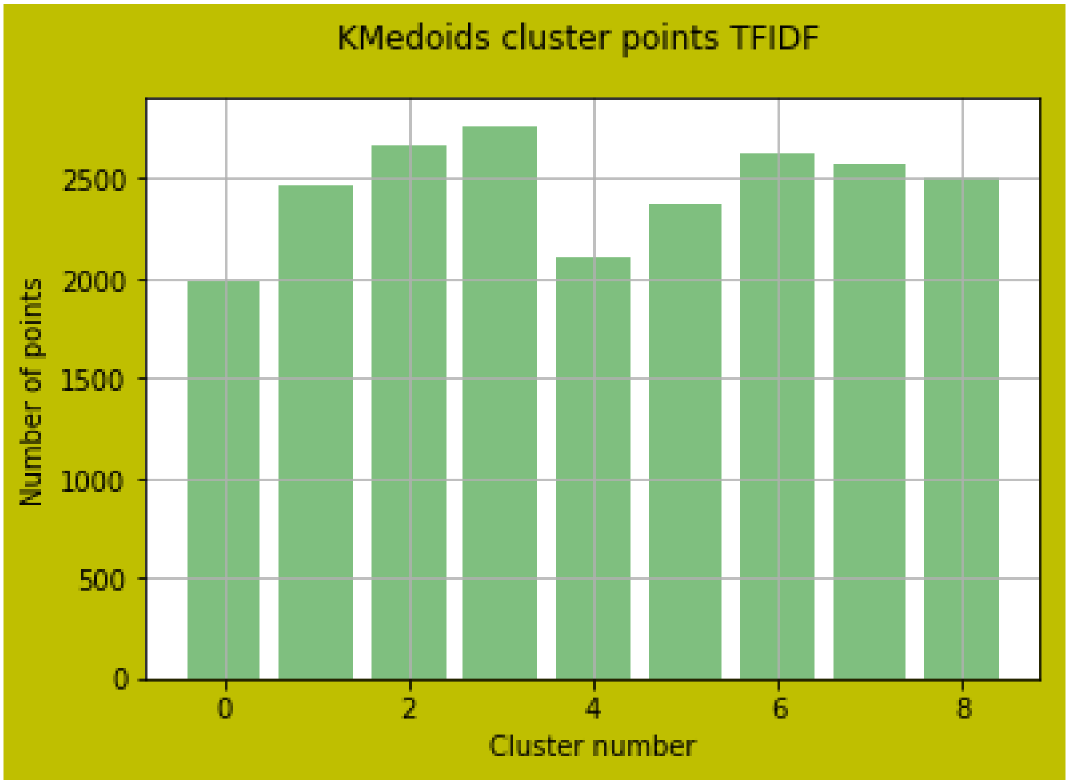
```
counts for  BOW== [2505.0, 2297.0, 2424.0, 2405.0, 2577.0, 1766.0]
```



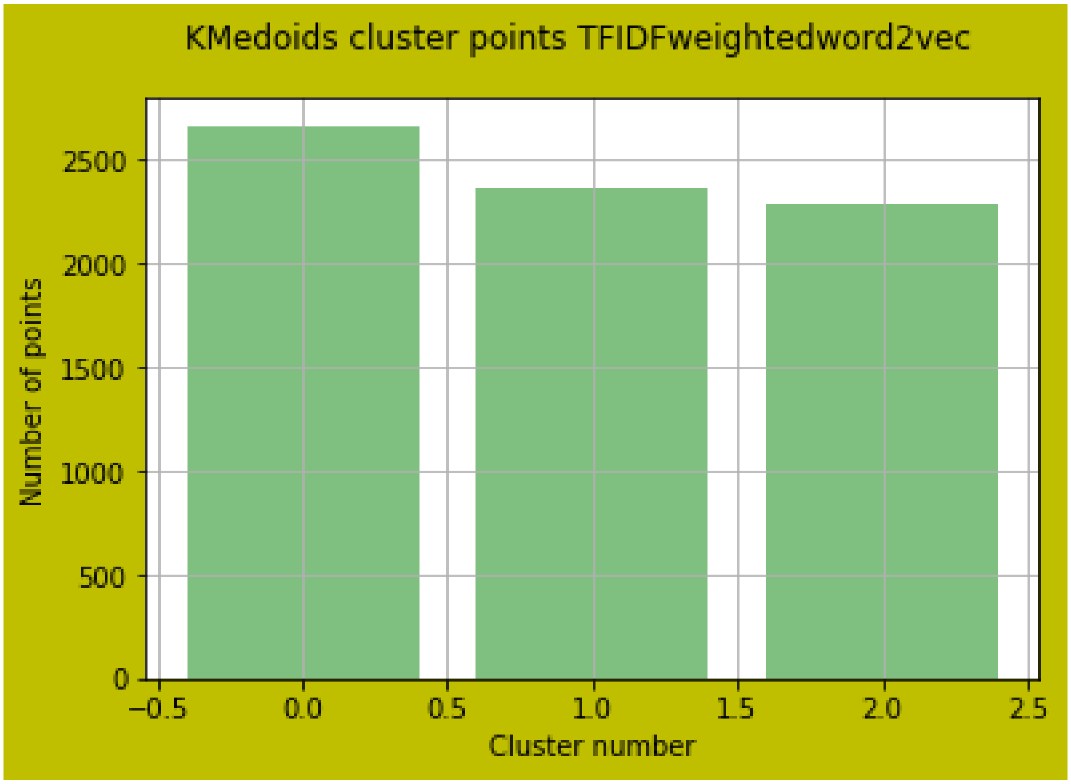

```
counts for  Avgword2vec== [2384.0, 2196.0, 2620.0, 2439.0, 2620.0, 2292.0, 2676.0, 2995.0, 2657.
```




```
counts for  TFIDF== [1986.0, 2472.0, 2672.0, 2764.0, 2101.0, 2372.0, 2630.0, 2569.0, 2508.0]
```




```
counts for  TFIDFweightedword2vec== [2664.0, 2362.0, 2283.0]
```



8.1.6 Observations for kmedoids

- Optimal k values and it's graph is visualized .Optimal k values differed with each vectorization techniques
- Elbow graph looks different .
- A review from sets belonging to particular cluster is displayed along with it's whole sets for particular cluster.
- Number of points with respect to cluster number is almost equally distributed with all techniques as comapred to kmeans++ algorithm as seen in bar graph.

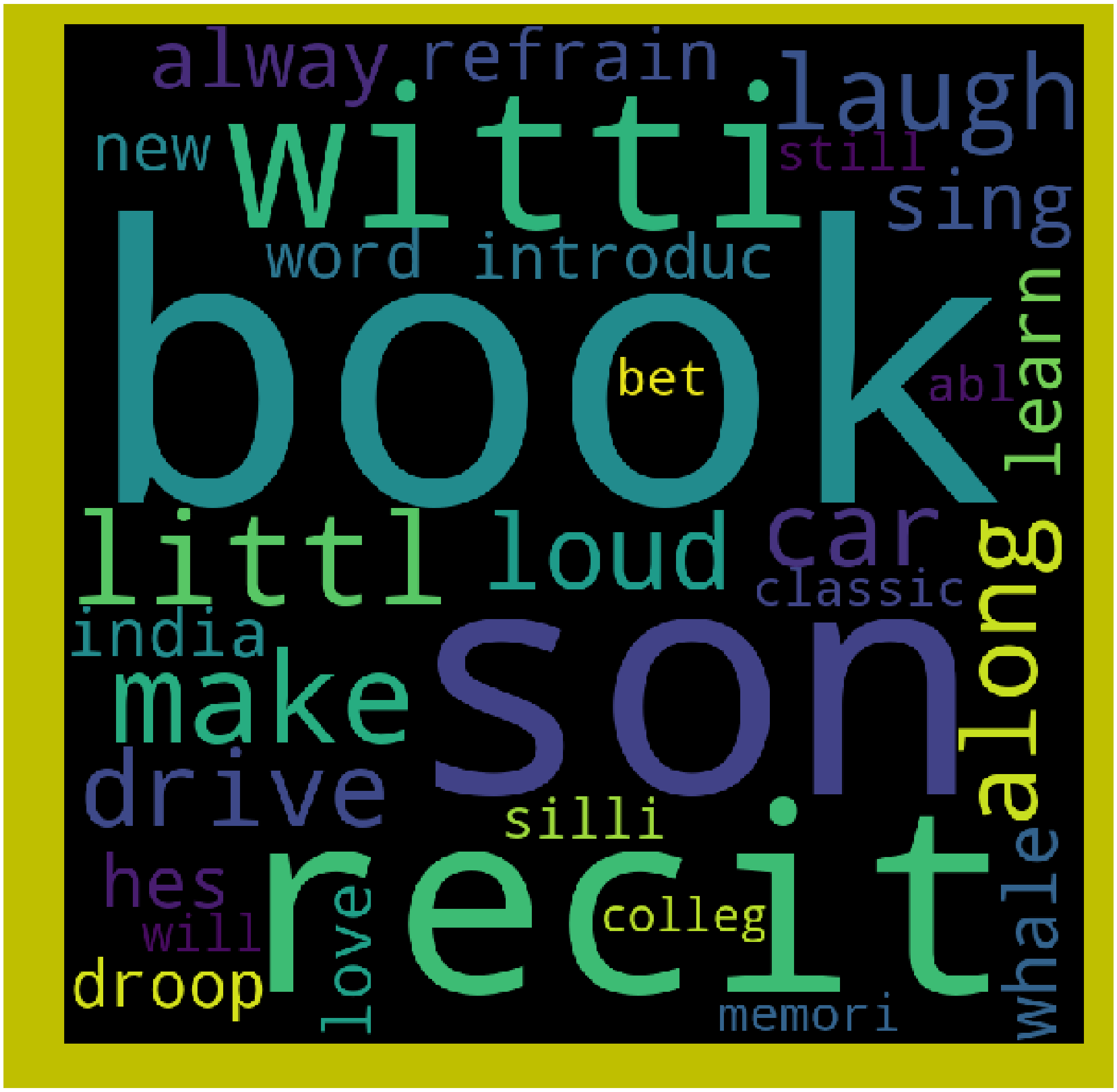
9 2.Hierarchical Clustering

```
In [40]: # Checking agglomerative Clustering groupings ->
         cluster_name=['cluster_BOW','cluster_Avgword2vec','cluster_tfidf','cluster_tfidfword2ve
         #cluster_optimal=
         def agglomerative_Cluster(vectorization_output,cluster_name):

             df = X_Text
             random_cluster=random.randint(0, (len(cluster_range)-3))
             #random_cluster=2
```

```
#for cluster in tqdm(range(len(cluster_range))):

agg = AgglomerativeClustering(n_clusters=cluster_range[random_cluster])
agg.fit(vectorization_output)

print("*" * 40, "  For Number of Clusters = ",random_cluster, "   ", "*" * 40)
print("\nReviews for each of the clusters : \n")
df = X_Text[:5000]
df[cluster_name] = agg.labels_

df = df.groupby([cluster_name])


# Printing two reviews from each cluster, if they contain at-least points.
for i in range(random_cluster):
    print("For cluster ", i, "\n")

    print("Review 1 -> \n")
    review_1=X_Text.loc[df.groups[i][0]]['CleanedText']
    print(review_1)
    word_cloud_form(review_1)



    if(len(df.groups[i]) > 1):

        print("\n")
        print("Review 2 ->   ,\n")
        review_2=X_Text.loc[df.groups[i][1]]['CleanedText']
        print(review_2)
        word_cloud_form(review_2)
    print("-" * 80)

print("_" * 80)
print("\n")
```

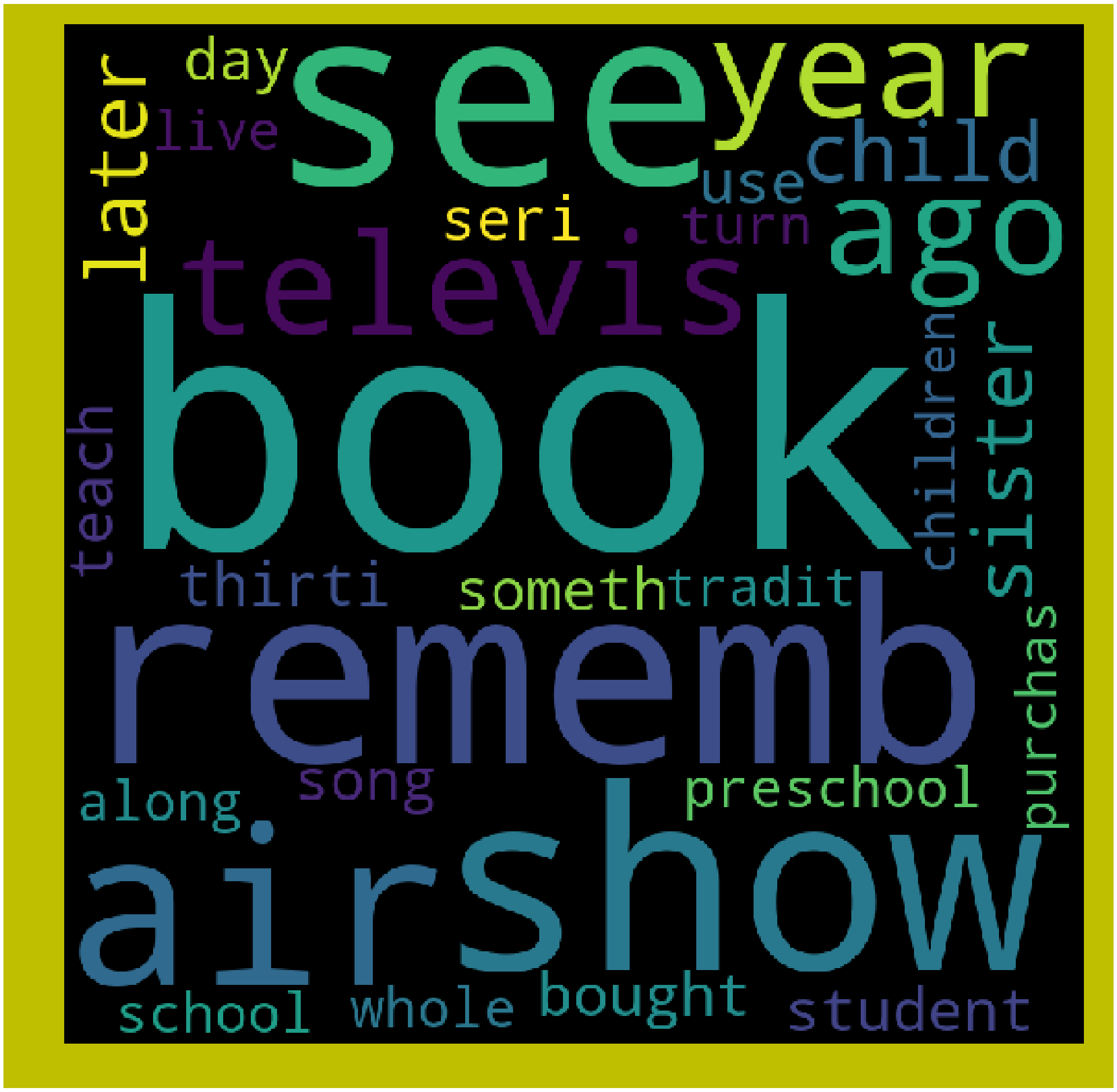
In [41]:
```
agglomerative_Cluster(vectorization_output[0],cluster_name[0])
```

```
****************************************   For Number of Clusters =  7    **********************

Reviews for each of the clusters :

For cluster  0

Review 1 ->

b'witti littl book make son laugh loud recit car drive along alway sing refrain hes learn whale
```



Review 2 -> ,

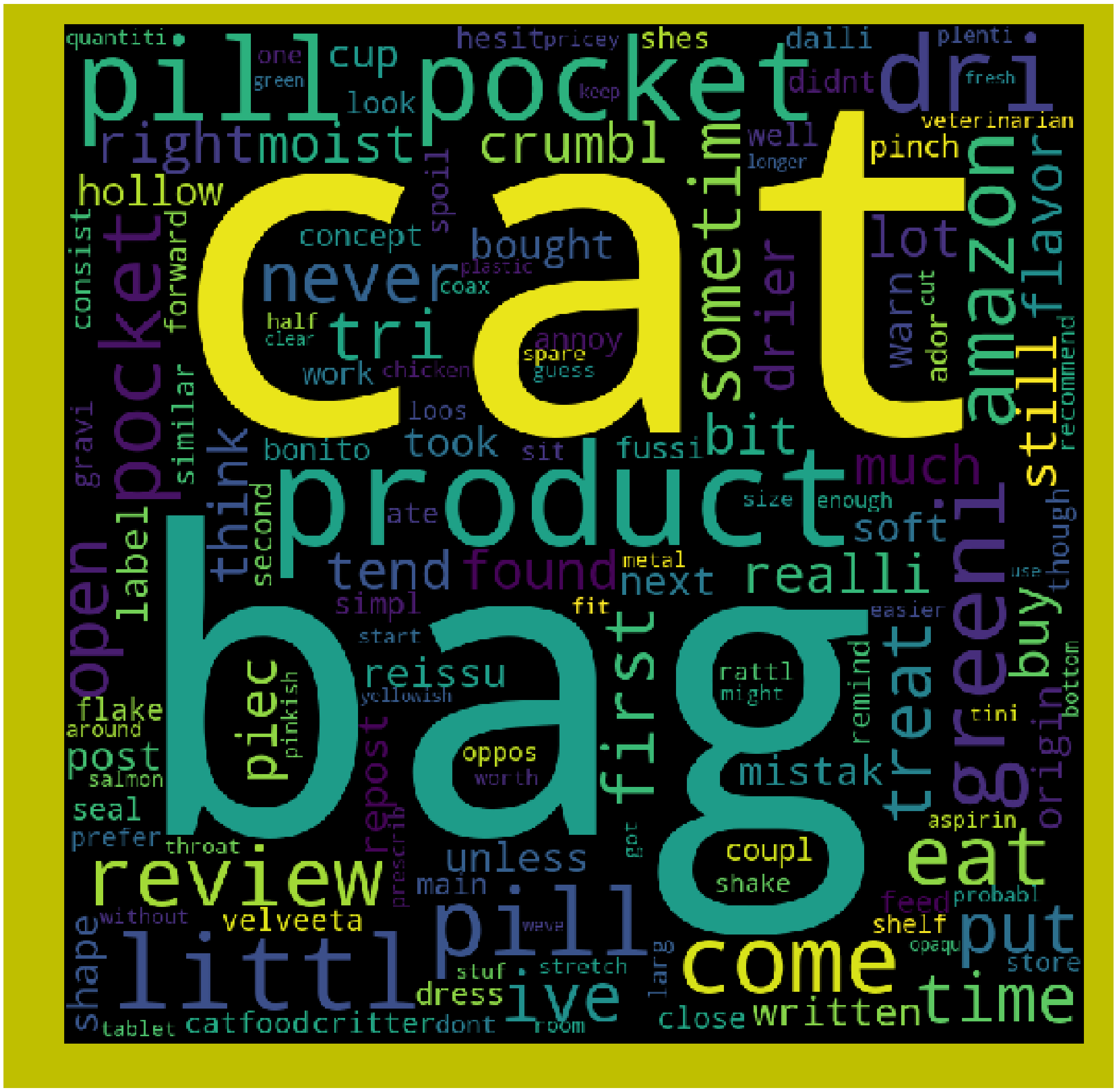
b'rememb see show air televis year ago child sister later bought day thirti someth use seri book



For cluster 1

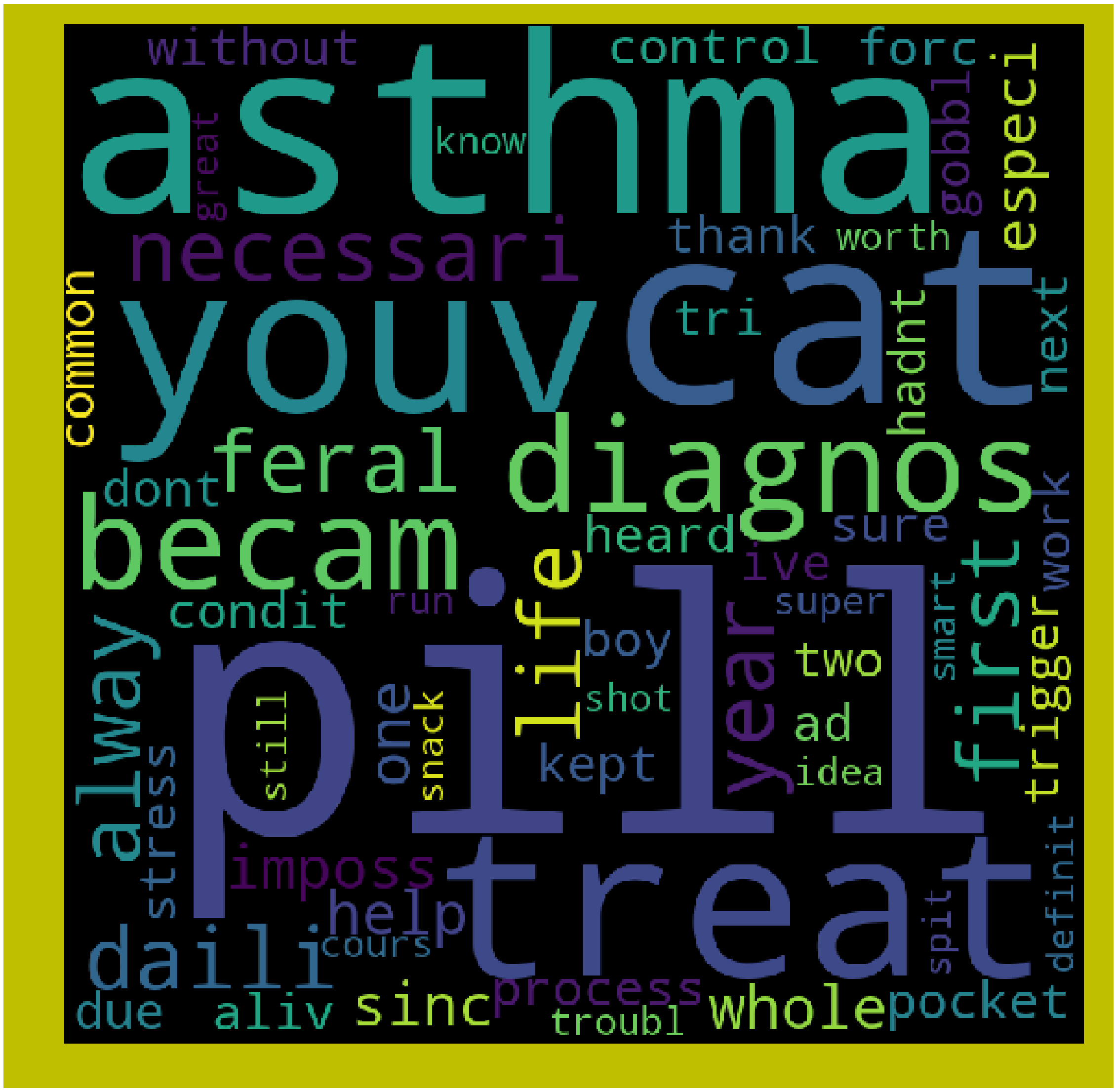
Review 1 ->

b'review written pill pocket cat amazon amazon sometim post review next greeni pill pocket unles



Review 2 -> ,

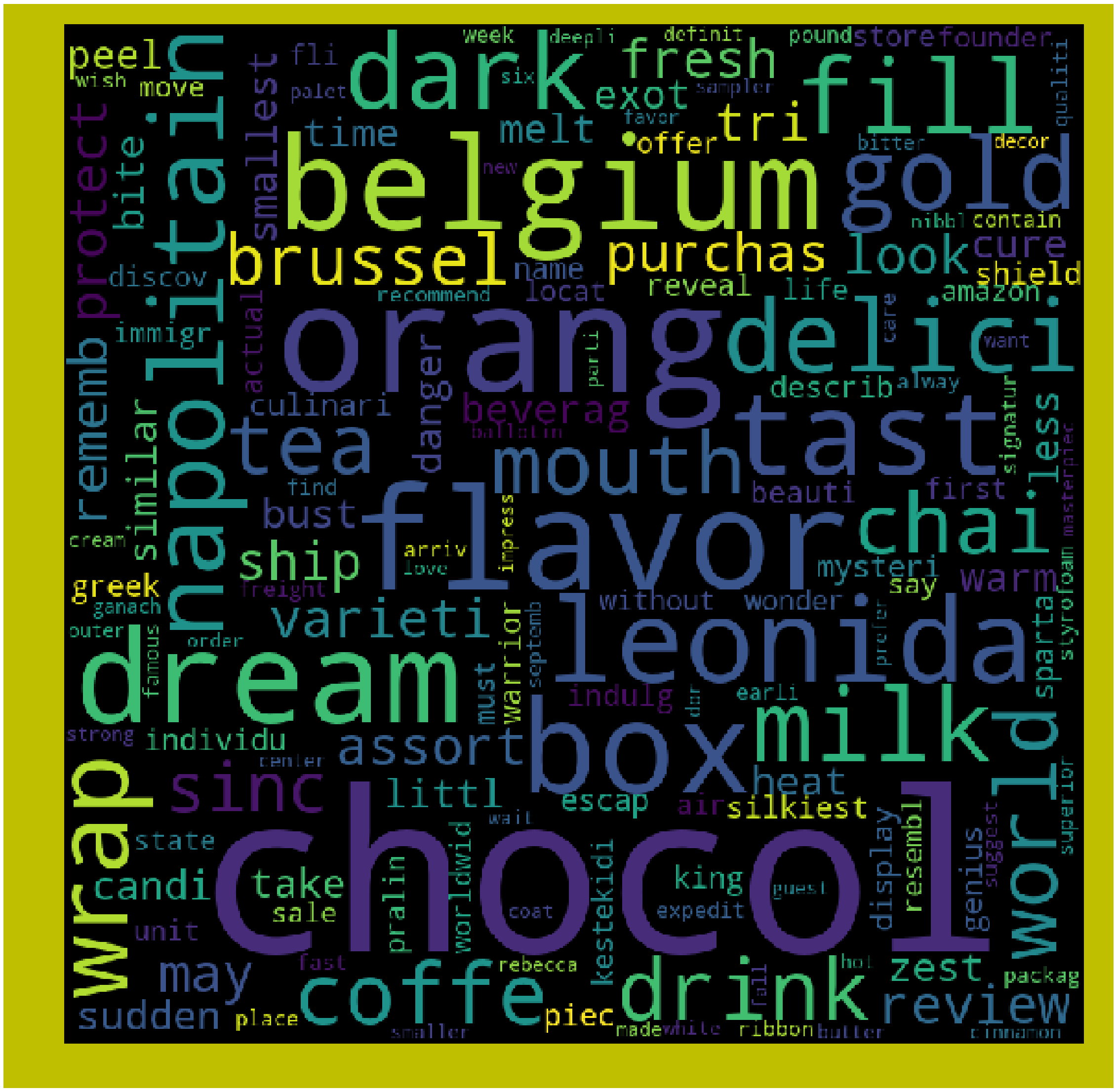
b'cat diagnos asthma becam necessari pill daili feral first year life pill alway imposs especi s



For cluster 2

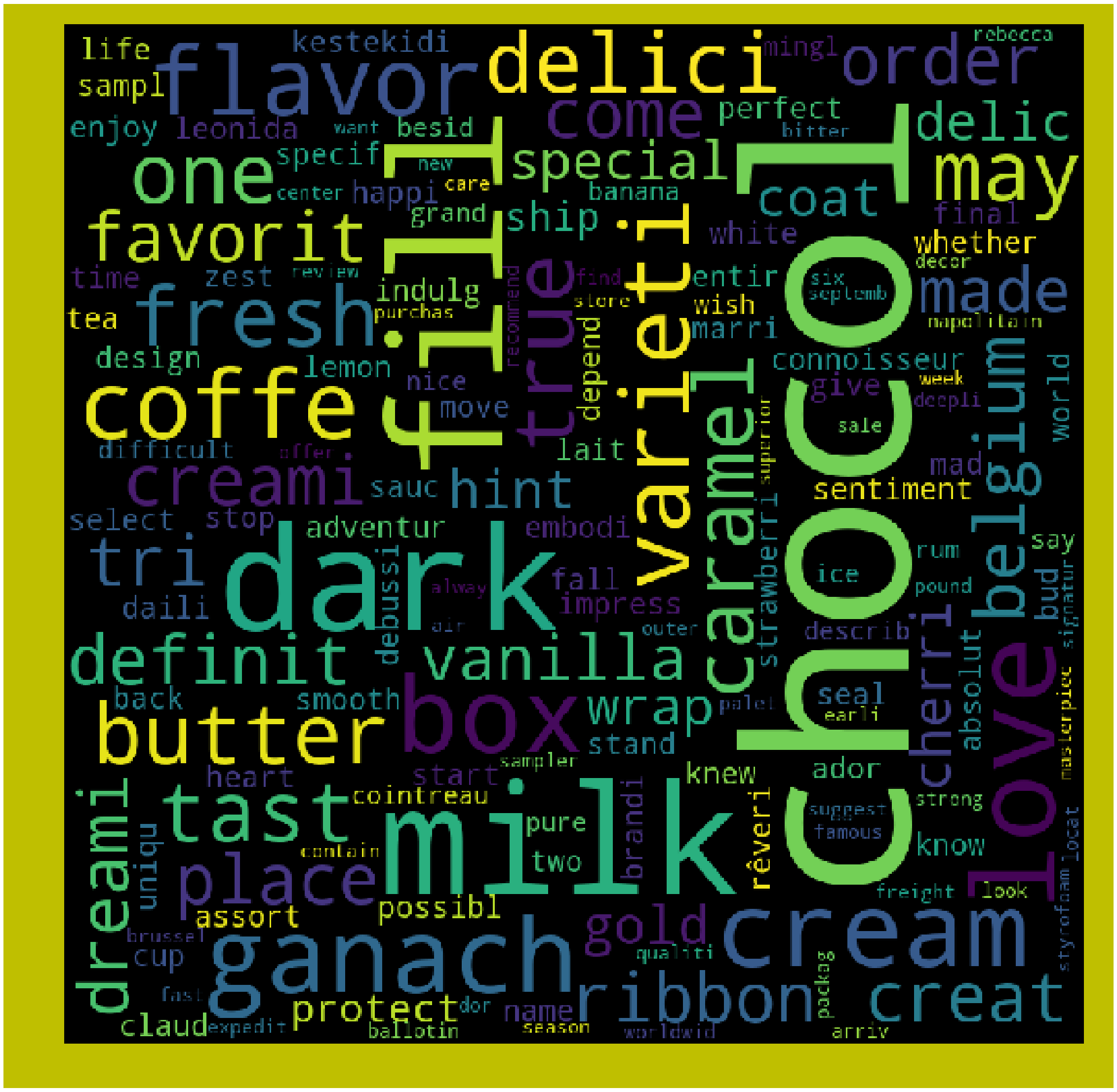
Review 1 ->

b'littl dream danger cure dream less dream dream time drink coffe chai tea mouth warm heat bever



Review 2 ->   ,

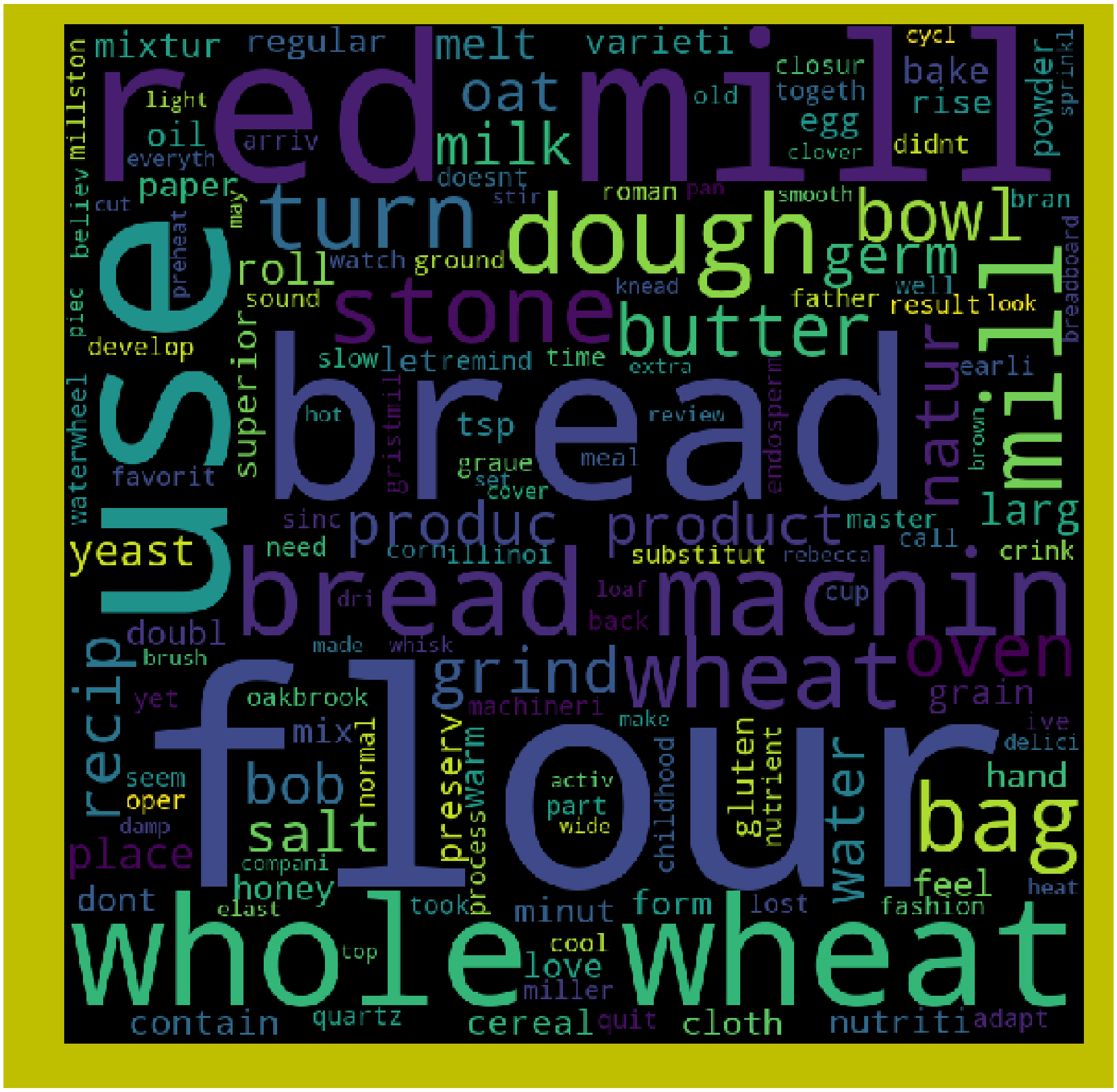
b'possibl fall mad love box chocol assort perfect place start adventur chocol name leonida keste



For cluster 3

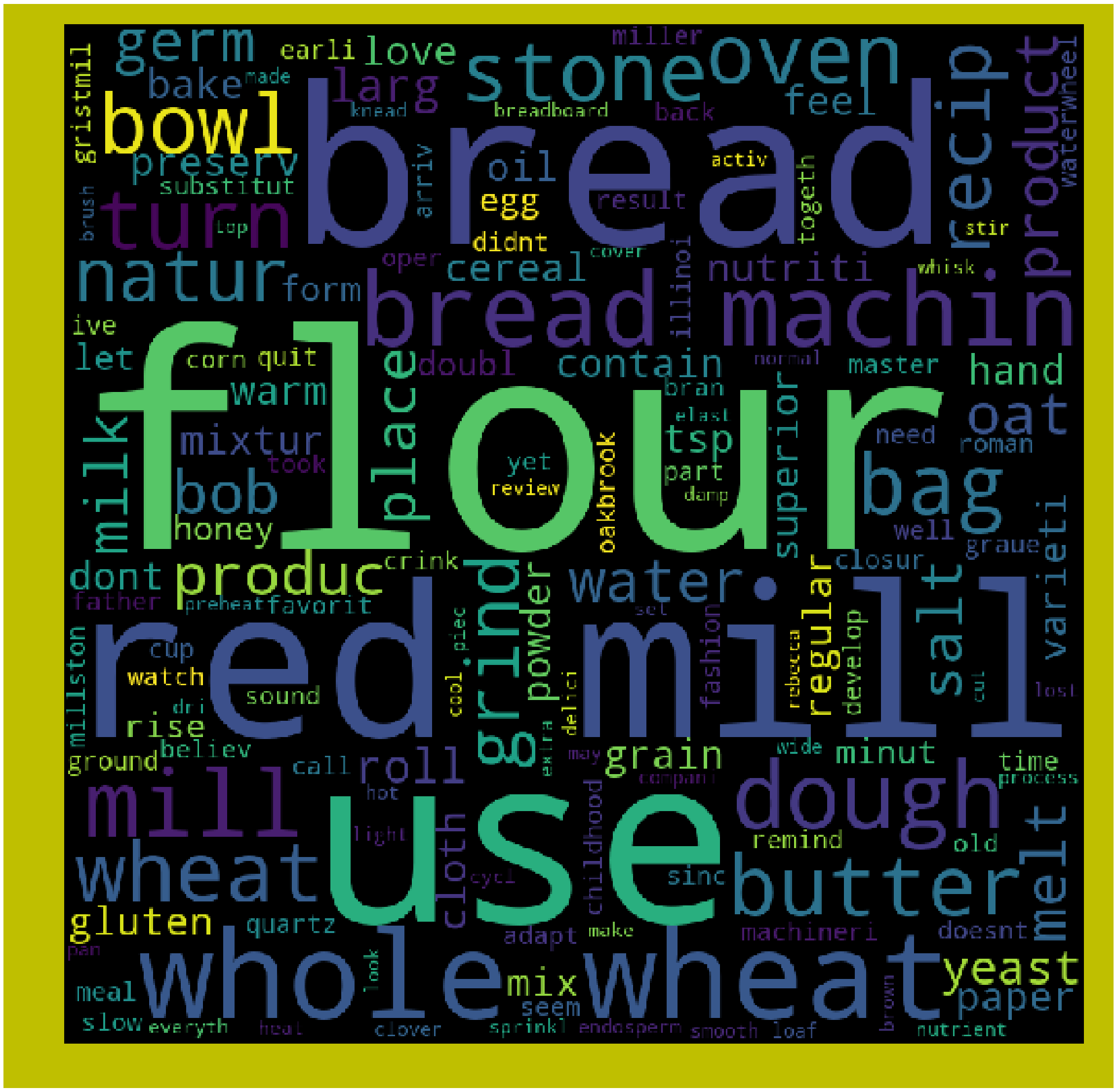
Review 1 ->

b'use believ stone mill machineri yet develop grind grain flour cereal meal quit well quartz sto



Review 2 ->   ,

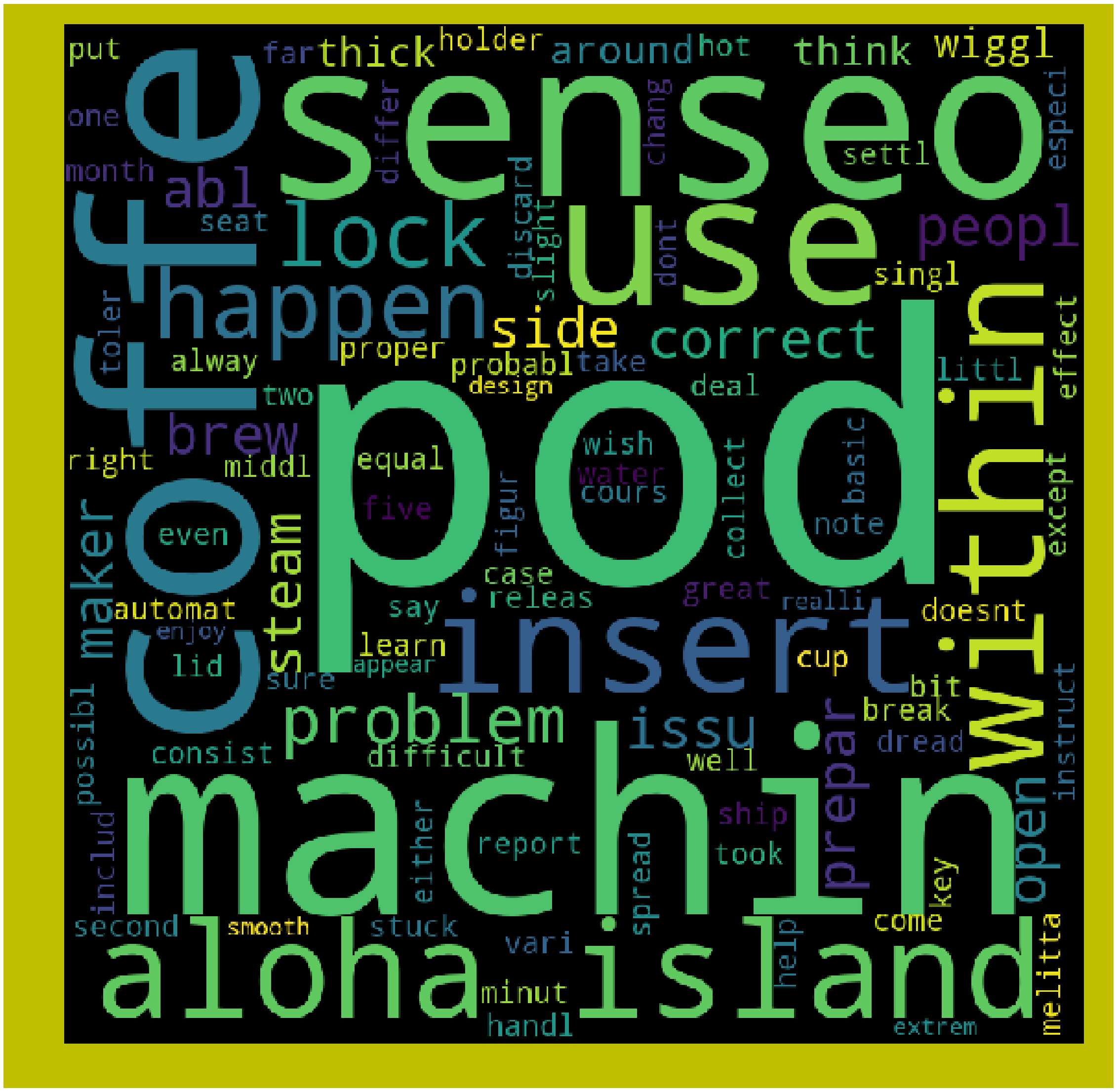
b'use believ stone mill machineri yet develop grind grain flour cereal meal quit well quartz sto



For cluster 4

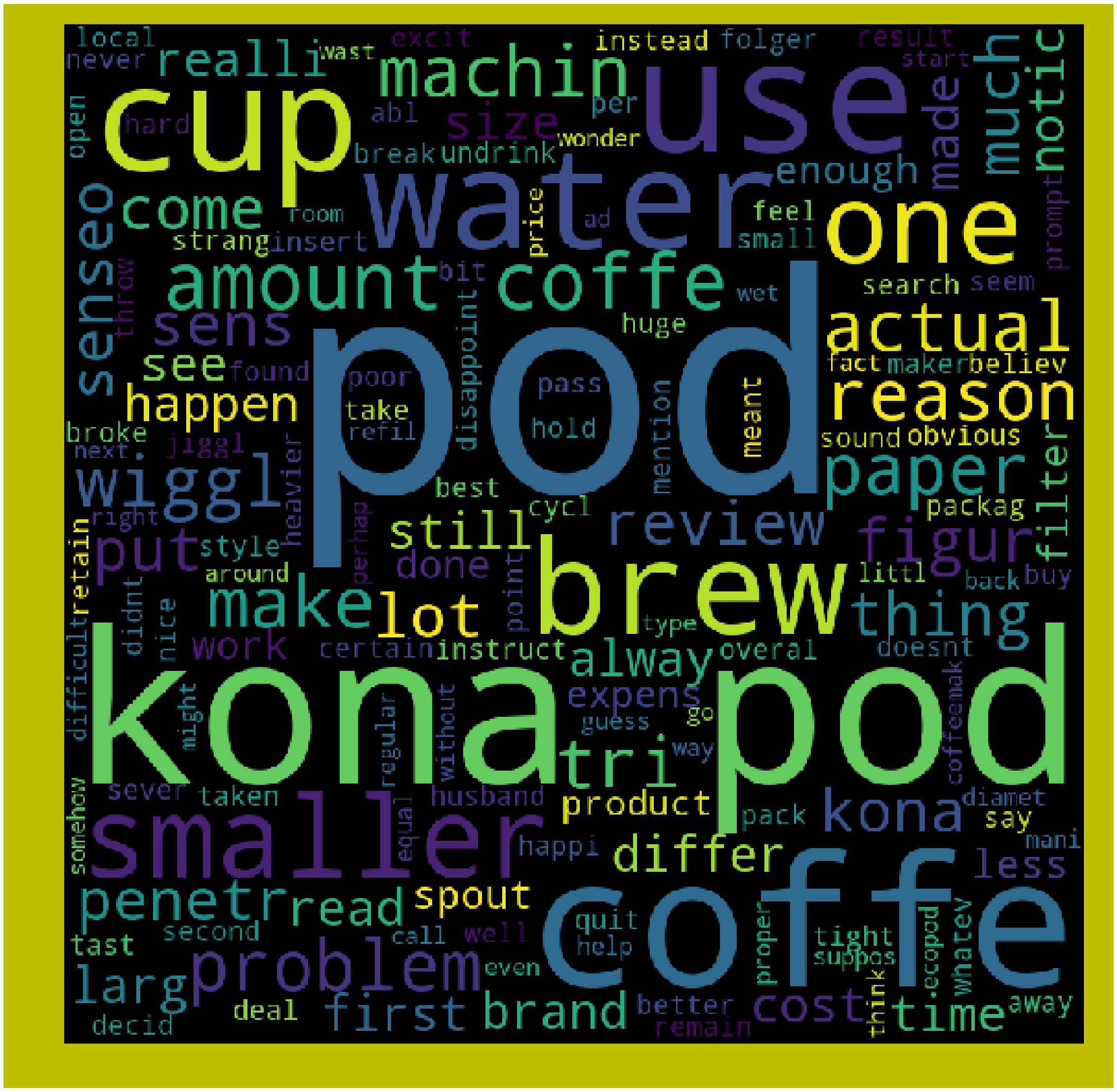
Review 1 ->

b'coffe great senseo machin difficult use far get pod correct sure happen peopl report steam loc



Review 2 -> ,

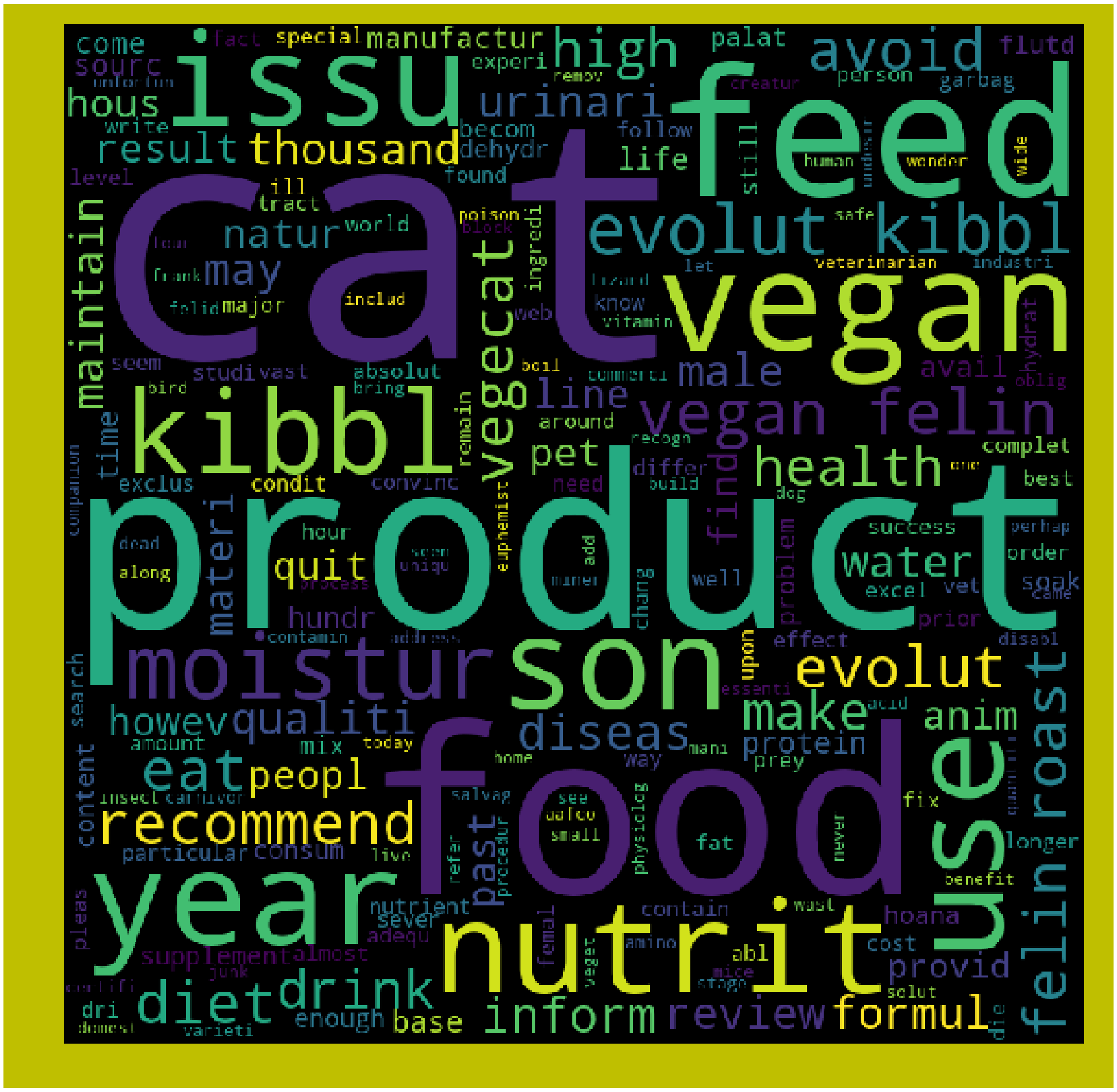
b'realli like senseo coffe maker like other review kona pod alway search better tast coffe pod u



For cluster 5

Review 1 ->

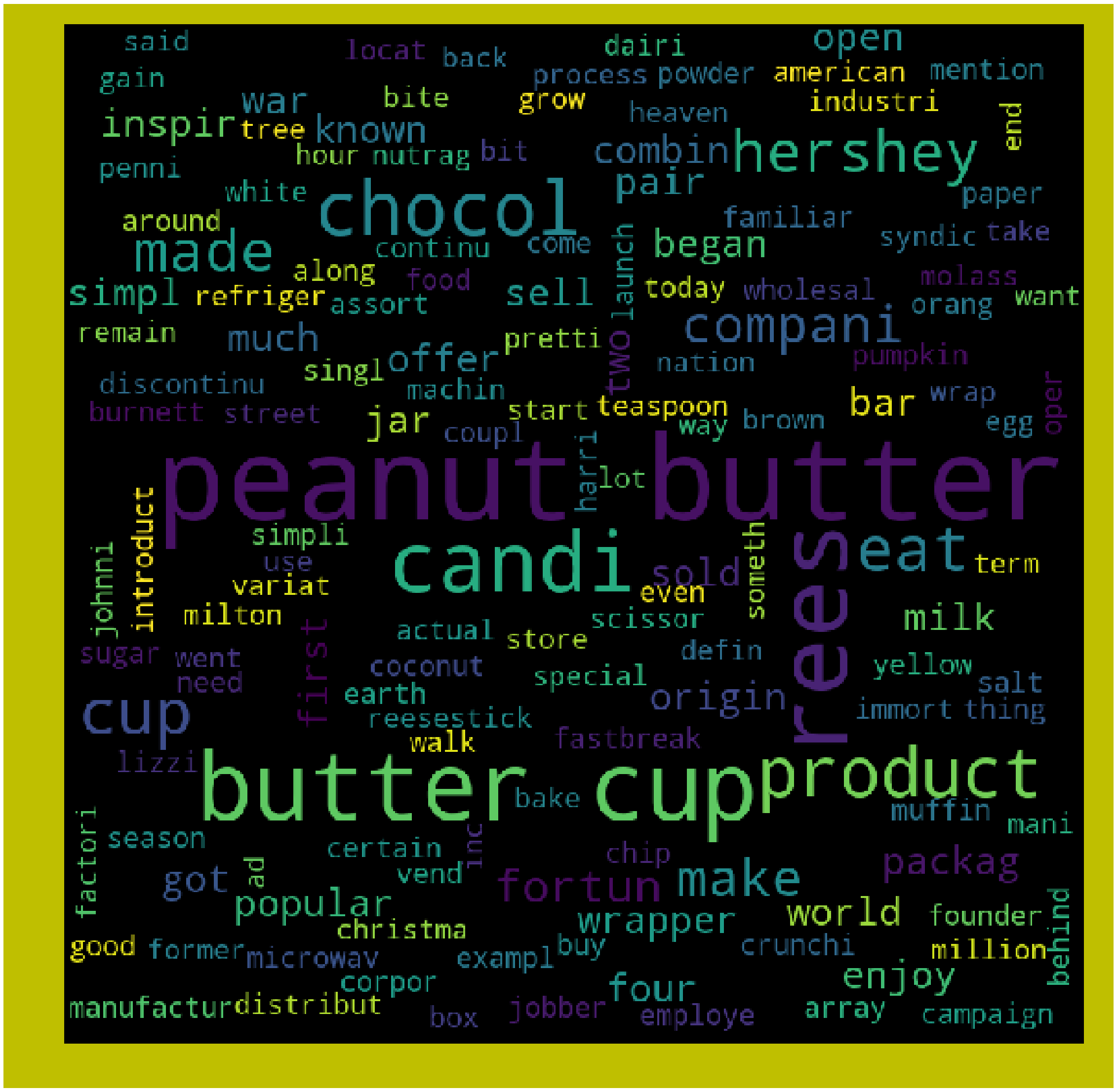
b'unfortun peopl ill inform vegan cat includ veterinarian cat fact oblig carnivor howev domest h



For cluster 6

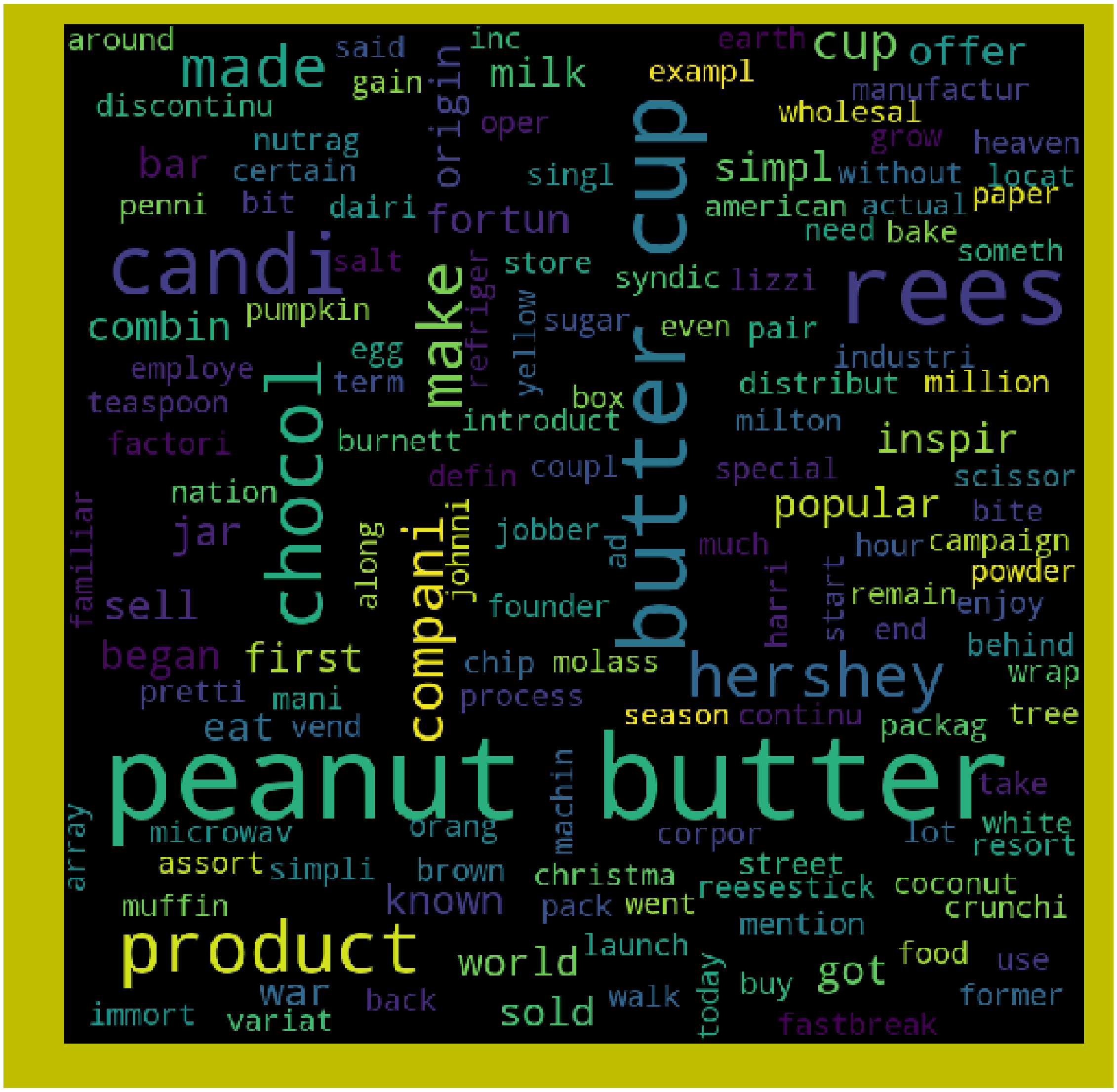
Review 1 ->

b'rees candi compani first began manufactur product made special process peanut butter hershey m



Review 2 -> ,

b'rees candi compani first began manufactur product made special process peanut butter hershey m



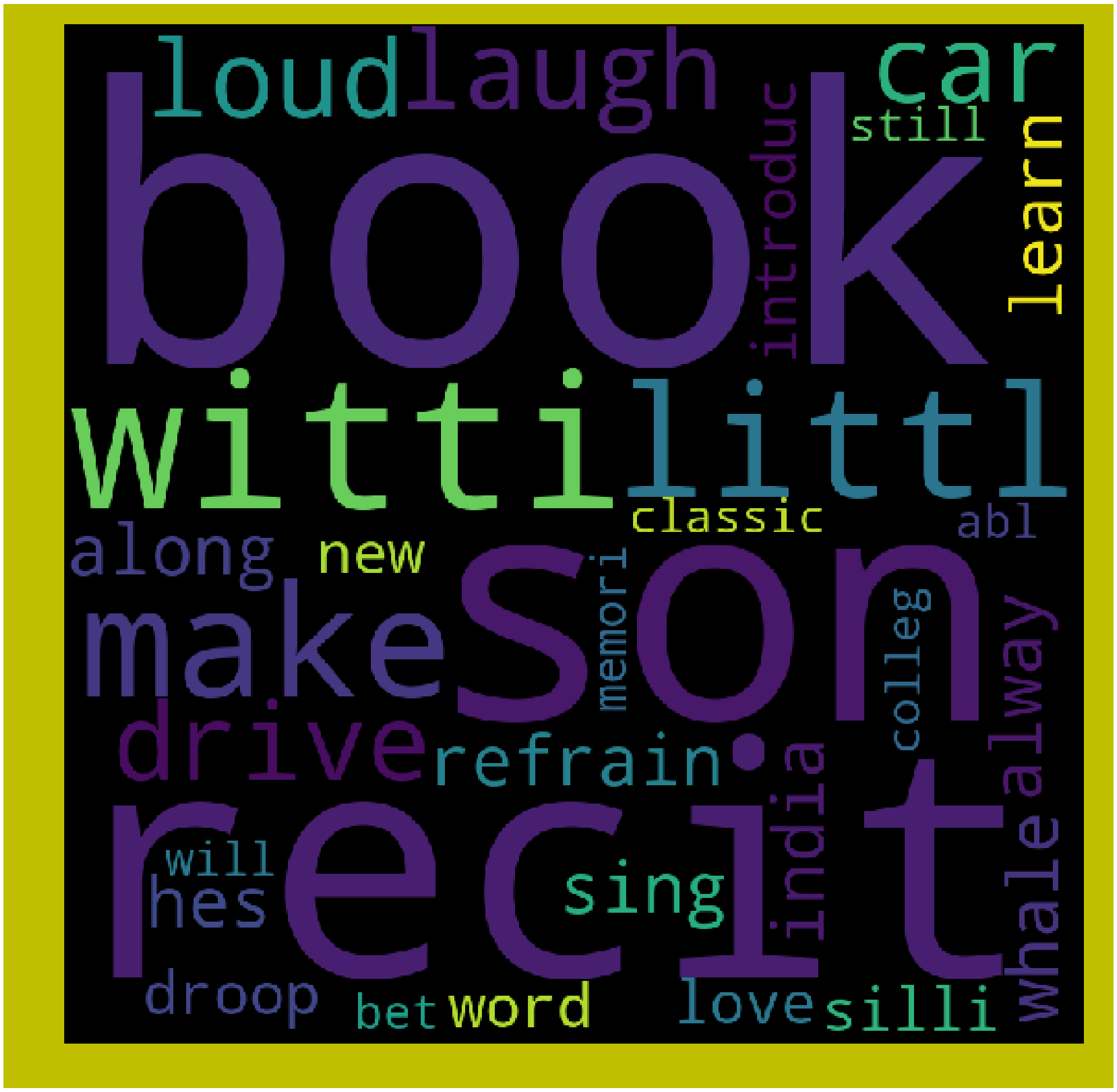
In [56]: agglomerative_Cluster(vectorization_output[1],cluster_name[1])

**   For Number of Clusters =   4   **********************

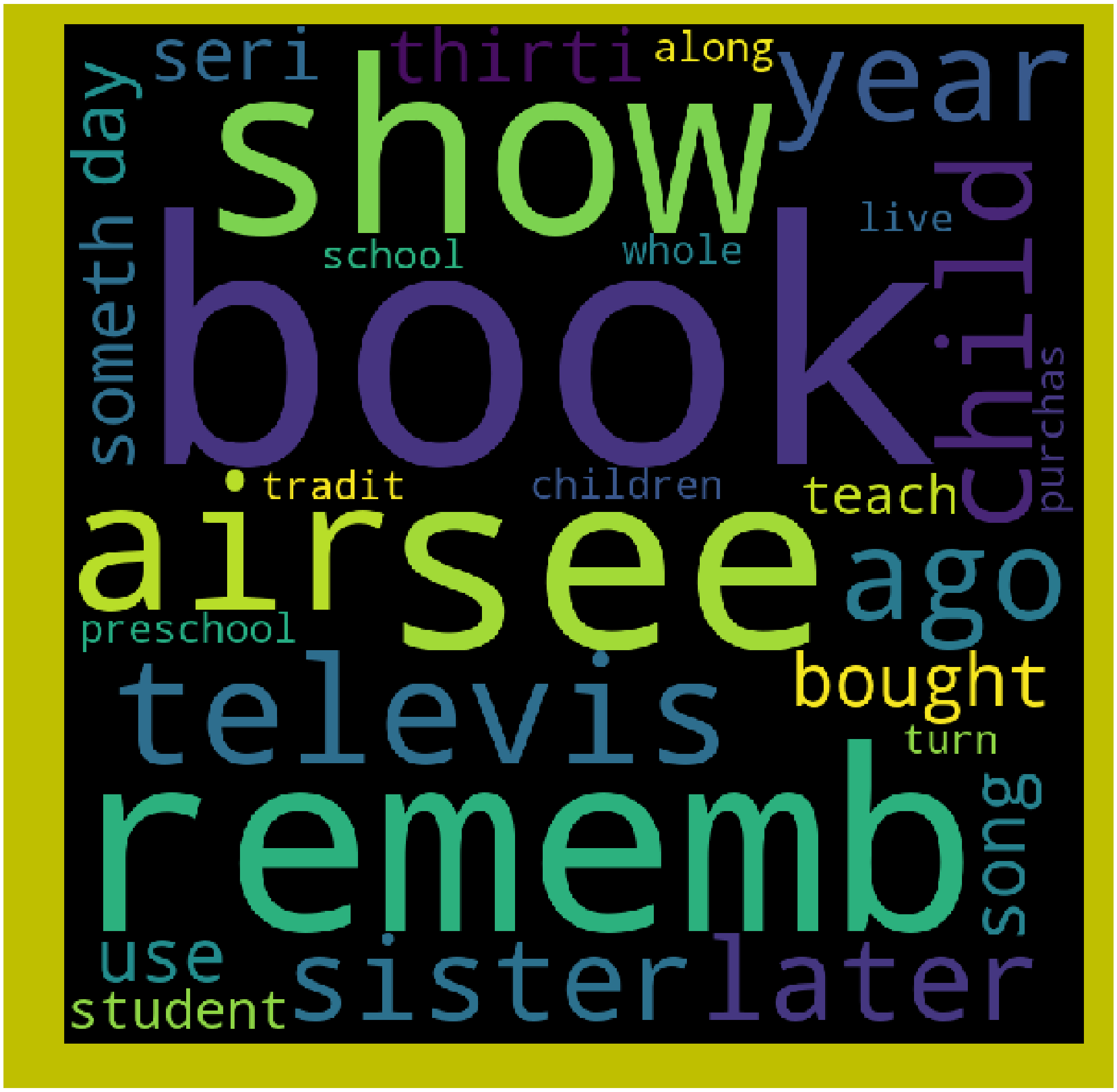
Reviews for each of the clusters :

For cluster 0

```
Review 1 ->

b'witti littl book make son laugh loud recit car drive along alway sing refrain hes learn whale
```



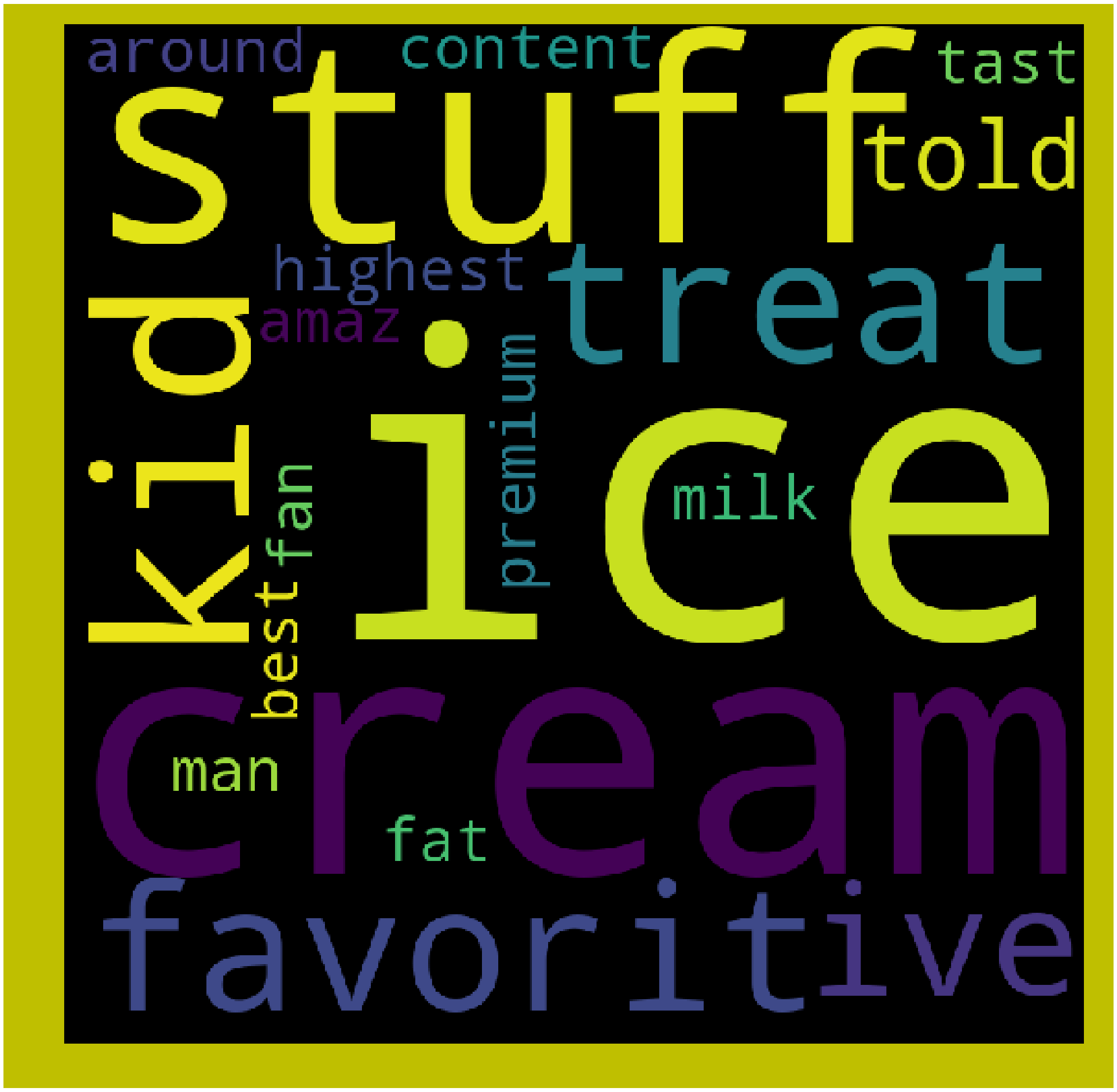

```
Review 2 ->  ,

b'rememb see show air televis year ago child sister later bought day thirti someth use seri book
```



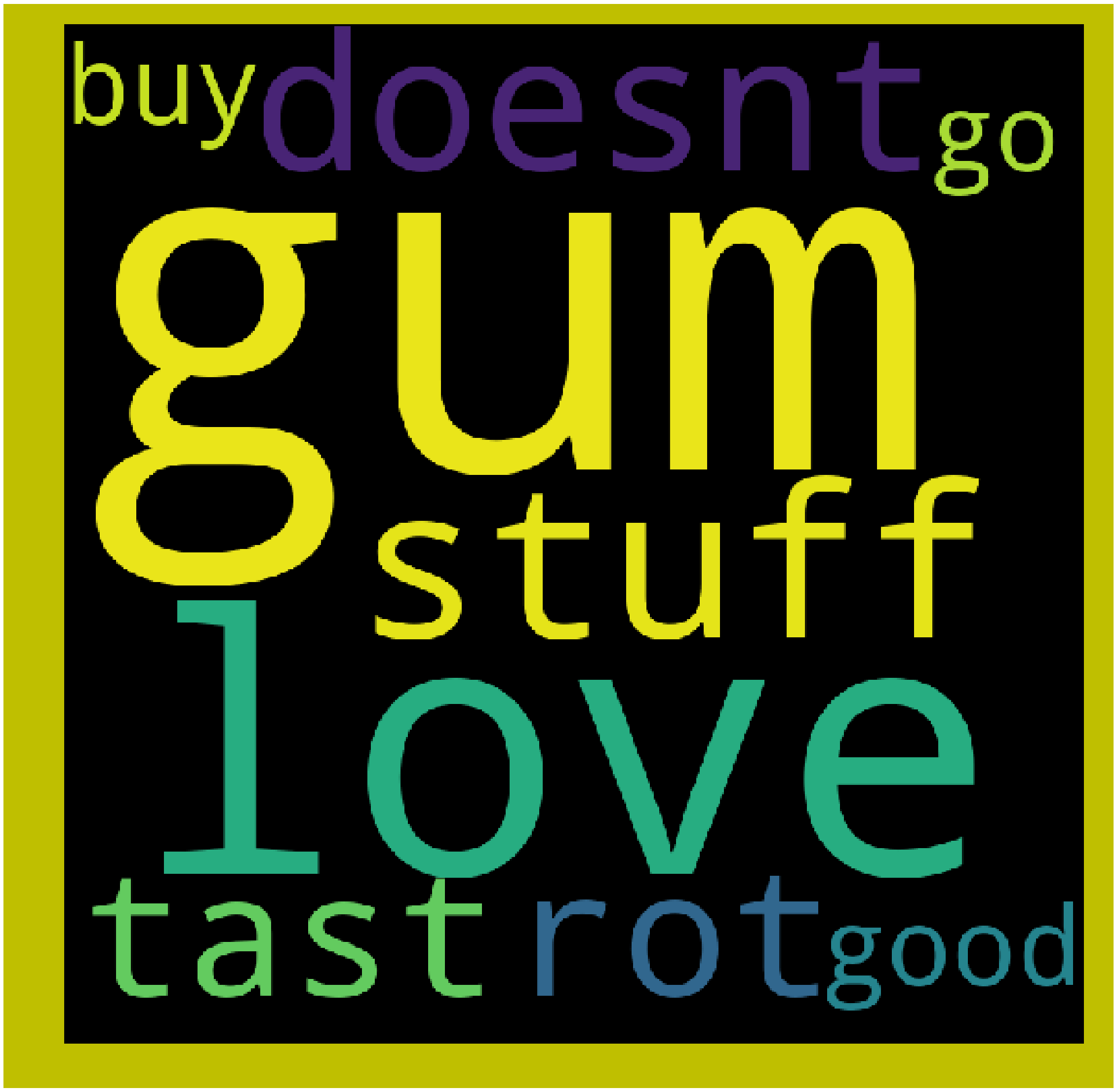
For cluster 1

Review 1 ->

b'kid ice cream favorit treat ive told highest milk fat content ice cream around man tast stuff




```
Review 2 ->  ,

b'love stuff doesnt rot gum tast good go buy gum get'
```



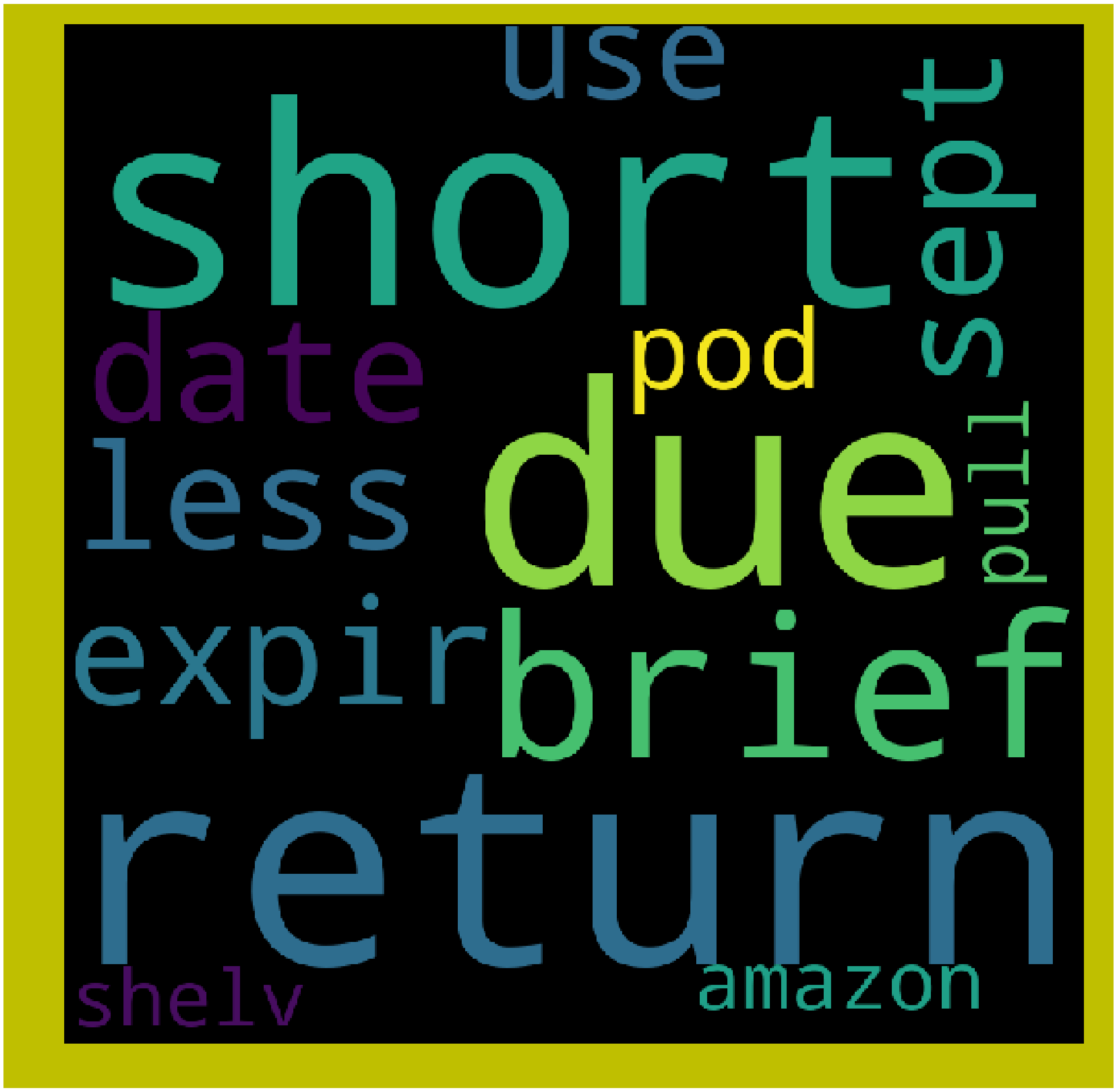
For cluster 2

Review 1 ->

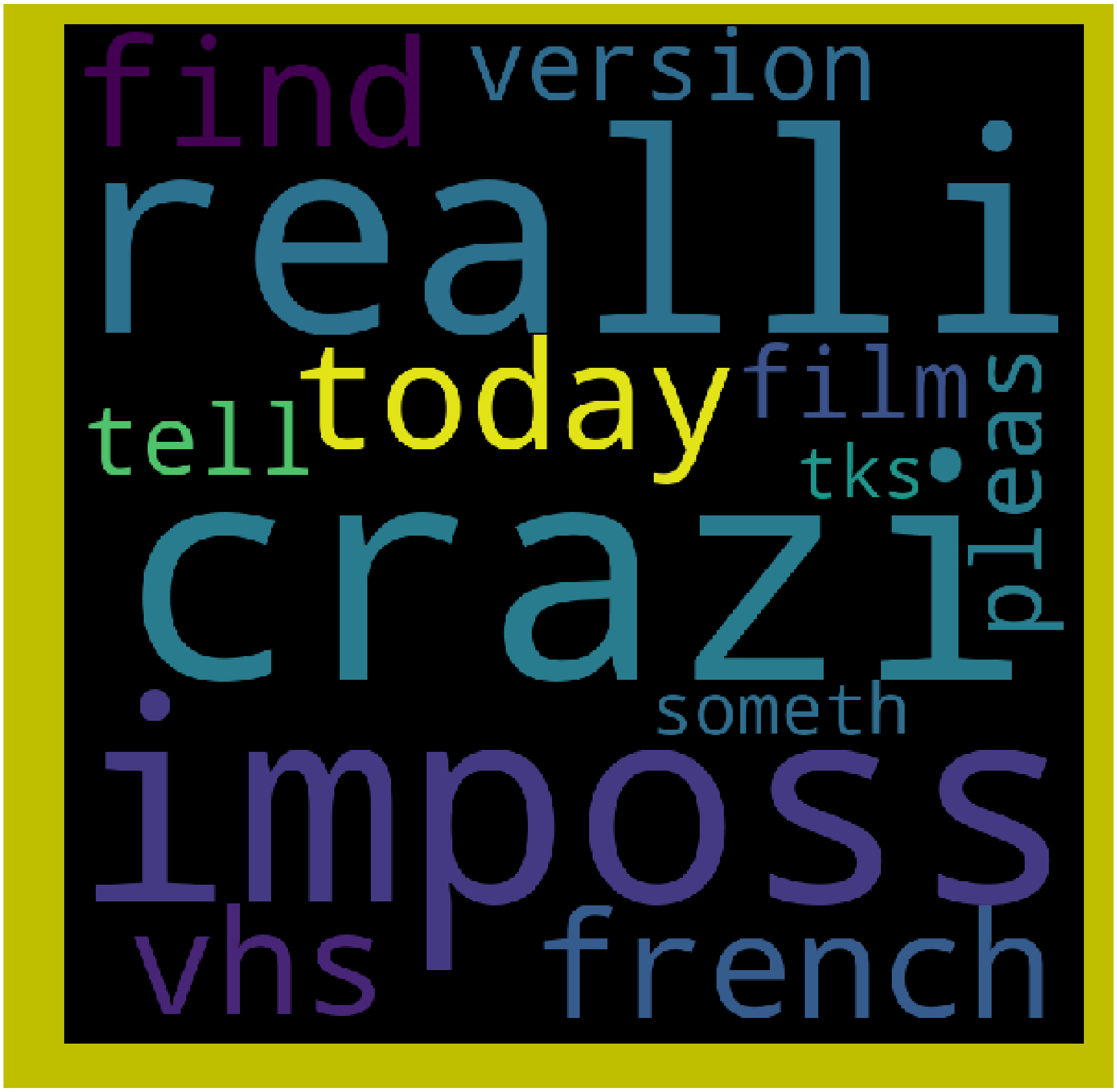
b'food color kit sound great except give ounc size bottl what would nice know much product get d

Review 2 -> ,

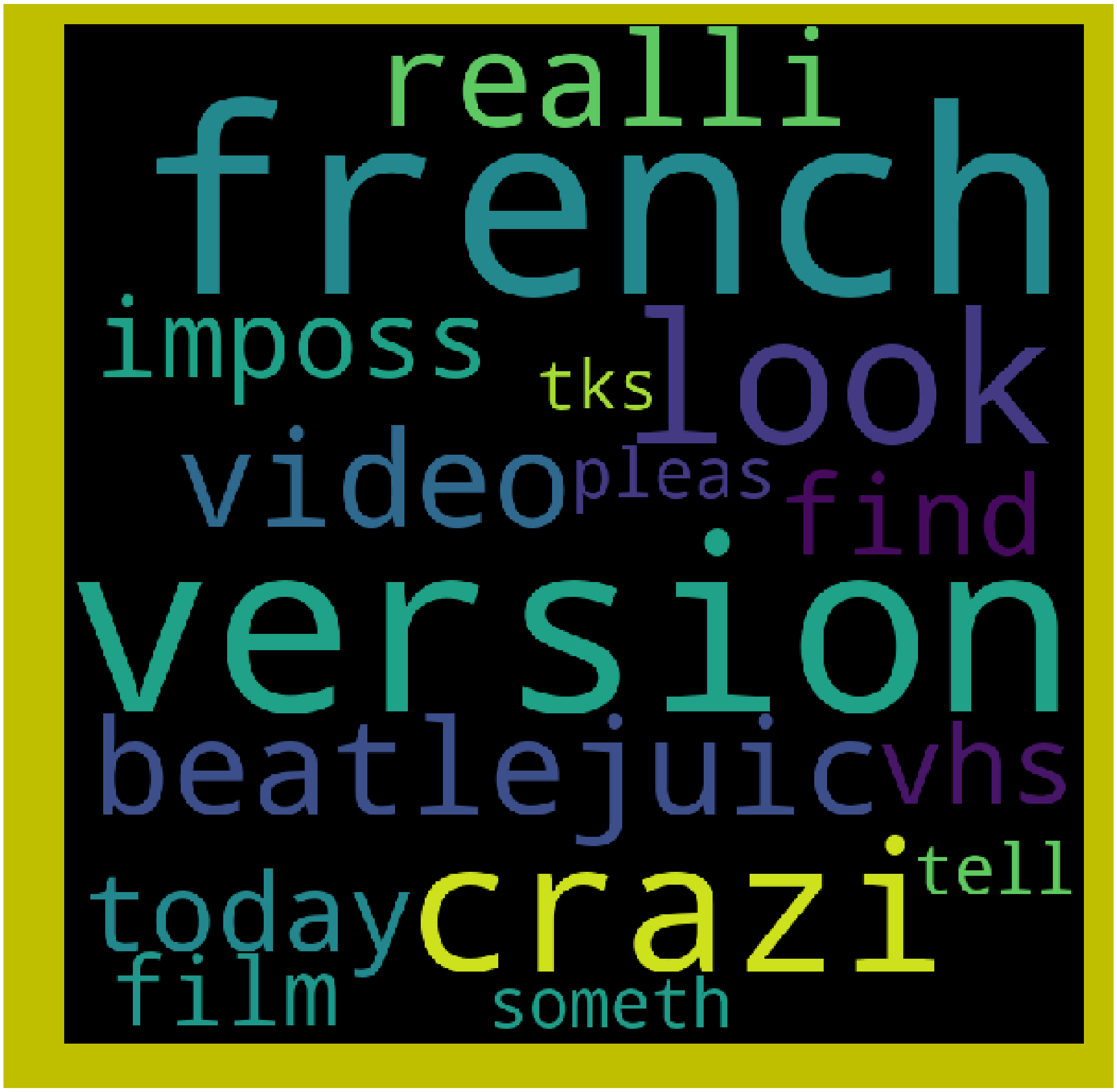
b'return due short brief expir date sept would less use pod amazon pull shelv'




```
--------------------------------------------------------------------------------
For cluster  3

Review 1 ->

b'get crazi realli imposs today find french vhs version film pleas tell someth tks'
```




```
Review 2 ->  ,

b'get crazi look beatlejuic french version video realli imposs today find french vhs version fil
```




```
---------------------------------------------------------------------------------
---------------------------------------------------------------------------------
```

```
In [40]:  # This code cell is for agglomerative  using Tf-IDf
          agglomerative_Cluster(vectorization_output[2],cluster_name[2])
```

```
In [41]: # This code cell is for agglomerative  usinf tf-idf weighted word2vec
          agglomerative_Cluster(vectorization_output[3],cluster_name[3])
```

9.1 Observation for Hierarchical clustering using agglomerative method

- In Agglomerative Clustering, Random Cluster number is selected and then How agglomerative cluster is clustered from cluster 0 to random cluster number is shown.
- Wordcloud visualized each cluster review as seen in above.

- here,Hierarchical clustering is using the types named as agglomerative hierarchical clustering.
- As in agglomerative methods,group of cluster is clustered based on similarity or distance between clusters.
- As above with each featurization techniques, 5k reviews are clustered with agglomerative method.
- we can see the similarity between review1 and review2 for particular sets(contains reviews) in given cluster.

10 DBSCAN(Density Based spital clustering of application with noise)

```
In [42]: # Computing 200th Nearest neighbour distance code.
         minPts = 2 * 100
         # Lower bound function copied from -> https://gist.github.com/m00nlight/0f9306b4d4e61ba
         def lower_bound(nums, target): # This function return the number in the array just grea
             l, r = 0, len(nums) - 1
             while l <= r: # Binary searching.
                 mid = int(l + (r - l) / 2)
                 if nums[mid] >= target:
                     r = mid - 1
                 else:
                     l = mid + 1
             return l

         def compute200_nearest_neighbour(x, data): # Returns the distance of 200th nearest neig
             dists = []
             for val in data:
                 dist = np.sum((x - val) **2 ) # computing distances.
                 if(len(dists) == 200 and dists[199] > dist): # If distance is larger than curre
                     l = int(lower_bound(dists, dist)) # Using the lower bound function to get t
                     if l < 200 and l >= 0 and dists[l] > dist:
                         dists[l] = dist
                 else:
                     dists.append(dist)
                     dists.sort()

             return dists[199] # Dist 199 contains the distance of 200th nearest neighbour.
```

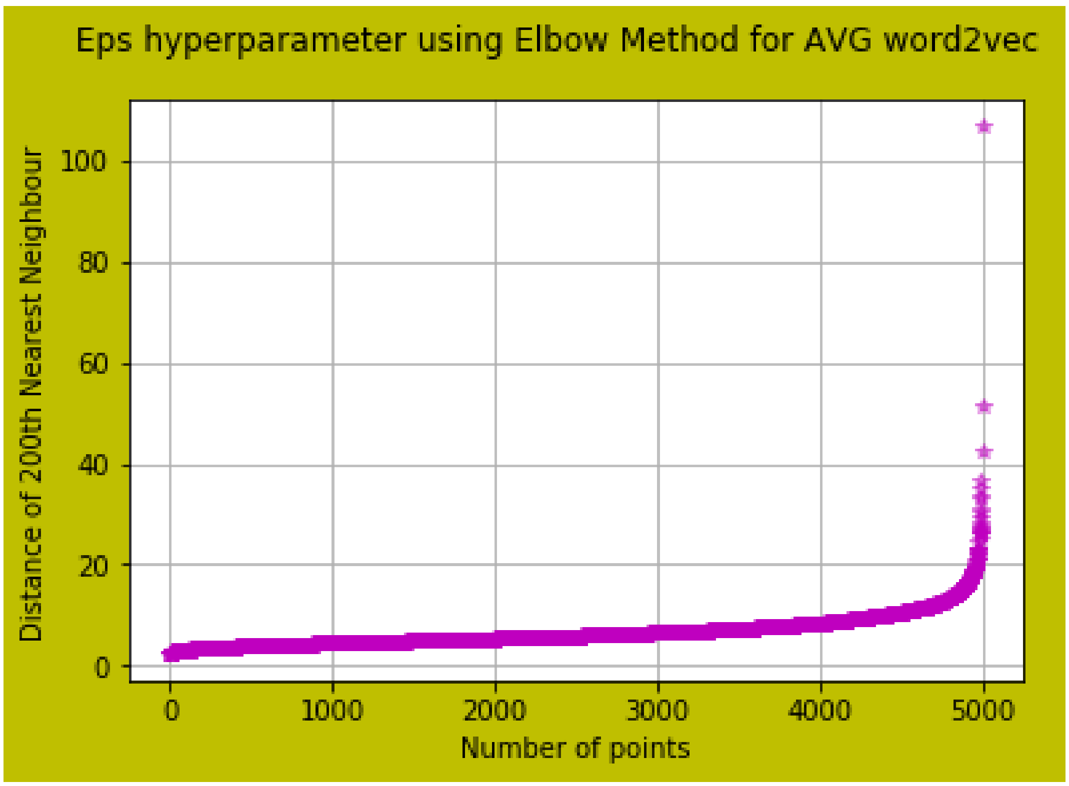
10.1 Computing the 200th Nearest Neighbour Distance of points in the dataset

```
In [78]: # Computing the 200th nearest neighbour distance of some point the dataset:
         neigh200 = []
```

```
for val in vectorization_output[1]:
    neigh200.append( compute200_nearest_neighbour(val, vectorization_output[1]) )
neigh200.sort()
```

10.1.1 Plotting for the Elbow Method

In [79]:
```
fig4 = plt.figure( facecolor='y', edgecolor='k')
fig4.suptitle('Eps hyperparameter using Elbow Method for AVG word2vec ', fontsize=12)
plt.plot([x for x in range(len(neigh200 ))], neigh200 ,'m*', alpha = 0.5)
plt.xlabel("Number of points")
plt.ylabel("Distance of 200th Nearest Neighbour")
plt.grid()
plt.show()
```



The Knee point seems to be 18. So Eps = 18

In [43]:
```
# Training DBSCAN :
model = DBSCAN(eps = 18, min_samples = minPts, n_jobs=-1)
model.fit(vectorization_output[1])
```

Out[43]:
```
DBSCAN(algorithm='auto', eps=18, leaf_size=30, metric='euclidean',
    metric_params=None, min_samples=200, n_jobs=-1, p=None)
```

In [44]:
```
df1 =X1[:5000]
```

```
#word_cloud_form(df1['CleanedText'][0])
df1['AVG-W2V_Label'] = model.labels_
df1.head(2)
```

```
Out[44]:                                              CleanedText  AVG-W2V_Label
         150523  b'witti littl book make son laugh loud recit c...              0
         150500  b'rememb see show air televis year ago child s...              0
```

```
In [45]: df1.groupby(['AVG-W2V_Label'])['CleanedText'].count()
```

```
Out[45]: AVG-W2V_Label
         0    5000
         Name: CleanedText, dtype: int64
```

All Cluster labels for each point in the dataset given to fit()(model).No noise point is lied within cluster at eps=18 and min_samples=200.

10.1.2 For different values of eps

Let's check the clustering with different values of eps with minpts=200

```
In [46]: diff_eps=[0.6,0.8,1,6,8,12,15,18,20]
```

```
In [47]: for eps_val in range(len(diff_eps)):

             model = DBSCAN(eps =diff_eps[eps_val], min_samples = minPts, n_jobs=-1)
             model.fit(vectorization_output[1])
             print ("\n")
             print ("*" * 70)
             print("for eps value ===",diff_eps[eps_val])
             df1 =X1[:5000]
             df1['AVG-W2V_Label'] = model.labels_
             df2=df1.groupby(['AVG-W2V_Label'])['CleanedText'].count()

             print(df2)
```

```


**********************************************************************
for eps value === 0.6
AVG-W2V_Label
-1    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 0.8
AVG-W2V_Label
-1    5000
```

```
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 1
AVG-W2V_Label
-1    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 6
AVG-W2V_Label
-1       1
 0    4999
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 8
AVG-W2V_Label
-1       1
 0    4999
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 12
AVG-W2V_Label
0    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 15
AVG-W2V_Label
0    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 18
AVG-W2V_Label
0    5000
Name: CleanedText, dtype: int64


**********************************************************************
```

```
for eps value === 20
AVG-W2V_Label
0    5000
Name: CleanedText, dtype: int64
```

Noisy samples are given the label -1 in a cluster.

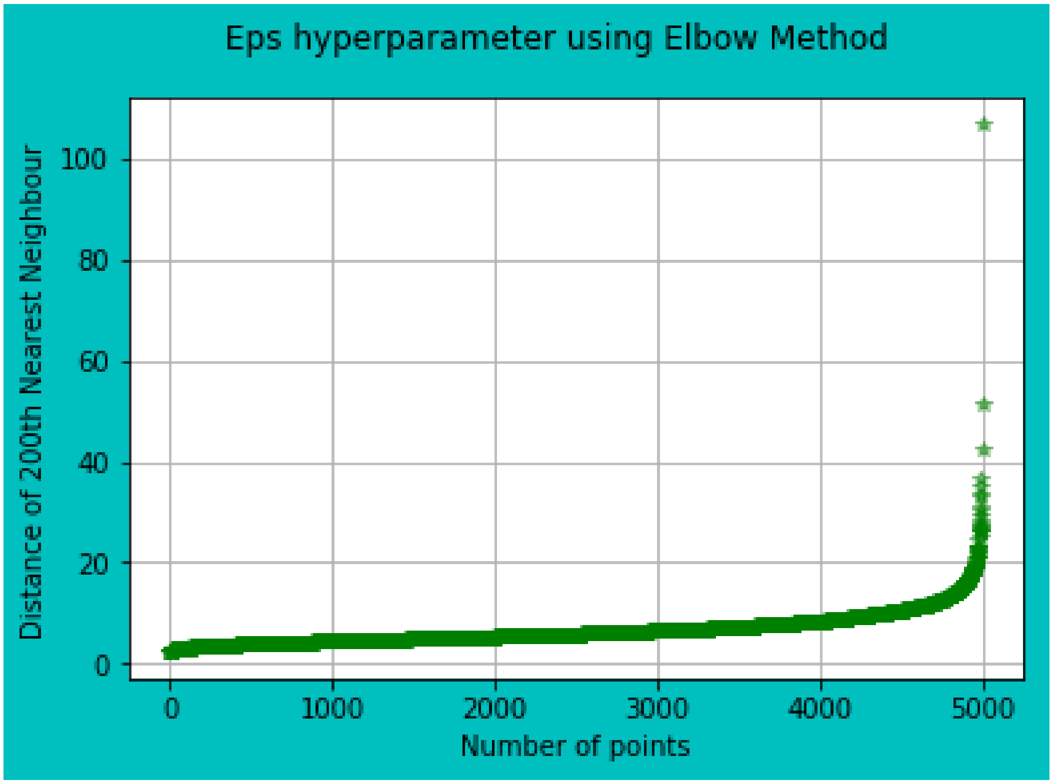
- eps value lies in this range [0.6,0.8,1] is showing all samples points are noise point.
- For eps value [6,8], one point is noise point and rest of point is cluster point
- eps value lies between [12,15,18,20] is labelling all points as cluster point

10.2 Computing the 200th Nearest Neighbour Distance of points in the dataset

```
In [80]: # Computing the 200th nearest neighbour distance of some point the dataset:
         neigh200_tf = []
         for val in vectorization_output[3]:
             neigh200_tf.append( compute200_nearest_neighbour(val, vectorization_output[3]) )
         neigh200_tf.sort()
```

10.2.1 Plotting for the Elbow Method

```
In [81]: fig4 = plt.figure( facecolor='c', edgecolor='k')
         fig4.suptitle('Eps hyperparameter using Elbow Method ', fontsize=12)
         plt.plot([x for x in range(len(neigh200_tf ))], neigh200_tf ,'g*', alpha = 0.5)
         plt.xlabel("Number of points")
         plt.ylabel("Distance of 200th Nearest Neighbour")
         plt.grid()
         plt.show()
```




```
In [48]: # Training DBSCAN :
         model = DBSCAN(eps = 20, min_samples = minPts, n_jobs=-1)
         model.fit(vectorization_output[3])
```

```
Out[48]: DBSCAN(algorithm='auto', eps=20, leaf_size=30, metric='euclidean',
             metric_params=None, min_samples=200, n_jobs=-1, p=None)
```

```
In [49]: df1['TFIDF-W2V_Label'] = model.labels_
         df1.head(2)
```

```
Out[49]:                                               CleanedText  AVG-W2V_Label  \
         150523  b'witti littl book make son laugh loud recit c...              0
         150500  b'rememb see show air televis year ago child s...              0

                 TFIDF-W2V_Label
         150523                0
         150500                0
```

All Cluster labels for each point in the dataset given to fit()(model).No noise point is lied within cluster at eps=20 and min_samples=200.

```
In [50]: df1.groupby(['TFIDF-W2V_Label'])['CleanedText'].count()
```

```
Out[50]: TFIDF-W2V_Label
         0    5000
         Name: CleanedText, dtype: int64
```

```
In [51]: for eps_val in range(len(diff_eps)):

             model = DBSCAN(eps =diff_eps[eps_val], min_samples = minPts, n_jobs=-1)
             model.fit(vectorization_output[3])
             print ("\n")
             print ("*" * 70)
             print("for eps value ===",diff_eps[eps_val])
             df1 =X1[:5000]
             df1['TFIDF-W2V_Label'] = model.labels_
             #df2=df.groupby(['AVG-W2V_Label'])['CleanedText'].count()
             df2=df1.groupby(['TFIDF-W2V_Label'])['CleanedText'].count()

             print(df2)
```

```
**********************************************************************
for eps value === 0.6
TFIDF-W2V_Label
-1    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 0.8
TFIDF-W2V_Label
-1    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 1
TFIDF-W2V_Label
-1    5000
Name: CleanedText, dtype: int64


**********************************************************************
for eps value === 6
TFIDF-W2V_Label
-1       1
 0    4999
Name: CleanedText, dtype: int64
```

```
*********************************************************************
for eps value === 8
TFIDF-W2V_Label
-1       1
 0    4999
Name: CleanedText, dtype: int64


*********************************************************************
for eps value === 12
TFIDF-W2V_Label
0    5000
Name: CleanedText, dtype: int64


*********************************************************************
for eps value === 15
TFIDF-W2V_Label
0    5000
Name: CleanedText, dtype: int64


*********************************************************************
for eps value === 18
TFIDF-W2V_Label
0    5000
Name: CleanedText, dtype: int64


*********************************************************************
for eps value === 20
TFIDF-W2V_Label
0    5000
Name: CleanedText, dtype: int64
```

Noisy samples are given the label -1 in a cluster.

- eps value lies in this range [0.6,0.81] is showing all samples points are noise point.
- eps value=[6,8] are labelling 1 ponit as noise points and rest of the point as a cluster points.
- eps value lies between [12,15,18,20] is labelling all points as cluster point

It can be observed that DBSCAN is sensitive to eps

Observations:

- Clustering techniques labelling varies based on size, density and globular shape.
- With Kmeans++, kmedoids,Hierarchical clustering(agglomerative clustering) and DBSCAN clustering on amazon reviews clustered the reviews as seen above.

```
In [ ]:
```