Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [16]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.co
m/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from sklearn.cluster import AgglomerativeClustering

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os
from wordcloud import WordCloud

from sklearn.cluster import KMeans
from sklearn.metrics import pairwise_distances_argmin_min # for
interpretability
```

Reading the dataset

In [18]:
```
#loading train and test and validation dataset

file=open("x_train.pkl","rb")
x_train=pickle.load(file) # loading 'train' dataset

file=open("x_cv.pkl",'rb')
x_cv=pickle.load(file) # loading 'validation' dataset
```

```
file=open("x_test.pkl",'rb')
x_test=pickle.load(file) # loading 'test' dataset

file=open("y_train.pkl","rb")
y_train=pickle.load(file) # loading 'train' dataset

file=open("y_cv.pkl",'rb')
y_cv=pickle.load(file) # loading 'validation' dataset

file=open("y_test.pkl",'rb')
y_test=pickle.load(file) # loading 'test' dataset

#loading train_bow and test _bow
file=open('x_train_bow.pkl','rb')
x_train_bow=pickle.load(file)

file=open('x_test_bow.pkl','rb')
x_test_bow=pickle.load(file)

file=open('x_cv_bow.pkl','rb')
x_cv_bow=pickle.load(file)

#loading train_tf_idf and test_tf_idf
file=open('train_tf_idf.pkl','rb')
train_tf_idf=pickle.load(file)

file=open('cv_tf_idf.pkl','rb')
cv_tf_idf=pickle.load(file)

file=open('test_tf_idf.pkl','rb')
test_tf_idf=pickle.load(file)

#loading train_w2v and test_w2v
file=open('train_w2v.pkl','rb')
train_w2v=pickle.load(file)

file=open('cv_w2v.pkl','rb')
cv_w2v=pickle.load(file)

file=open('test_w2v.pkl','rb')
test_w2v=pickle.load(file)

#loading train_tf_idf_w2v and test_tf_idf_w2v
file=open('train_tf_idf_w2v.pkl','rb')
train_tf_idf_w2v=pickle.load(file)

file=open('cv_tf_idf_w2v.pkl','rb')
cv_tf_idf_w2v=pickle.load(file)

file=open('test_tf_idf_w2v.pkl','rb')
test_tf_idf_w2v=pickle.load(file)
```

[5] Assignment 10: K-Means, Agglomerative & DBSCAN Clustering

1. **Apply K-means Clustering on these feature sets:**

- SET 1:Review text, preprocessed one converted into vectors using (BOW)
- SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
- SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
- SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)
- Find the best 'k' using the elbow-knee method (plot k vs inertia_)
- Once after you find the k clusters, plot the word cloud per each cluster so that at a single go we can analyze the words in a cluster.

2. **Apply Agglomerative Clustering on these feature sets:**
    - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
    - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)
    - Apply agglomerative algorithm and try a different number of clusters like 2,5 etc.
    - Same as that of K-means, plot word clouds for each cluster and summarize in your own words what that cluster is representing.
    - You can take around 5000 reviews or so(as this is very computationally expensive one)

3. **Apply DBSCAN Clustering on these feature sets:**
    - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
    - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)
    - Find the best 'Eps' using the elbow-knee method.
    - Same as before, plot word clouds for each cluster and summarize in your own words what that cluster is representing.
    - You can take around 5000 reviews for this as well.

[5.1] K-Means Clustering

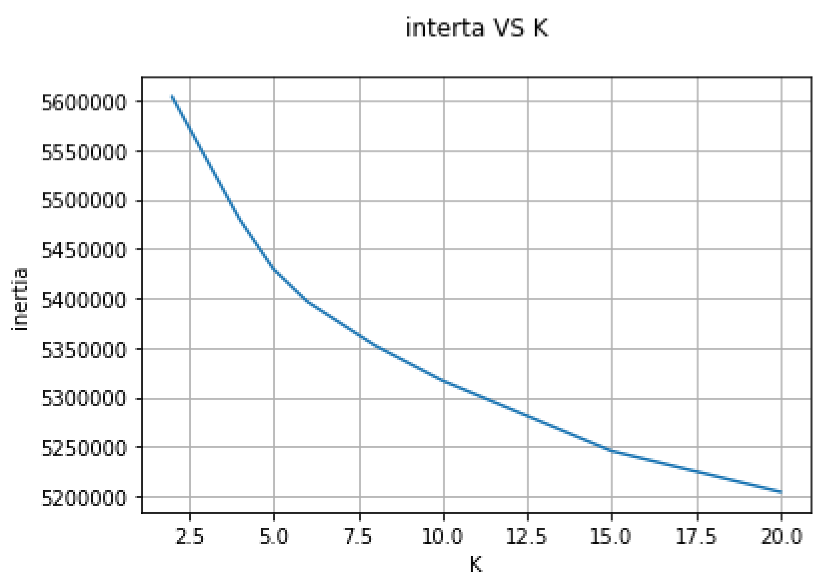
[5.1.1] Applying K-Means Clustering on BOW, SET 1

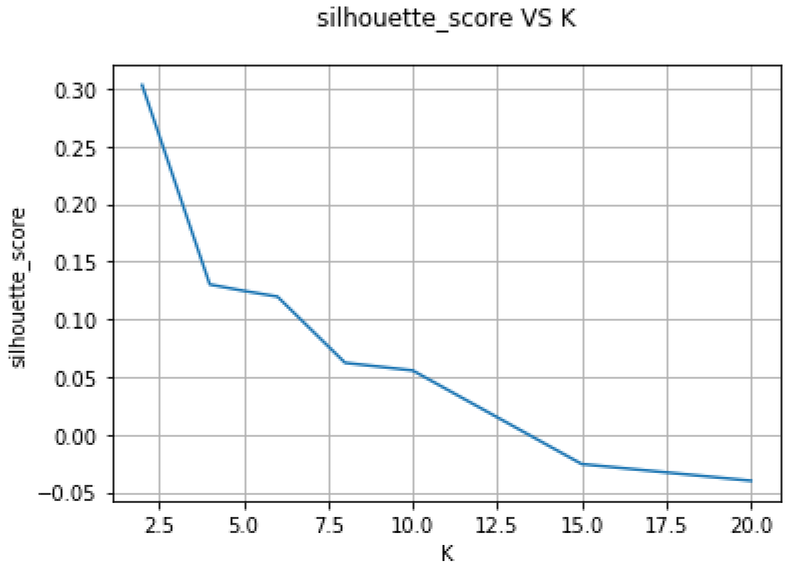
In [19]:
```
# removing all the reviews with no text
x_train=pd.DataFrame(x_train)
x_train=x_train[(x_train[0].apply(lambda x : len(x)))>0]

# BOW of x_train(reviews)
cv=CountVectorizer()
x_train_bow=cv.fit_transform(x_train[0])
```

In [24]:
```
# using silhouette score for choosing best K
from sklearn.metrics import silhouette_score
```

```
# Choosing right K using elbow method
ss=[]
inertia=[]
k=[2,4,5,6,8,10,15,20]

for i in k:
    km=KMeans(n_clusters=i,
                        init='k-means++',
                        n_init=10,
                        n_jobs=-2)
    km.fit(x_train_bow[:100000])
    inertia.append(round(km.inertia_,3))
    ss.append(silhouette_score(x_train_bow[:100000],km.predict(
x_train_bow[:100000])))
```

In [25]:
```
plt.plot(k,inertia)
plt.title("interta VS K\n")
plt.xlabel("K")
plt.ylabel("inertia")
plt.grid()
plt.show()

plt.plot(k,ss)
plt.title("silhouette_score VS K\n")
plt.xlabel("K")
plt.ylabel("silhouette_score")
plt.grid()
plt.show()
```





Elbow or knee point is at k=5

In [20]:
```
# clustering using right K
k=5
km=KMeans(n_clusters=k,
                    init='k-means++',
                    n_jobs=-2)
predict=km.fit_predict(x_train_bow[:100000])
```

In [21]:
```
(round(km.inertia_,3))
```

```
5429246.208
```

[5.1.2] Wordclouds of clusters obtained after applying k-means on BOW SET 1

In [24]:
```
# giving datapoints which is closest to k centroid
closest, _ = pairwise_distances_argmin_min(km.cluster_centers_,
x_train_bow[:100000])
closest
```

```
array([22793, 44716, 43704, 80540, 36626], dtype=int64)
```

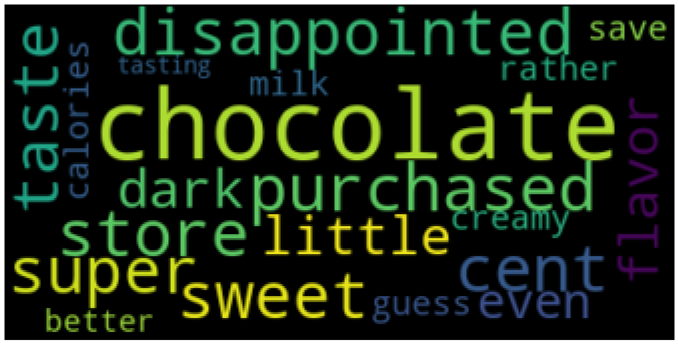
a. word cloud of k_cenroids

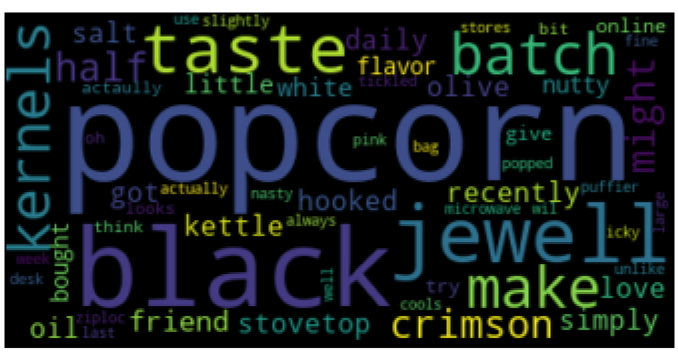
In [30]:

```
0    tea not tavalon tea chrysanthemum tea one clum...
Name: 22855, dtype: object
```

In [34]:
```
from wordcloud import WordCloud

text=[]
```

```
for i in closest:
    text=((x_train).loc[i][0])

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```

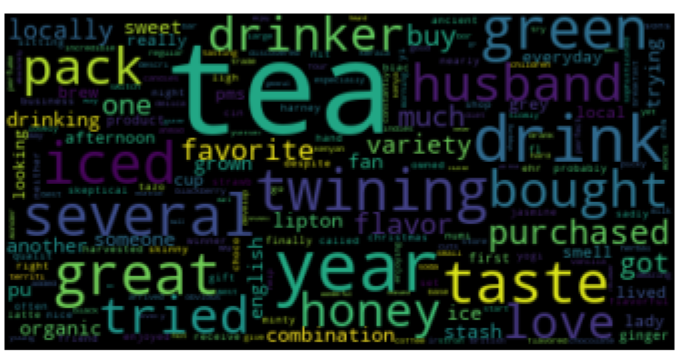




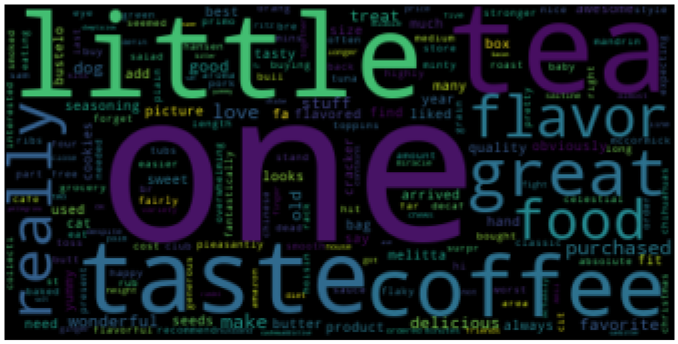
b. word cloud of each cluster

```
In [38]: for i in np.unique(predict):
             text=(x_train).iloc[np.argwhere(predict==i).ravel()]

             # Create and generate a word cloud image:
             wordcloud = WordCloud().generate(str(text))

             # Display the generated image:
             plt.imshow(wordcloud, interpolation='bilinear')
             plt.title(f"wordcloud of cluster: {i} \n")
             plt.axis("off")
             plt.show()
```

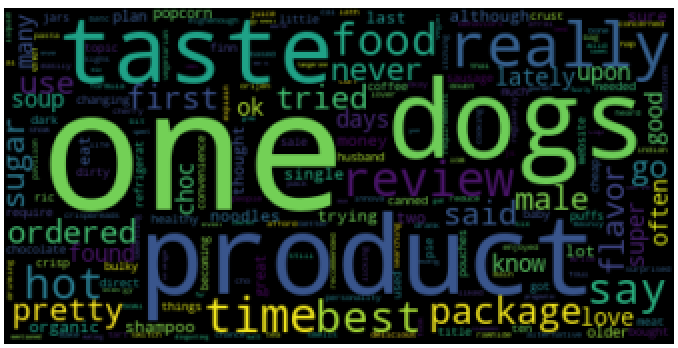
wordcloud of cluster: 0



wordcloud of cluster: 1

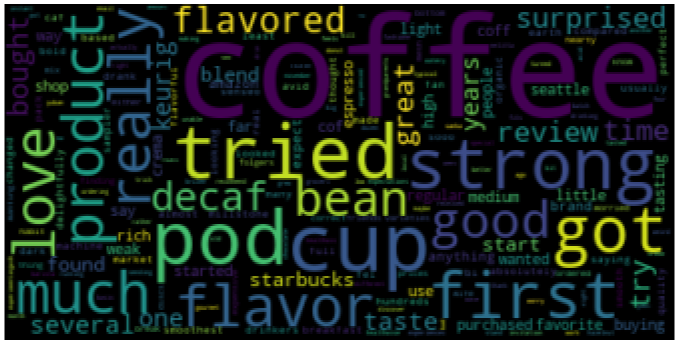


wordcloud of cluster: 2



wordcloud of cluster: 3

wordcloud of cluster: 4

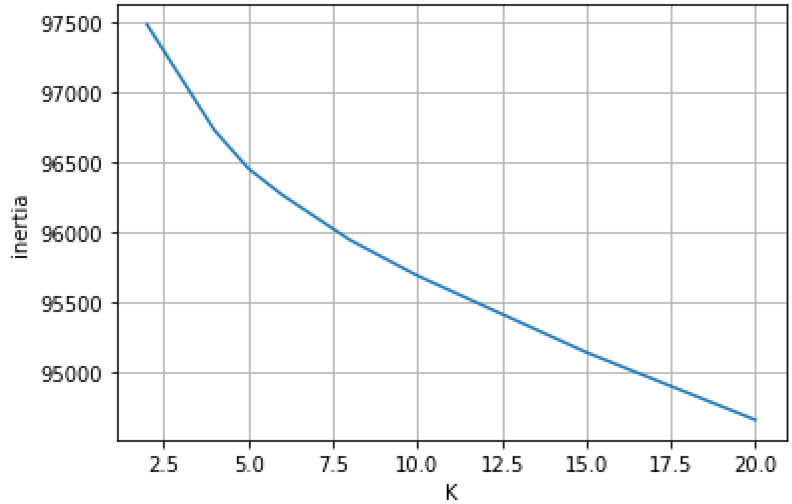


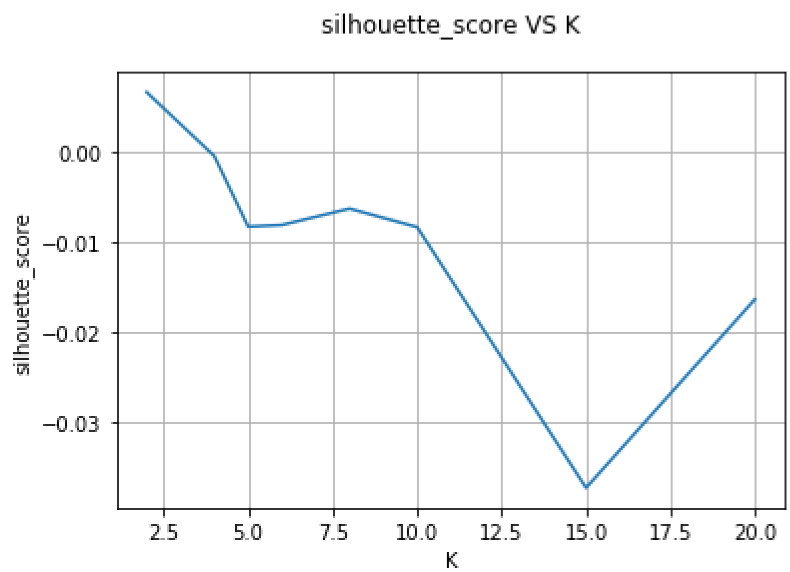
[5.1.3] Applying K-Means Clustering on TFIDF, SET 2

In [3]:
```
# removing all the reviews with no text
x_train=pd.DataFrame(x_train)
x_train=x_train[(x_train[0].apply(lambda x : len(x)))>0]

# BOW of x_train(reviews)
tf=TfidfVectorizer()
train_tfidf=tf.fit_transform(x_train[0][:100000])
```

In [4]:
```
# using silhouette score
from sklearn.metrics import silhouette_score
# Choosing right K using elbow method
ss=[]
inertia=[]
k=[2,4,5,6,8,10,15,20]

for i in k:
    km=KMeans(n_clusters=i,
                        init='k-means++',
                        n_init=10,
                        n_jobs=-2)
    km.fit(train_tfidf[:100000])
    inertia.append(round(km.inertia_,3))
    ss.append(silhouette_score(train_tf_idf[:100000],km.predict
(train_tfidf[:100000])))

#ploting
plt.plot(k,inertia)
plt.title("interta VS K\n")
plt.xlabel("K")
plt.ylabel("inertia")
plt.grid()
plt.show()

plt.plot(k,ss)
plt.title("silhouette_score VS K\n")
plt.xlabel("K")
plt.ylabel("silhouette_score")
plt.grid()
plt.show()
```

interta VS K





Elbow or knee point is at k=5

In [41]:
```
# clustering using right K
k=5
km=KMeans(n_clusters=k,
                     init='k-means++',
                     n_jobs=-2)
predict=km.fit_predict(train_tfidf[:100000])
```

In [42]:
```
(round(km.inertia_,3))
```

```
96457.159
```

[5.1.4] Wordclouds of clusters obtained after applying k-means on TFIDF SET 2

In [43]:
```
# giving datapoints which is closest to k centroid
# Reason i am choosing consine distace because of high dimensio
n which cause curse of dimentionality
closest, _ = pairwise_distances_argmin_min(km.cluster_centers_,
train_tfidf[:100000],metric='cosine')
closest
```

```
array([83198, 69666, 99692, 36626, 59436], dtype=int64)
```

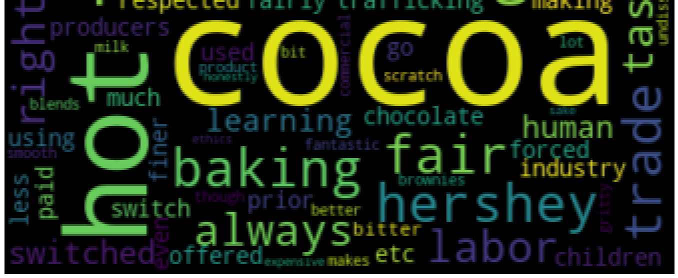
a. word cloud of k_cenroids

```
In [53]: # word cloud of k_cenroids
from wordcloud import WordCloud

for idx,closest_pt in enumerate(closest):
    text=(x_train[closest_pt])

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {idx} \n")
    plt.axis("off")
    plt.show()
```

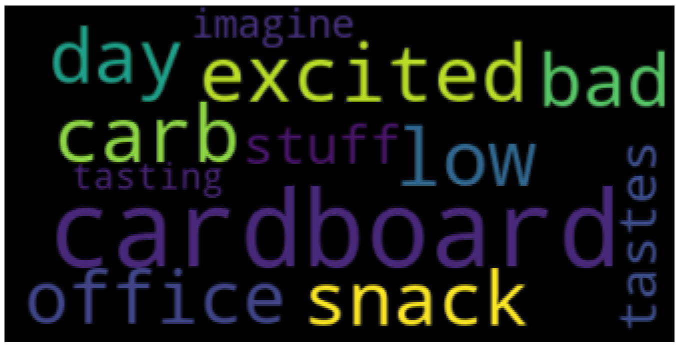
wordcloud of cluster: 0

wordcloud of cluster: 1

wordcloud of cluster: 2



wordcloud of cluster: 3



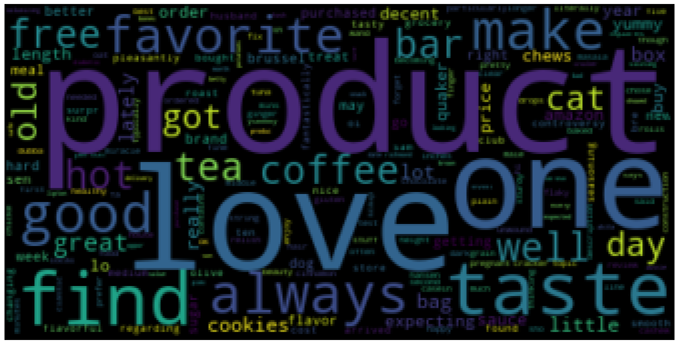
wordcloud of cluster: 4

b. word cloud of each cluster

```
In [52]: # word cloud of each cluster
for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {i} \n")
```

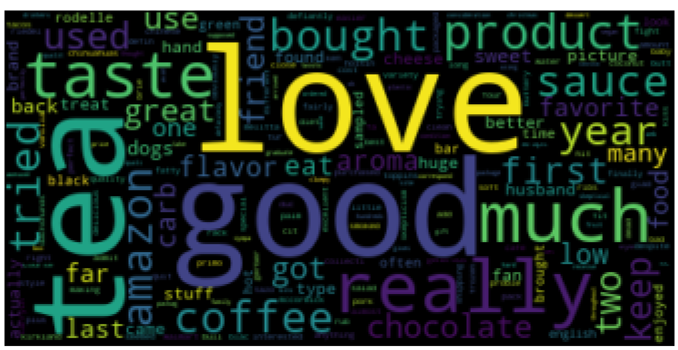
```
    plt.axis("off")
    plt.show()
```

wordcloud of cluster: 0

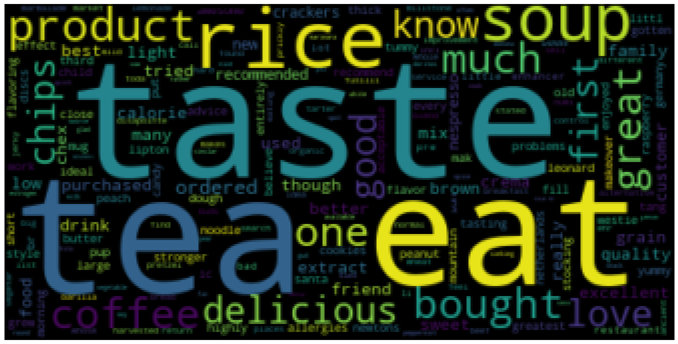


wordcloud of cluster: 1

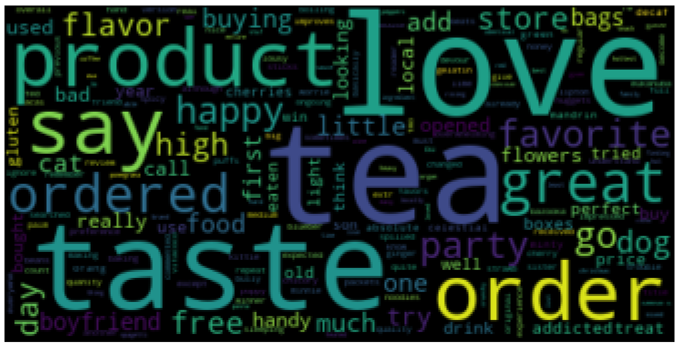
wordcloud of cluster: 2



wordcloud of cluster: 3



wordcloud of cluster: 4

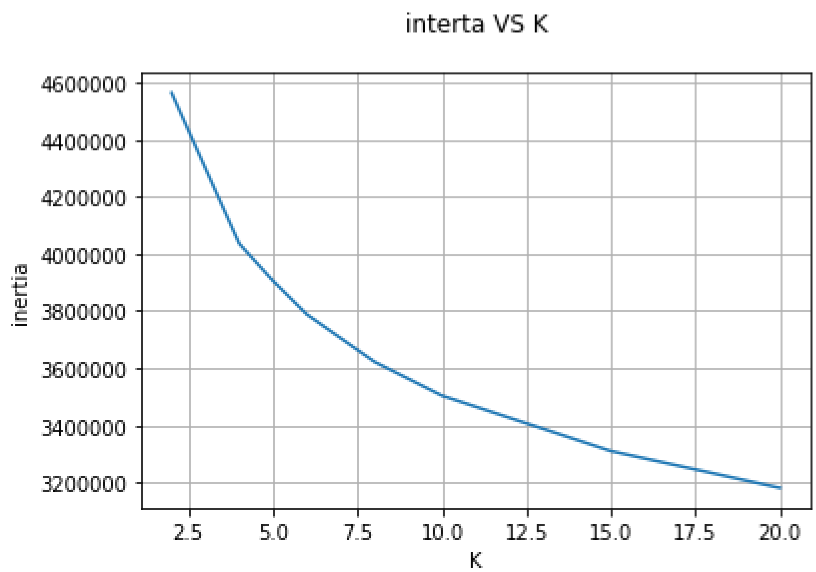


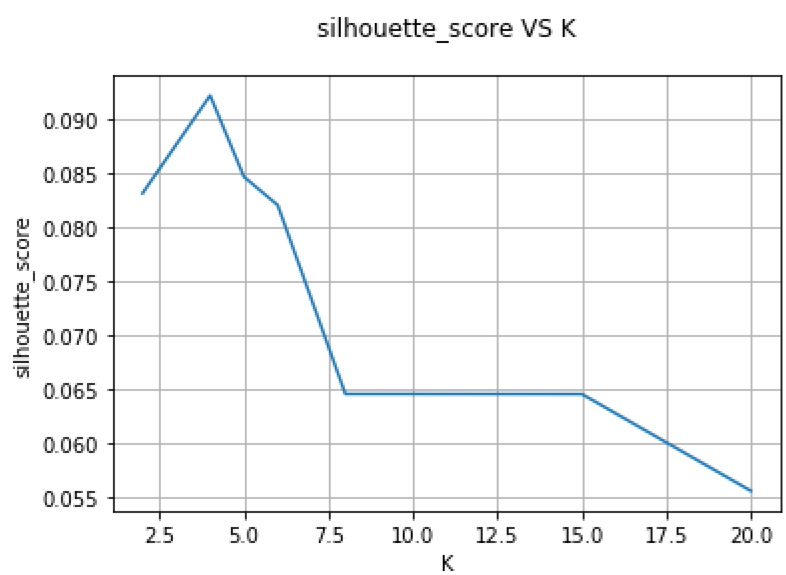
[5.1.5] Applying K-Means Clustering on AVG W2V, SET 3

In [59]:

```
# using silhouette score
from sklearn.metrics import silhouette_score
# Choosing right K using elbow method
ss=[]
inertia=[]
k=[2,4,5,6,8,10,15,20]

for i in k:
    km=KMeans(n_clusters=i,
                        init='k-means++',
                        n_init=10,
                        n_jobs=-2)
    km.fit(train_w2v[:100000])
    inertia.append(round(km.inertia_,3))
    ss.append(silhouette_score(train_w2v[:100000],km.predict(tr
ain_w2v[:100000])))

# ploting
plt.plot(k,inertia)
plt.title("interta VS K\n")
plt.xlabel("K")
plt.ylabel("inertia")
```

```
plt.grid()
plt.show()

plt.plot(k,ss)
plt.title("silhouette_score VS K\n")
plt.xlabel("K")
plt.ylabel("silhouette_score")
plt.grid()
plt.show()
```





Elbow or knee point is at k=4

In [77]:
```
# clustering using optimal K
k=4
km=KMeans(n_clusters=k,
                    init='k-means++',
                    n_jobs=-2)
predict=km.fit_predict(train_w2v[:100000])

(round(km.inertia_,3))
```

```
4035882.246
```

[5.1.6] Wordclouds of clusters obtained after applying k-means on AVG W2V SET 3

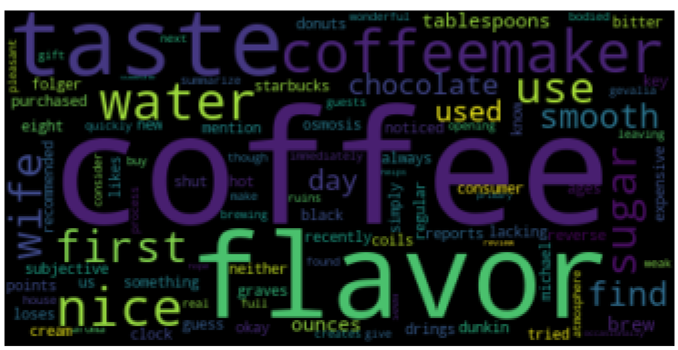
```
In [95]: # giving datapoints which is closest to k centroid
         closest, _ = pairwise_distances_argmin_min(km.cluster_centers_,
         train_w2v)
         closest
```

```
array([147132, 161268,  73895, 200115], dtype=int64)
```

a. word cloud of k_cenroids

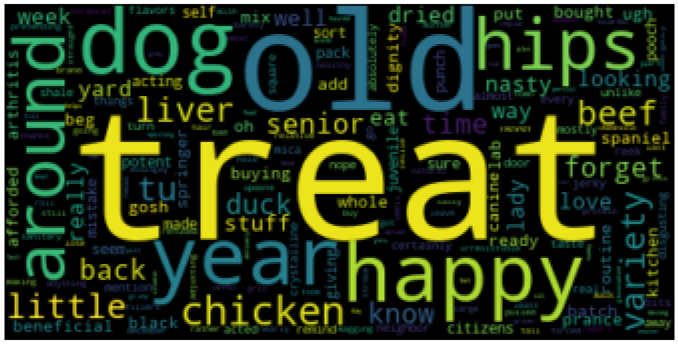
```
In [99]: # word cloud of k_cenroids
         from wordcloud import WordCloud

         for idx,closest_pt in enumerate(closest):
             text=(x_train[closest_pt])

             # Create and generate a word cloud image:
             wordcloud = WordCloud().generate(str(text))

             # Display the generated image:
             plt.imshow(wordcloud, interpolation='bilinear')
             plt.title(f"wordcloud of cluster: {idx} \n")
             plt.axis("off")
             plt.show()
```

wordcloud of cluster: 0



wordcloud of cluster: 1

wordcloud of cluster: 2

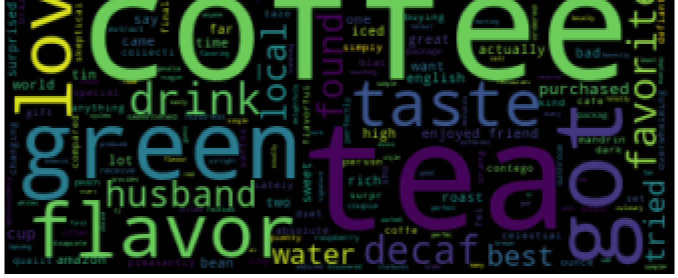


wordcloud of cluster: 3

b. word cloud of each cluster

In [101]:
```python
# word cloud of each cluster
for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {i} \n")
    plt.axis("off")
    plt.show()
```

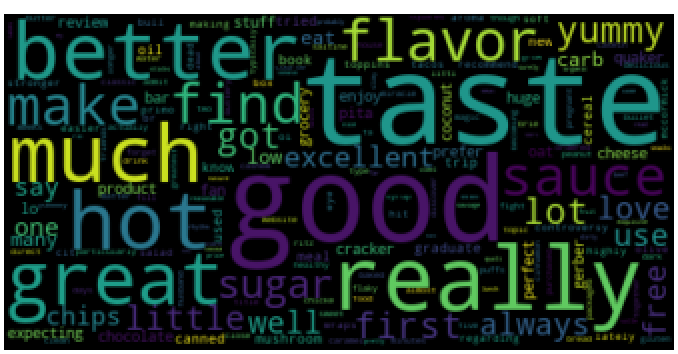
wordcloud of cluster: 0



wordcloud of cluster: 1

wordcloud of cluster: 2

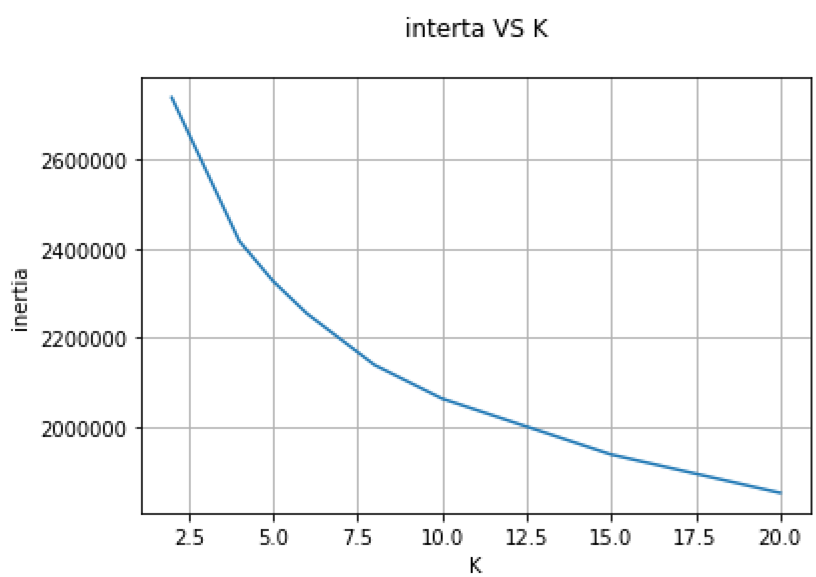
wordcloud of cluster: 3



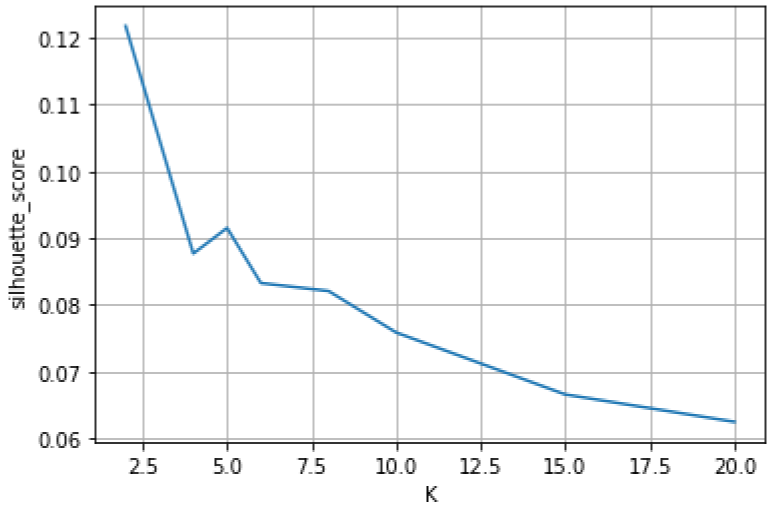
[5.1.7] Applying K-Means Clustering on TFIDF W2V, SET 4

```
In [104]: # using silhouette score
```

```
from sklearn.metrics import silhouette_score
# Choosing right K using elbow method
ss=[]
inertia=[]
k=[2,4,5,6,8,10,15,20]

for i in k:
    km=KMeans(n_clusters=i,
                        init='k-means++',
                        n_init=10,
                        n_jobs=-2)
    km.fit(train_tf_idf_w2v[:100000])
    inertia.append(round(km.inertia_,3))
    ss.append(silhouette_score(train_tf_idf_w2v[:100000],km.pre
dict(train_tf_idf_w2v[:100000])))


plt.plot(k,inertia)
plt.title("interta VS K\n")
plt.xlabel("K")
plt.ylabel("inertia")
plt.grid()
plt.show()

plt.plot(k,ss)
plt.title("silhouette_score VS K\n")
plt.xlabel("K")
plt.ylabel("silhouette_score")
plt.grid()
plt.show()
```



silhouette_score VS K



Elbow or knee point is at k=4

In [105]:
```
# clustering using right K
k=4
km=KMeans(n_clusters=k,
                    init='k-means++',
                    n_jobs=-2)
km.fit(train_tf_idf_w2v[:100000])

(round(km.inertia_,3))
```

```
2417368.286
```

[5.1.8] Wordclouds of clusters obtained after applying k-means on TFIDF W2V SET 4

In [106]:
```
# giving datapoints which is closest to k centroid
closest, _ = pairwise_distances_argmin_min(km.cluster_centers_,
train_tf_idf_w2v[:100000])
closest
```

```
array([59666, 19999, 44717,  8096], dtype=int64)
```

a. word cloud of k_cenroids

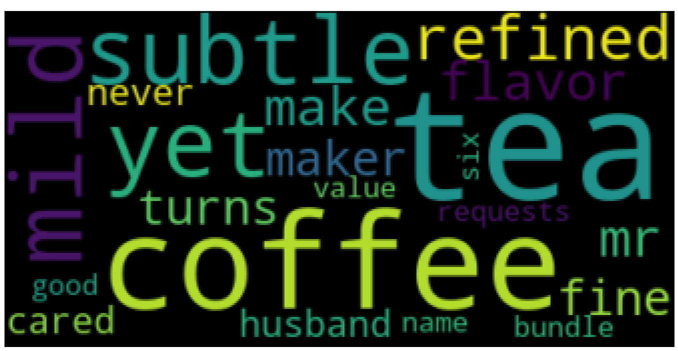
In [107]:
```
# word cloud of k_cenroids
from wordcloud import WordCloud

for idx,closest_pt in enumerate(closest):
    text=(x_train[closest_pt])

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
```

```
    plt.title(f"wordcloud of cluster: {idx} \n")
    plt.axis("off")
    plt.show()
```

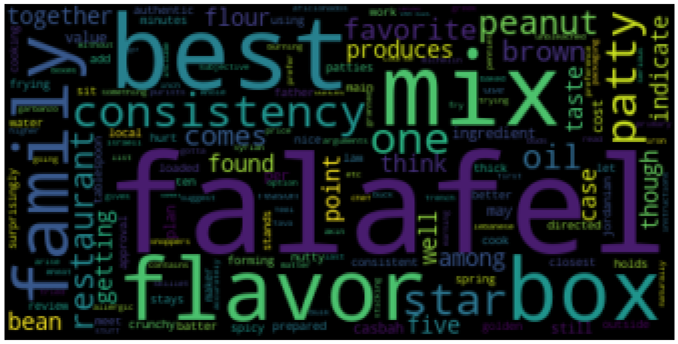
wordcloud of cluster: 0

wordcloud of cluster: 1

wordcloud of cluster: 2



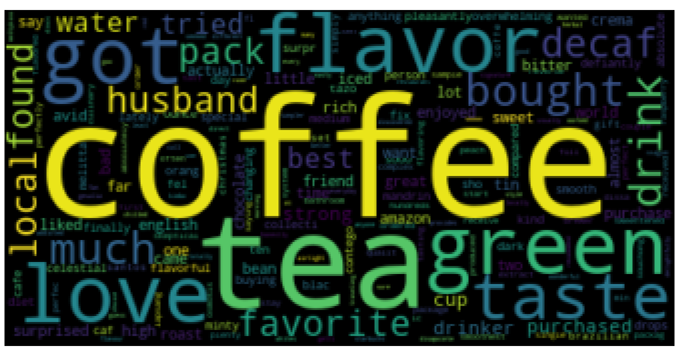
wordcloud of cluster: 3



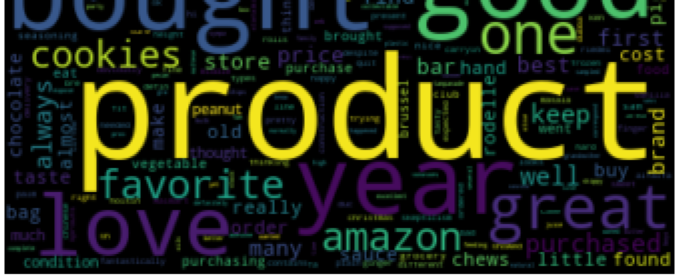
b. word cloud of each cluster

```
In [108]: # word cloud of each cluster
for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {i} \n")
    plt.axis("off")
    plt.show()
```

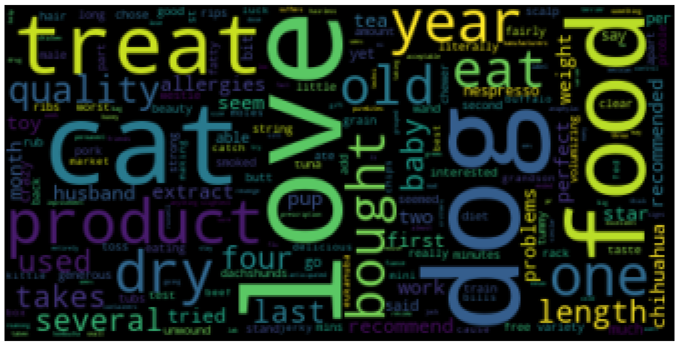
wordcloud of cluster: 0



wordcloud of cluster: 1



wordcloud of cluster: 2

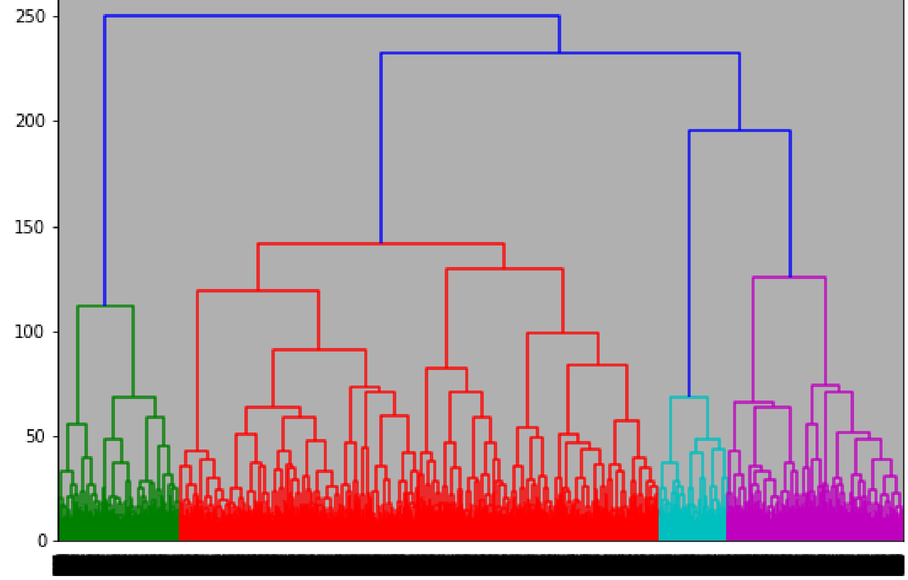


wordcloud of cluster: 3

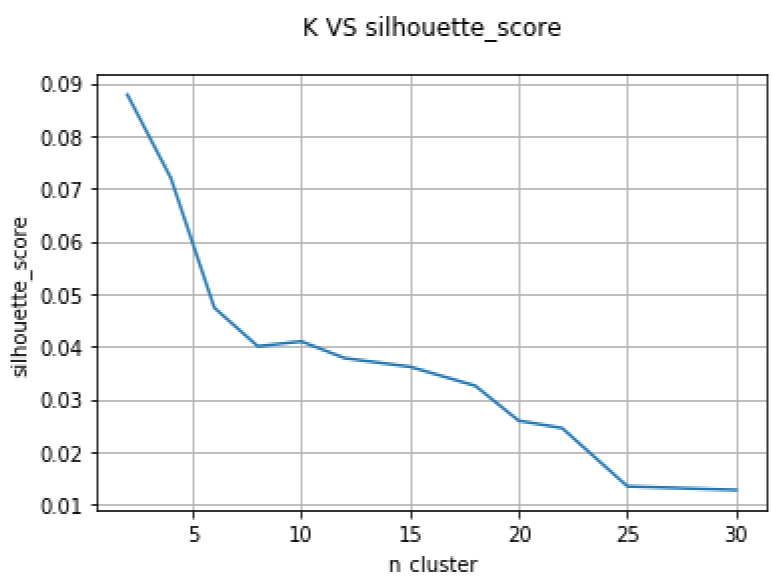
[5.2] Agglomerative Clustering

[5.2.1] Applying Agglomerative Clustering on AVG W2V, SET 3

In [99]:
```
from scipy.cluster.hierarchy import dendrogram, linkage

Z = linkage(train_w2v[:10000],'ward')

plt.figure(figsize=(9,6))
dendrogram(Z,)
plt.grid()
plt.show()
```

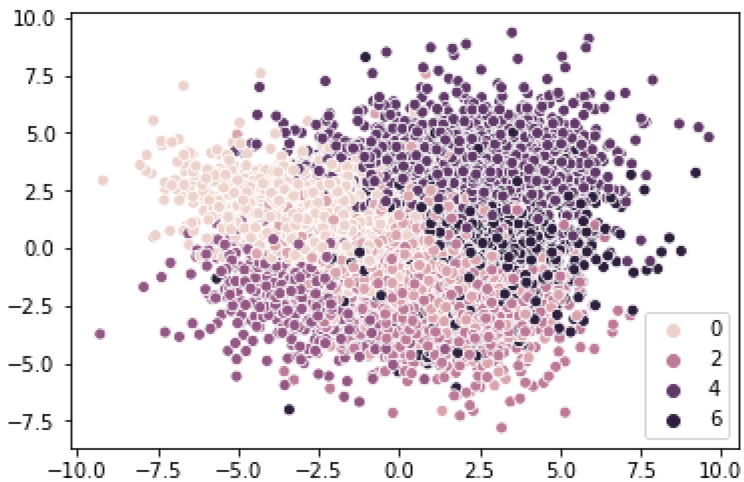



```
In [109]: # using silhouette score
from sklearn.metrics import silhouette_score
# Choosing right K using elbow method

k=[2,4,6,8,10,12,15,18,20,22,25,30]
ss=[]
for i in k:
    agg_clust=AgglomerativeClustering(n_clusters=i,linkage='war
d')
    p=agg_clust.fit_predict(train_w2v[:10000])
    ss.append(silhouette_score(train_w2v[:10000],p))

plt.plot(k,ss)
plt.grid()
plt.title("K VS silhouette_score\n ")
plt.xlabel("n_cluster")
plt.ylabel("silhouette_score")
plt.show()
```




```
In [110]: # optimal k=6
agg_clust=AgglomerativeClustering(n_clusters=6)
predict=agg_clust.fit_predict(train_w2v[:10000])

# visualising clusters
```

```python
from sklearn.decomposition import TruncatedSVD
svd=TruncatedSVD(n_components=2)
svd_transform=svd.fit_transform(train_w2v[:10000])
sns.scatterplot(svd_transform[:,0],svd_transform[:,1],hue=predi
ct)
plt.show()
```



[5.2.2] Wordclouds of clusters obtained after applying Agglomerative Clustering on AVG W2V SET 3

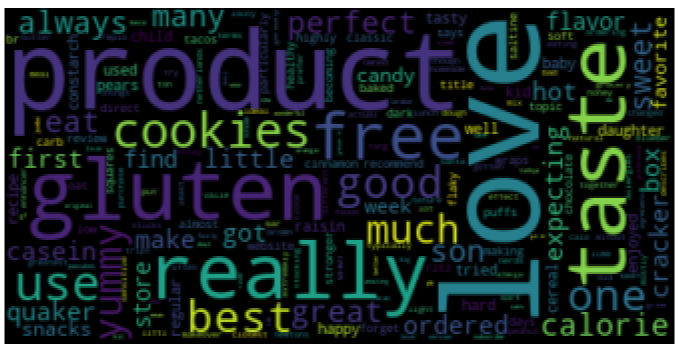
a. word cloud of each cluster

```python
In [111]: # word cloud of each cluster
for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {i} \n")
    plt.axis("off")
    plt.show()
```

wordcloud of cluster: 0

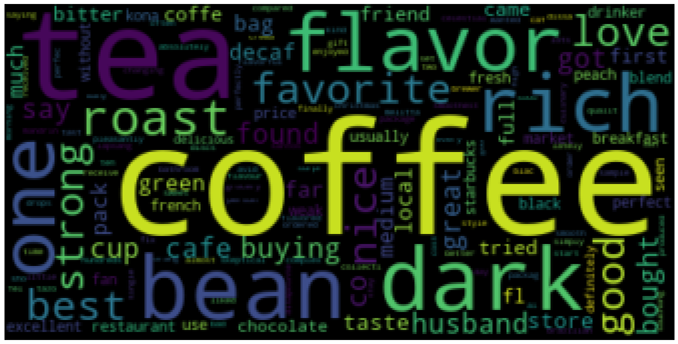
wordcloud of cluster: 1

wordcloud of cluster: 2



wordcloud of cluster: 3

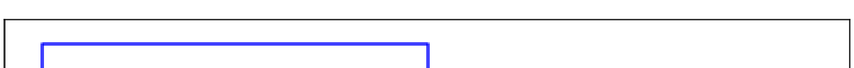
wordcloud of cluster: 4

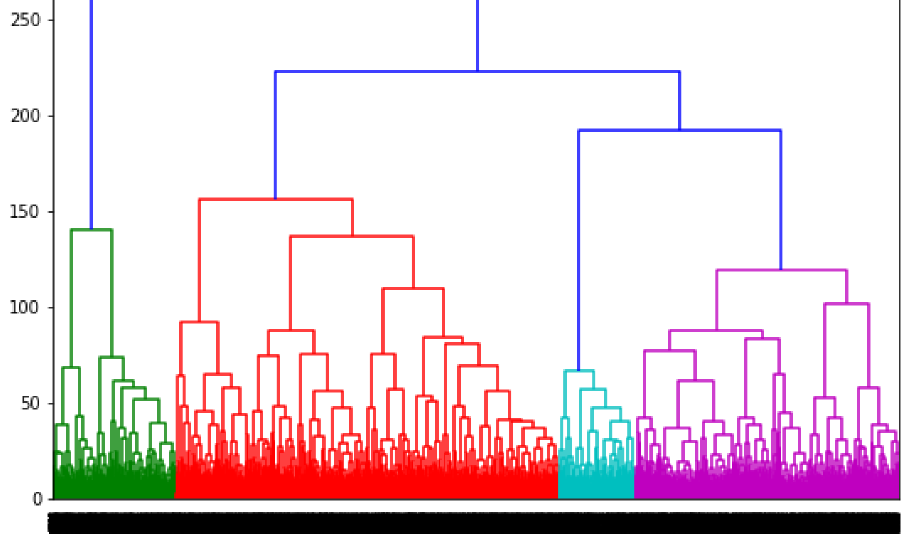


wordcloud of cluster: 5

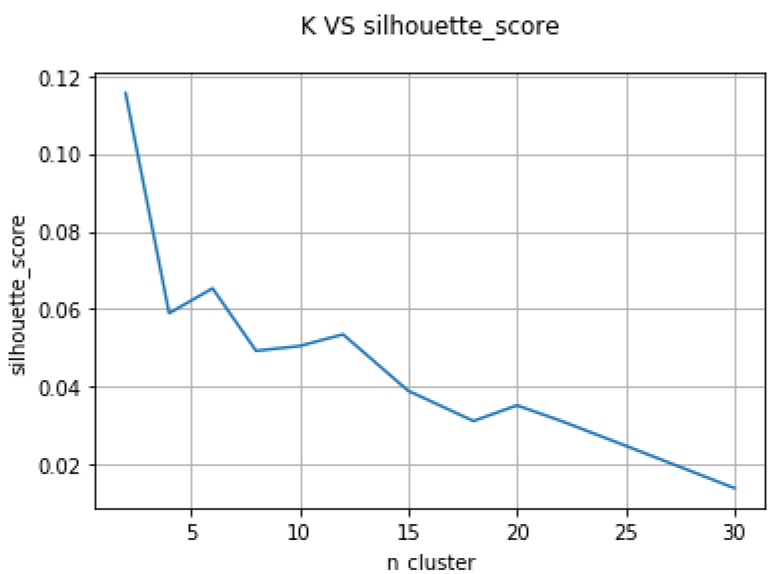
[5.2.3] Applying Agglomerative Clustering on TFIDF W2V, SET 4

In [100]:
```
from scipy.cluster.hierarchy import dendrogram, linkage

Z = linkage(train_tf_idf_w2v[:10000],'ward')

plt.figure(figsize=(9,6))
dendrogram(Z,)
plt.show()
```



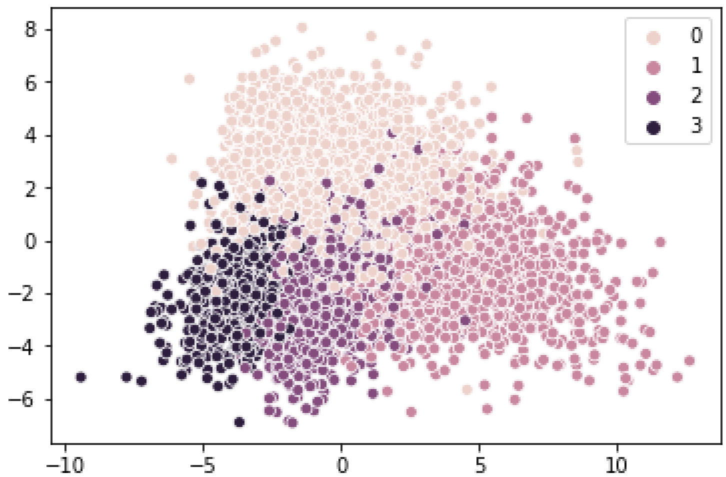


In [112]:
```
# using silhouette score
from sklearn.metrics import silhouette_score
# Choosing right K using elbow method

k=[2,4,6,8,10,12,15,18,20,22,25,30]
ss=[]
for i in k:
    agg_clust=AgglomerativeClustering(n_clusters=i,linkage='war
d')
    p=agg_clust.fit_predict(train_tf_idf_w2v[:10000])
    ss.append(silhouette_score(train_tf_idf_w2v[:10000],p))

plt.plot(k,ss)
plt.grid()
plt.title("K VS silhouette_score\n ")
plt.xlabel("n_cluster")
plt.ylabel("silhouette_score")
plt.show()
```



In [113]:
```
# optimal k=4
agg_clust=AgglomerativeClustering(n_clusters=4)
predict=agg_clust.fit_predict(train_tf_idf_w2v[:10000])

# visualising clusters
from sklearn.decomposition import TruncatedSVD
```

```
svd=TruncatedSVD(n_components=2)
svd_transform=svd.fit_transform(train_tf_idf_w2v[:10000])
sns.scatterplot(svd_transform[:,0],svd_transform[:,1],hue=predi
ct)
plt.show()
```



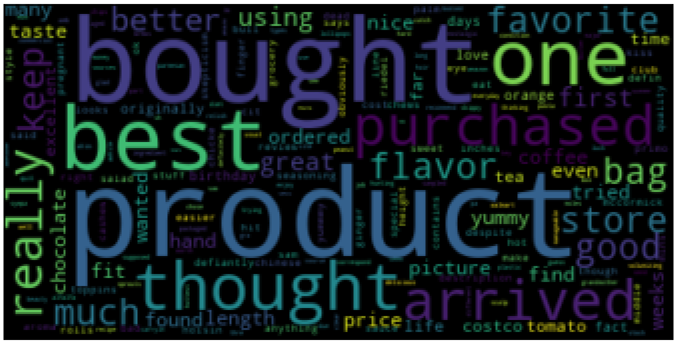
[5.2.4] Wordclouds of clusters obtained after applying Agglomerative Clustering on TFIDF W2V SET 4

```
In [114]: # word cloud of each cluster
for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {i} \n")
    plt.axis("off")
    plt.show()
```

wordcloud of cluster: 0

wordcloud of cluster: 1

wordcloud of cluster: 2



wordcloud of cluster: 3

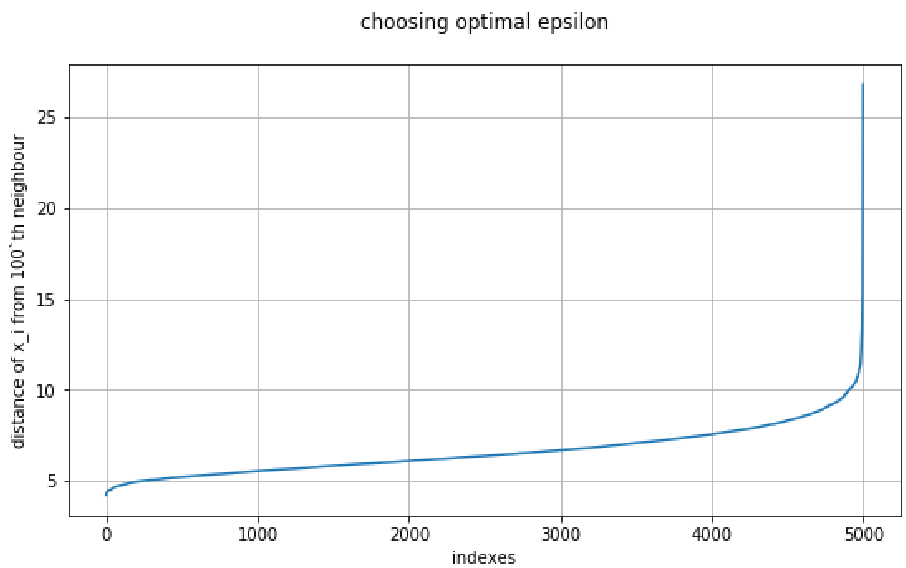
[5.3] DBSCAN Clustering

[5.3.1] Applying DBSCAN on AVG W2V, SET 3

choosing correct epsilon and min_pts using elbow method

In [104]:
```
from sklearn.neighbors import NearestNeighbors

min_pts = train_w2v.shape[1]*2   # optimal number of min_pts

nn=NearestNeighbors(n_neighbors=min_pts,n_jobs=-2)
nn.fit(train_w2v[:5000])
neighbours=nn.kneighbors(X=train_w2v[:5000], n_neighbors=min_pts
, return_distance=True)
```

```
# choosing correct epsilon and min_pts using
d_i=[]
for i in (range(0,len(train_w2v[:5000]))):
    d_i.append(neighours[0][i][99])
d_i.sort()

plt.figure(figsize=(9,5))
plt.title("choosing optimal epsilon\n")
plt.xlabel("indexes")
plt.ylabel("distance of x_i from 100`th neighbour")
plt.plot(range(0,len(d_i)),d_i)
plt.grid()
plt.show()
```



Optimal hyperparameter:

min_pts=100

epsilon=10

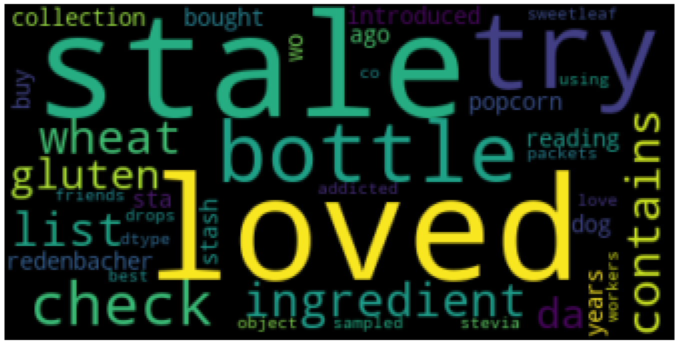
In [111]:
```
from sklearn.cluster import DBSCAN

optimum_epsilon=10
db_scan=DBSCAN(eps=optimum_epsilon,
    min_samples=min_pts,
    metric='euclidean',
    n_jobs=-2)
predict=db_scan.fit_predict(train_w2v[:10000])
```

[5.3.2] Wordclouds of clusters obtained after applying DBSCAN on AVG W2V SET 3

In [113]:
```
for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
```

```python
    plt.title(f"wordcloud of cluster: {i} \n")
    plt.axis("off")
    plt.show()
```

wordcloud of cluster: -1



wordcloud of cluster: 0

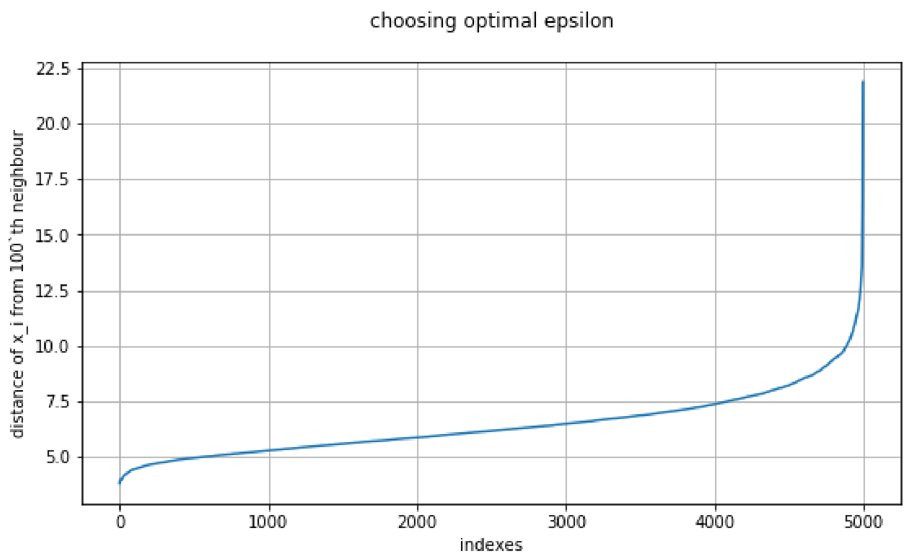
[5.3.3] Applying DBSCAN on TFIDF W2V, SET 4

choosing correct epsilon and min_pts using elbow method

In [115]:

```python
from sklearn.neighbors import NearestNeighbors

min_pts = train_tf_idf_w2v.shape[1]*2  # optimal number of min_
pts

nn=NearestNeighbors(n_neighbors=min_pts,n_jobs=-2)
nn.fit(train_tf_idf_w2v[:5000])
neighours=nn.kneighbors(X=train_tf_idf_w2v[:5000], n_neighbors=
min_pts, return_distance=True)

# choosing correct epsilon and min_pts
d_i=[]
for i in (range(0,len(train_tf_idf_w2v[:5000]))):
    d_i.append(neighours[0][i][99])
d_i.sort()

plt.figure(figsize=(9,5))
plt.title("choosing optimal epsilon\n")
plt.xlabel("indexes")
plt.ylabel("distance of x_i from 100`th neighbour")
plt.plot(range(0,len(d_i)),d_i)
```

```
plt.grid()
plt.show()
```



Optimal hyperparameter:

min_pts=100

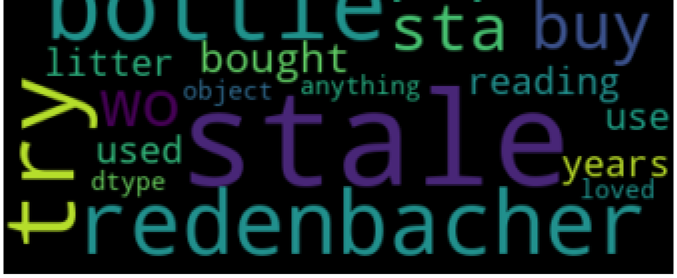
epsilon=10

```
In [116]: from sklearn.cluster import DBSCAN

optimum_epsilon=10
db_scan=DBSCAN(eps=optimum_epsilon,
    min_samples=min_pts,
    metric='euclidean',
    n_jobs=-2)
predict=db_scan.fit_predict(train_tf_idf_w2v[:10000])
```

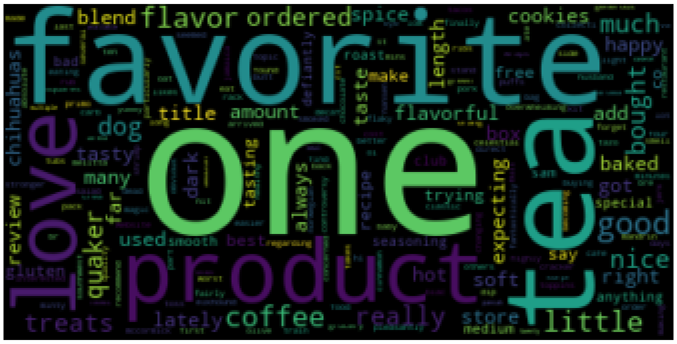
[5.3.4] Wordclouds of clusters obtained after applying DBSCAN on TFIDF W2V SET 4

```
In [118]: for i in np.unique(predict):
    text=pd.Series(x_train).iloc[np.argwhere(predict==i).ravel
()]

    # Create and generate a word cloud image:
    wordcloud = WordCloud().generate(str(text))

    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f"wordcloud of cluster: {i} \n")
    plt.axis("off")
    plt.show()
```

wordcloud of cluster: -1



wordcloud of cluster: 0



[6] Conclusions

```
In [39]: # Please compare all your models using Prettytable library
from prettytable import PrettyTable

print("*"*100)
print(" Model: K_mean")
x = PrettyTable()
x.field_names = ["featurization", "optimum_ckuster:K"]
x.add_row(["BOW", 5])
x.add_row(["TF-IDF", 5])
x.add_row([" W2V", 4])
x.add_row([" TF-IDF W2V", 4])
print(x)


print("\n","*"*100)
print(" Model: Hierarchical - Agglomerative")
print(" *note: Only 5k datapoints are used")
x = PrettyTable()
x.field_names = ["featurization", "optimum_ckuster:K"]
x.add_row([" W2V", 6])
x.add_row([" TF-IDF W2V", 4])
print(x)


print("\n","*"*100)
print(" Model: DBSCAN")
print(" *note: Only 5k datapoints are used")
x = PrettyTable()
x.field_names = ["featurization", "optimum_ckuster:K"]
x.add_row([" W2V", 2])
x.add_row([" TF-IDF W2V", 2])
print(x)
```

```
****************************************************************************************************
 Model: K_mean
+----------------+--------------------+
| featurization | optimum_ckuster:K |
+----------------+--------------------+
|      BOW       |         5          |
|     TF-IDF     |         5          |
|      W2V       |         4          |
|   TF-IDF W2V   |         4          |
+----------------+--------------------+

 ****************************************************************************************************
 Model: Hierarchical - Agglomerative
 *note: Only 5k datapoints are used
+----------------+--------------------+
| featurization | optimum_ckuster:K |
+----------------+--------------------+
|      W2V       |         6          |
|   TF-IDF W2V   |         4          |
+----------------+--------------------+

 ****************************************************************************************************
 Model: DBSCAN
 *note: Only 5k datapoints are used
+----------------+--------------------+
| featurization | optimum_ckuster:K |
+----------------+--------------------+
|      W2V       |         2          |
|   TF-IDF W2V   |         2          |
+----------------+--------------------+
```

1. Feature interpretation given by K_mean cluster is better than other in terms of interpretabilty.

1. K_mean and Agglomerative cluster seems to work better than DBSCAN (may be because of using very less datapoint)