Kmeans, Agglomerative, DBSCAN

```
In [1]: #to ignore warnings
        import warnings
        warnings.filterwarnings("ignore")
        #to use salite3 database
        import sqlite3
        import numpy as np
        import pandas as pd
        import string
        import nltk
        import matplotlib.pyplot as plt
        from nltk.stem.porter import PorterStemmer
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        import re
        from sklearn.feature extraction.text import CountVectorizer
        from sklearn import cross validation
        from sklearn.cross validation import cross val score
        from sklearn.feature extraction.text import TfidfTransformer
        from sklearn.feature extraction.text import TfidfVectorizer
        C:\Users\krush\Anaconda3\lib\site-packages\sklearn\cross validation.py:
        41: DeprecationWarning: This module was deprecated in version 0.18 in f
        avor of the model selection module into which all the refactored classe
        s and functions are moved. Also note that the interface of the new CV i
        terators are different from that of this module. This module will be re
        moved in 0.20.
          "This module will be removed in 0.20.", DeprecationWarning)
```

PREPROCESSING

```
In [2]: con = sqlite3.connect('database.sqlite')
        filtered data = pd.read sql query(""" SELECT * FROM Reviews WHERE Score
         != 3 """, con)
        # Give reviews with Score>3 a positive rating, and reviews with a score
        <3 a negative rating.</pre>
        def partition(x):
            if x < 3:
                return 0
            return 1
        #changing reviews with score less than 3 to be positive and vice-versa
        actualScore = filtered data['Score']
        positiveNegative = actualScore.map(partition)
        filtered data['Score'] = positiveNegative
In [3]: stop = set(stopwords.words('english')) #set of stopwords
        sno = nltk.stem.SnowballStemmer('english') #initialising the snowball s
        temmer
        def cleanhtml(sentence): #function to clean the word of any html-tags
            cleanr = re.compile('<.*?>')
            cleantext = re.sub(cleanr, ' ', sentence)
            return cleantext
        def cleanpunc(sentence): #function to clean the word of any punctuation
         or special characters
            cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
            cleaned = re.sub(r'[.],|)|(||/|)',r'',cleaned)
            return cleaned
In [4]: #Code for implementing step-by-step the checks mentioned in the pre-pro
        cessing phase
        # this code takes a while to run as it needs to run on 500k sentences.
        i=0
        str1=' '
```

```
final string=[]
all positive words=[] # store words from +ve reviews here
all negative words=[] # store words from -ve reviews here.
S=11
for sent in filtered data['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 (filtered data['Score'].values)[i] == 'positive'
                       all positive words.append(s) #list of all words
used to describe positive reviews
                   if(filtered data['Score'].values)[i] == 'negative':
                       all negative words.append(s) #list of all words
used to describe negative reviews reviews
                else:
                    continue
           else:
                continue
   #print(filtered sentence)
    str1 = b" ".join(filtered sentence) #final string of cleaned words
   #print("**
final string.append(str1)
    i+=1
```

```
In [5]: filtered_data['CleanedText']=final_string #adding a column of CleanedTe
    xt which displays the data after pre-processing of the review
    filtered_data['CleanedText']=filtered_data['CleanedText'].str.decode("u
    tf-8")
```

KMEANS FOR BOW, TF-IDF , AVG W2V, TFIDF-W2V

```
In [6]: sorted_data=filtered_data.sort_values(by=['Time'])
    sampledata = sorted_data.head(50000)

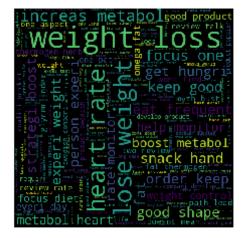
In [7]: count_vect = CountVectorizer(min_df=10) #in scikit-learn
    vec = count_vect.fit(sampledata['CleanedText'].values)
    X_vec = vec.transform(sampledata['CleanedText'].values)

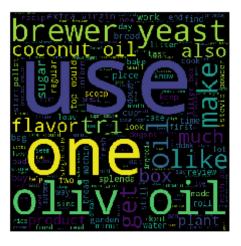
In [24]: from sklearn.cluster import KMeans
    K = [2,5,10,15,20,25,30,35,40,45,50]
    inertia = []
    for k in K:
        kmeans = KMeans(n_clusters=k, random_state=0).fit(X_vec)
        inertia.append(kmeans.inertia_)

In [40]: plt.plot(K,inertia)
    plt.ylabel('K')
    plt.ylabel('inertia')
    plt.show()
```

```
2600000
            2500000
          inertia
            2400000
            2300000
                          10
                                  20
                                          30
In [8]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=20, random_state=0).fit(X_vec)
In [9]: kmeans.labels
Out[9]: array([ 9,  9,  9, ..., 18,  6,  9])
In [11]: def againcleaning(X):
              comment words=' '
              for words in X:
                  comment words = comment words + words + ' '
              return comment words
         count=0
         review=sampledata['CleanedText'].values
         topn class1 = sorted(zip(kmeans.labels , review))
         feature =[]
         for coef, feat in topn class1:
                  if coef == count:
                      feature.append(feat)
                  else:
                      a=againcleaning(feature)
                      print(" cluster =", count)
```

```
from wordcloud import WordCloud, STOPWORDS
            import matplotlib.pyplot as plt
            word cloud=WordCloud(background color='black', stopwords=sto
p,width=500,height=500).generate(a)
            plt.imshow(word cloud)
            plt.axis("off")
            plt.show()
            count = count + 1
            feature =[]
            feature.append(feat)
#for\ label = 19
a=againcleaning(feature)
print(" cluster =", count)
#print(a, " " , count)
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
word cloud=WordCloud(background color='black', stopwords=stop, width=500,
height=500).generate(a)
plt.imshow(word cloud)
plt.axis("off")
plt.show()
```





cluster = 2



cluster = 3

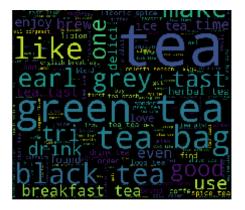


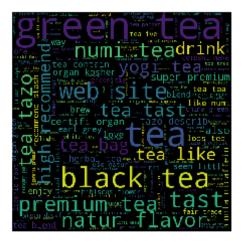














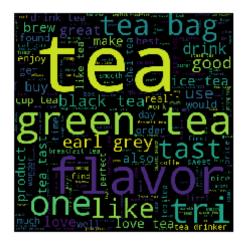








cluster = 12

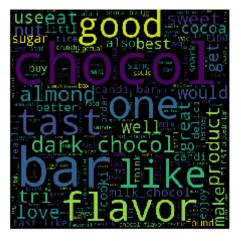


cluster = 13

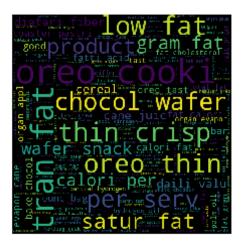




cluster = 14



cluster = 15

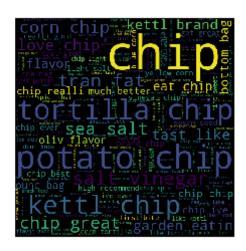




cluster = 17



cluster = 18





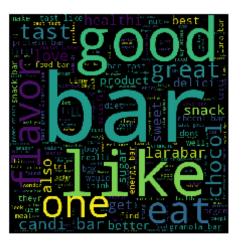


In [97]:	print(x)
	+
	CLUSTER OBSERVATION
	+
	+
	0 Cluster - 0 talks about all the health re lated things, here in word cloud we can see heart rate , metabolism, we ight loss etc
	Cluster 1 talks about all the food item names like cocunut oil , olive oil , sugar , scoop etc
	2 This cluster mainly contains natural ingredients like quinoa and saponin
	This cluster contains all the reviews which contain the word food
	4 This cluster c ontains all the reviews which tell the product experience
	5 This cluster co ntains all negative points like dont kill trap etc
	LIKE , GOOD , LO VE , FLAVOUR ALL This type of reviews are in this cluster
	7 This contain type and taste of the tea like green tea, black tea, grey , etc

8 Even this contain about the taste of tea , as well as the colour it contains some words like , highly recommond etc	
9 I Think cluster 9 and cluster 6 are more similar	
This contains state of the product as it is liquid and soda type cool , fizz etc	
11 Duplicate of 8	
12 Duplicate of 7,8	
13 It contains all the reviews which contains a word cat mostly	
14 ALL the food items reviews are here, like almond , chocol	
15 here we have all the reviews stating the fat present in the product like low fat, satur fat etc and also about items like oreo and also reviews of size thin etc	
16 This is like , highly positive review love, like drink etc	
17 Even this is something about taste of the product , like chewing etc	
This contain ns all the reviews ,which contain the word chip in it	
19 T his is again same like highly positive review	
 ++	

```
In [12]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df=10)
         tf idf vect1 = TfidfVectorizer(ngram range=(1,2))
         final_tf_idf = tf_idf_vect.fit(sampledata['CleanedText'].values)
         final tf idf1 = tf idf vect1.fit(sampledata['CleanedText'].values)
In [13]: X tf idf = final tf idf.transform(sampledata['CleanedText'].values)
In [44]: from sklearn.cluster import KMeans
         K = [2,5,10,15,20,25,30,35,40,45,50]
         inertia = []
         for k in K:
              kmeans = KMeans(n_clusters=k, random_state=0).fit(X_tf_idf)
             inertia.append(kmeans.inertia )
In [45]: plt.plot(K,inertia)
         plt.xlabel('K')
         plt.ylabel('inertia')
         plt.show()
            49000
            48750
            48500
            48250
            48000
            47750
            47500
            47250
            47000
                        10
                                20
                                        30
                                                40
                                                        50
                                     Κ
```

```
In [14]: kmeans = KMeans(n clusters=20, random state=0).fit(X tf idf)
In [15]: count=0
         reviews=sampledata['CleanedText'].values
         topn class1 = sorted(zip(kmeans.labels , reviews))
         feature =[]
         for coef, feat in topn class1:
                 if coef == count:
                     feature.append(feat)
                 else:
                     a=againcleaning(feature)
                     print(" cluster =", count)
                     from wordcloud import WordCloud, STOPWORDS
                     import matplotlib.pyplot as plt
                     word cloud=WordCloud(background color='black', stopwords=sto
         p,width=500,height=500).generate(a)
                     plt.imshow(word cloud)
                     plt.axis("off")
                     plt.show()
                     count = count + 1
                     feature =[]
                     feature.append(feat)
         #for\ label = 19
         a=againcleaning(feature)
         print(" cluster =", count)
         #print(a, " " , count)
         from wordcloud import WordCloud, STOPWORDS
         import matplotlib.pyplot as plt
         word cloud=WordCloud(background color='black', stopwords=stop, width=500,
         height=500).generate(a)
         plt.imshow(word cloud)
         plt.axis("off")
         plt.show()
```



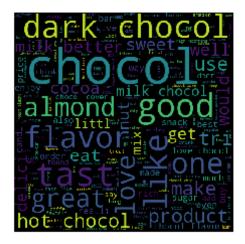
cluster = 1



cluster = 2

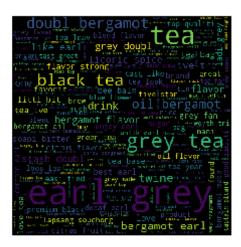
















cluster = 7



cluster = 8







cluster = 10

















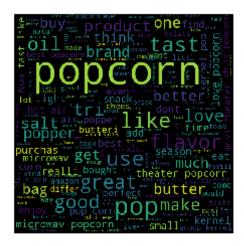
cluster = 15



cluster = 16



cluster = 17



cluster = 18



cluster = 19



Cluster-0,1,8,12,14,16 is all about positive reviews, where we have words like good, like etc, cluster-2 is about all the food items like cooki, chocol, chip, oreo etc.. cluster-3 is about the reviews with type of chocol used like dark chocol,hot chocol, and also about items like almond etc.. I think, cluster-4 is all about that it is also found in local store like we have local groceri, food store etc, cluster - 5 is all about the reviews with type of tea like grey tea, black tea etc.. cluster -6,7 is about the taste of the product which are positive.. cluster 9 is about the taste as well as the way the product is.. liquid, drink, fizz etc.. cluster 10, i think it has all the differentreviews as it is a mixture of all..cluster-11 are the reviews which compare it with coffee, cluster-13 is about shipping of amazon and the way it is shipped in box..cluster-15 is about, the reviews which contain the word chip in it ... like potato chip, love chip, tortilla chip..cluster-17 is about combination with the product -- popcorn, pop etc.. cluster 18 and 19 are about all the positive reviews and flavour

```
In [16]: from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
i=0
list_of_sent=[]
for sent in sampledata['CleanedText'].values:
    list_of_sent.append(sent.split())
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
In [17]: from tqdm import tqdm
```

```
import os
         sent vectors = []; # the avg-w2v for each sentence/review is stored in
          this list
         for sent in tqdm(list_of_sent): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             cnt words =0; # num of words with a valid vector in the sentence/re
         view
             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)
         100%|
                    50000/50000 [01:03<00:00, 790.02it/s]
In [52]: from sklearn.cluster import KMeans
         K = [2,5,10,15,20,25,30,35,40,45,50]
         inertia = []
         for k in K:
             kmeans = KMeans(n_clusters=k, random_state=0).fit(sent_vectors)
             inertia.append(kmeans.inertia )
In [53]: plt.plot(K,inertia)
         plt.xlabel('K')
         plt.ylabel('inertia')
         plt.show()
```

```
450000 - 425000 - 400000 - 375000 - 325000 - 300000 - 275000 - 250000 - 10 20 30 40 50 K
```

```
In [18]:
         kmeans1 = KMeans(n clusters=20, random state=0).fit(sent vectors)
In [19]:
         count=0
         reviews=sampledata['CleanedText'].values
         topn_class1 = sorted(zip(kmeans1.labels_, reviews))
         feature =[]
         for coef, feat in topn class1:
                 if coef == count:
                     feature.append(feat)
                 else:
                      a=againcleaning(feature)
                     print(" cluster =", count)
                     from wordcloud import WordCloud, STOPWORDS
                     import matplotlib.pyplot as plt
                     word cloud=WordCloud(background color='black', stopwords=sto
         p, width=500, height=500).generate(a)
                      plt.imshow(word cloud)
                     plt.axis("off")
                      plt.show()
                     count = count + 1
                     feature =[]
                     feature.append(feat)
```

```
#for label = 19
a=againcleaning(feature)
print(" cluster =", count)
#print(a, " " , count)
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
word_cloud=WordCloud(background_color='black',stopwords=stop,width=500,
height=500).generate(a)
plt.imshow(word_cloud)
plt.axis("off")
plt.show()
```













cluster = 6



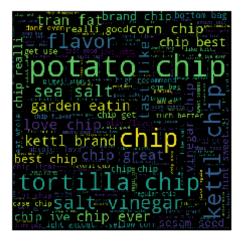
cluster = 7



cluster = 8



cluster = 9



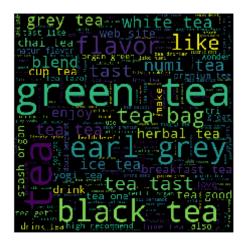
cluster = 10



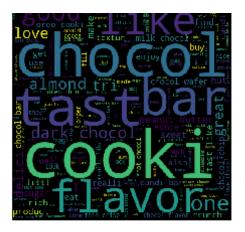
cluster = 11



cluster = 12



cluster = 13



cluster = 14

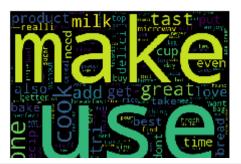


cluster = 15



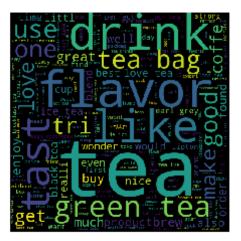












Cluster -0,2,5,6,10,11,12,14,15 It contains some of the food items reviews and and some positive Cluster-1,19 contains its state and also positive reviews..... Cluster - 3 contains about packing ..reviews about packing in bag box etc cluster - 4 is about price and the thing it says is that it is also available in local stores .. cluster - 7,8 contains all the reviews which specify animals and with word food and how to eat it.. cluster - 9 contains the word chip in it.. potato chip , kettl chip etc , cluster -11 contains reviews with type of tea, green tea , grey tea etc , cluster -13 contains all the items which are in it like chocol, cooki , almond etc cluster -16 is about delivery of the item... cluster 17 is about how to prepare like mix milk cook etc cluster-18 is comparing with coffee

```
In [20]: from tqdm import tqdm
         import os
         # TF-IDF weighted Word2Vec
         tfidf feat = tf idf vect.get feature names()
         dictionary = dict(zip(tf idf vect1.get feature names(), list(tf idf vec
         t1.idf )))# tfidf words/col-names
         # final tf idf is the sparse matrix with row= sentence, col=word and ce
         ll val = tfidf
         tfidf sent vectors = []; # the tfidf-w2v for each sentence/review is st
         ored in this list
         row=0;
         for sent in tqdm(list of sent): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             weight sum =0; # num of words with a valid vector in the sentence/r
         eview
             for word in sent: # for each word in a review/sentence
                 if word in w2v words:
                     vec = w2v model.wv[word]
                     # obtain the tf idfidf of a word in a sentence/review
                     tf idf = dictionary[word]*(sent.count(word)/len(sent))
                     sent vec += (vec * tf idf)
                     weight sum += tf idf
             if weight sum != 0:
                 sent vec /= weight sum
             tfidf sent vectors.append(sent vec)
             row += 1
         100%|
```

```
50000/50000 [01:27<00:00, 571.57it/s]
In [58]: from sklearn.cluster import KMeans
         K = [2,5,10,15,20,25,30,35,40,45,50]
         inertia = []
         for k in K:
              kmeans = KMeans(n clusters=k, random state=0).fit(tfidf sent vector
         s)
              inertia.append(kmeans.inertia )
In [59]: plt.plot(K,inertia)
         plt.xlabel('K')
         plt.ylabel('inertia')
         plt.show()
            600000
            550000
            500000
          500000
.E 450000
            400000
            350000
            300000
                                         30
                                 20
                                                 40
                         10
                                      Κ
In [21]: kmeans2 = KMeans(n clusters=20, random state=0).fit(tfidf sent vectors)
In [22]: count=0
          reviews=sampledata['CleanedText'].values
         topn_class1 = sorted(zip(kmeans2.labels_, reviews))
          feature =[]
```

```
for coef, feat in topn class1:
        if coef == count:
            feature.append(feat)
        else:
            a=againcleaning(feature)
            print(" cluster =", count)
            from wordcloud import WordCloud, STOPWORDS
            import matplotlib.pyplot as plt
            word cloud=WordCloud(background color='black', stopwords=sto
p, width=500, height=500).generate(a)
            plt.imshow(word cloud)
            plt.axis("off")
            plt.show()
            count = count + 1
            feature =[]
            feature.append(feat)
#for\ label = 19
a=againcleaning(feature)
print(" cluster =", count)
#print(a, " " , count)
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
word cloud=WordCloud(background color='black', stopwords=stop, width=500,
height=500).generate(a)
plt.imshow(word cloud)
plt.axis("off")
plt.show()
```



cluster = 1



cluster = 2



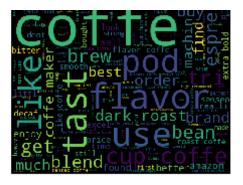




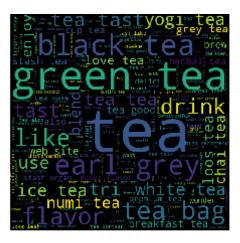


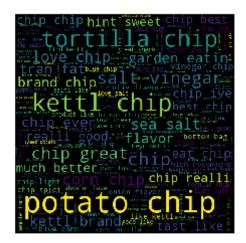


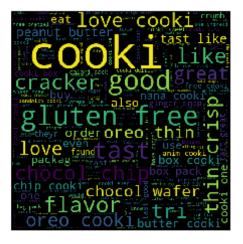
















cluster = 13



















cluster-0 is about Product, shipping of product.. boxbag etc..cluster -1,19 is about the state of product, gum, drink etc... cluster-2 is all about the positive reviews about the product the packaging in bag is lovable etc..cluster-3 is about that it is also found in groceri store and something about price and amazon... cluster-4 is positive as well as it is also something about animals cat, dog etc..cluster-5 is about food items like almond, chocol taste etc..cluster-6 is positive about the product and comparing with the coffee.. cluster-7,11,17,18 is about positive about product taste.. flavour, tast, like good etc cluster-8,15 is about type of tea... green tea, grey tea and ice tea...cluster-9 is all about chip word kettl chip, brand chip etc... Cluster-10 is about cooki and size of the cooki is thin crisp....cluster 13 is all about food, pet food dog, cat etc.. cluster 14 is procedure to cook that food..cluster-16 is positive as well as the way it can be taken ass snacks etc

Agglomerative Clustering on AVG-W2V and TF-IDF W2V

```
In [23]: sampledata1 = sorted_data.head(5000)
In [24]: from gensim.models import Word2Vec
    from gensim.models import KeyedVectors
    import pickle
```

```
i=0
         list of sent1=[]
         for sent in sampledata1['CleanedText'].values:
             list of sent1.append(sent.split())
         w2v model=Word2Vec(list of sent1,min count=5,size=50, workers=4)
         w2v words = list(w2v model.wv.vocab)
In [25]: from tqdm import tqdm
         import os
         sent vectors1 = []; # the avg-w2v for each sentence/review is stored in
          this list
         for sent in tqdm(list of sent1): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             cnt words =0; # num of words with a valid vector in the sentence/re
         view
             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 vectors1.append(sent vec)
         100%|
                      5000/5000 [00:06<00:00, 797.11it/s]
In [44]: from sklearn.cluster import AgglomerativeClustering
         from sklearn.metrics import silhouette score
         cluster = [2,5,10,15,20,25,30,40,50,60]
         met = []
         for k in cluster:
             clu = AgglomerativeClustering(n clusters=k).fit(sent vectors1)
             met.append(silhouette score(sent vectors1,clu.labels ))
In [46]: plt.scatter(cluster,met)
         plt.xlabel('cluster')
```

```
plt.ylabel('silhouette_score')
          plt.show()
             0.24
             0.22
             0.20
           silhouette_score
             0.18
             0.16
             0.14
             0.12
             0.10
             0.08
                                                  50
                       10
                             20
                                    30
                                           40
                                                        60
                Ó
                                    duster
In [26]: from sklearn.cluster import AgglomerativeClustering
          clu = AgglomerativeClustering(n clusters=2).fit(sent vectors1)
In [27]: clu.fit predict(sent vectors1)
Out[27]: array([1, 1, 1, ..., 0, 1, 1], dtype=int64)
In [28]: def againcleaning(X):
              comment words=' '
              for words in X:
                  comment words = comment words + words + ' '
              return comment words
          count=0
          reviews=sampledata1['CleanedText'].values
          topn class1 = sorted(zip(clu.labels_, reviews))
          feature =[]
          for coef,feat in topn_class1:
                  if coef == count:
                      feature.append(feat)
```

```
else:
            a=againcleaning(feature)
            print(" cluster =", count)
            from wordcloud import WordCloud, STOPWORDS
            import matplotlib.pyplot as plt
            word cloud=WordCloud(background color='black', stopwords=sto
p,width=1200,height=1200).generate(a)
            plt.imshow(word cloud)
            plt.axis("off")
            plt.show()
            count = count + 1
            feature =[]
            feature.append(feat)
#for\ label = 19
a=againcleaning(feature)
print(" cluster =", count)
#print(a, " " , count)
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
word cloud=WordCloud(background color='black', stopwords=stop, width=1200
,height=1200).generate(a)
plt.imshow(word cloud)
plt.axis("off")
plt.show()
```





Cluster-1 is focussing on all the aspects like flavour taste and alll and why does the reviewers like..tea, taste, flavour ,use Cluster 2 it mainly focuses on the reviews where people love it and some reviews are like get,try etc

```
In [29]: tf_idf_vect2 = TfidfVectorizer(ngram_range=(1,2))
final_tf_idf2 = tf_idf_vect2.fit(sampledata1['CleanedText'].values)
```

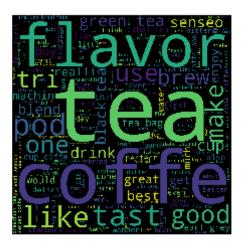
```
In [30]: from tqdm import tqdm
         import os
         # TF-IDF weighted Word2Vec
         tfidf feat = tf idf vect2.get feature names()
         dictionary = dict(zip(tf idf vect2.get feature names(), list(tf idf vec
         t2.idf )))# tfidf words/col-names
         # final tf idf is the sparse matrix with row= sentence, col=word and ce
         ll val = tfidf
         tfidf sent vectors1 = []; # the tfidf-w2v for each sentence/review is s
         tored in this list
         row=0:
         for sent in tqdm(list of sent1): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             weight sum =0; # num of words with a valid vector in the sentence/r
         eview
             for word in sent: # for each word in a review/sentence
                 if word in w2v words:
                     vec = w2v model.wv[word]
                     # obtain the tf idfidf of a word in a sentence/review
                     tf idf = dictionary[word]*(sent.count(word)/len(sent))
                     sent vec += (vec * tf idf)
                     weight sum += tf idf
             if weight sum != 0:
                 sent vec /= weight sum
             tfidf sent vectors1.append(sent vec)
             row += 1
         100%
                      5000/5000 [00:08<00:00, 611.70it/s]
In [27]: from sklearn.cluster import AgglomerativeClustering
         from sklearn.metrics import silhouette score
         cluster = [2,5,10,15,20,25,30,40,50,60]
         met = []
         for k in cluster:
             clu = AgglomerativeClustering(n clusters=k).fit(tfidf sent vectors1
```

```
met.append(silhouette_score(tfidf_sent_vectors1,clu.labels_))
In [28]:
         plt.scatter(cluster,met)
          plt.xlabel('cluster')
          plt.ylabel('silhouette score')
          plt.show()
            0.40
            0.35
           silhouette_score
            0.30
            0.25
            0.20
            0.15
            0.10
                       10
                                                  50
                             20
                                    30
                                                        60
                                   duster
In [31]: clu = AgglomerativeClustering(n clusters=2).fit(tfidf sent vectors1)
          clu.fit predict(tfidf sent vectors1)
Out[31]: array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
In [32]: count=0
          reviews=sampledata1['CleanedText'].values
          topn class1 = sorted(zip(clu.labels_, reviews))
          feature =[]
          for coef, feat in topn class1:
                  if coef == count:
                      feature.append(feat)
                  else:
                       a=againcleaning(feature)
```

```
print(" cluster =", count)
            from wordcloud import WordCloud, STOPWORDS
            import matplotlib.pyplot as plt
            word cloud=WordCloud(background color='black', stopwords=sto
p,width=1200,height=1200).generate(a)
            plt.imshow(word cloud)
            plt.axis("off")
            plt.show()
            count = count + 1
            feature =[]
            feature.append(feat)
#for\ label = 19
a=againcleaning(feature)
print(" cluster =", count)
#print(a, " " , count)
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
word cloud=WordCloud(background color='black', stopwords=stop, width=1200
,height=1200).generate(a)
plt.imshow(word cloud)
plt.axis("off")
plt.show()
```



cluster = 1



cluster-0 is all about liking, get it etc while cluster - 1 contains tea, word that is specifications of the product, shape etc and comparing it with coffee etcand specifying that it has good shape

DBSCAN on Avg W2V and TF-IDF W2V

I am using the following to find best eps... 3) sensitivity analysis Basically we want to chose a radius that is able to cluster more truly regular points (points that are similar to other points), while at the same time detect out more noise (outlier points). We can draw a percentage of regular points (points belong to a cluster) VS. epsilon analysis, where we set different epsilon values as the x-axis, and their corresponding percentage of regular points as the y axis, and hopefully we can spot a segment where the percentage of regular points value is more sensitive to the epsilon value, and we choose the upper bound epsilon value as our optimal parameter.

```
In [68]: from sklearn.cluster import DBSCAN
         from sklearn.neighbors import NearestNeighbors
         from sklearn.metrics import silhouette score
         eps = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]
         Regularpt = []
         for k in eps:
             clu = DBSCAN(eps=k,min samples=100).fit(sent vectors1)
             sampl = len(clu.core sample indices )
             avgsampl = float(sampl/5000)
             Regularpt.append(avgsampl)
             #met = NearestNeighbors(n neighbors=300, radius=k).fit(sent vectors
         1)
             #kthdistance.append(knn(met,sent vectors1))
In [44]: len(sampl)
Out[44]: 5000
In [69]: plt.scatter(eps,Regularpt)
         plt.xlabel('eps')
         plt.ylabel('Regularpt')
         plt.show()
```

```
1.0 - 0.8 - 1.0 - 0.6 - 0.8 - 0.2 - 0.2 - 0.4 - 0.6 - 0.8 - 1.0 - 0.2 - 0.2 - 0.4 - 0.6 - 0.8 - 0.8 - 0.0 - 0.2 - 0.4 - 0.6 - 0.8 - 0.8 - 0.0 - 0.8 - 0.8 - 0.0 - 0.8 - 0.8 - 0.0 - 0.8 - 0.8 - 0.8 - 0.0 - 0.8 - 0.8 - 0.8 - 0.8 - 0.0 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.0 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 - 0.8 -
```

```
In [85]: from sklearn.cluster import DBSCAN
         from sklearn.neighbors import NearestNeighbors
         clu = DBSCAN(eps=0.6,min samples=100).fit(sent vectors1)
In [86]: clu.labels
Out[86]: array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
In [87]: count=-1
         reviews=sampledata1['CleanedText'].values
         topn class1 = sorted(zip(clu.labels , reviews))
         feature =[]
         for coef,feat in topn class1:
                 if coef == count:
                     feature.append(feat)
                 else:
                     a=againcleaning(feature)
                     print(" cluster =", count)
                     from wordcloud import WordCloud, STOPWORDS
                     import matplotlib.pyplot as plt
                     word cloud=WordCloud(background color='black', stopwords=sto
         p,width=1200,height=1200).generate(a)
```

```
plt.imshow(word_cloud)
            plt.axis("off")
            plt.show()
            count = count + 1
            feature =[]
            feature.append(feat)
#for\ label = 19
a=againcleaning(feature)
print(" cluster =", count)
#print(a, " " , count)
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
word cloud=WordCloud(background color='black',stopwords=stop,width=1200
,height=1200).generate(a)
plt.imshow(word cloud)
plt.axis("off")
plt.show()
```

cluster = -1

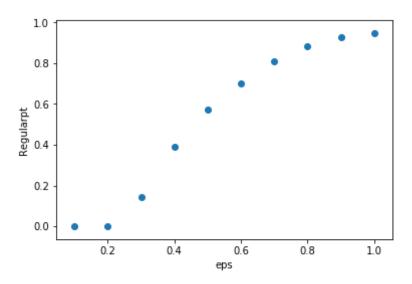






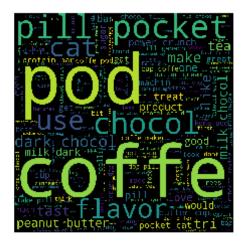
It is differentiating generally noise from imp reviews I am using the following to find best eps... 3) sensitivity analysis Basically we want to chose a radius that is able to cluster more truly regular points (points that are similar to other points), while at the same time detect out more noise (outlier points). We can draw a percentage of regular points (points belong to a cluster) VS. epsilon analysis, where we set different epsilon values as the x-axis, and their corresponding percentage of regular points as the y axis, and hopefully we can spot a segment where the percentage of regular points value is more sensitive to the epsilon value, and we choose the upper bound epsilon value as our optimal parameter.

```
In [88]: from sklearn.cluster import DBSCAN
    from sklearn.meighbors import NearestNeighbors
    from sklearn.metrics import silhouette_score
    eps = [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]
    Regularpt = []
    for k in eps:
        clu = DBSCAN(eps=k,min_samples=100).fit(tfidf_sent_vectors1)
        sampl = len(clu.core_sample_indices_)
        avgsampl = float(sampl/5000)
        Regularpt.append(avgsampl)
In [89]: plt.scatter(eps,Regularpt)
    plt.xlabel('eps')
    plt.ylabel('Regularpt')
    plt.show()
```

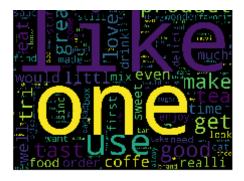


```
In [90]: from sklearn.cluster import DBSCAN
         from sklearn.neighbors import NearestNeighbors
         clu = DBSCAN(eps=0.8,min samples=100).fit(tfidf sent vectors1)
In [91]: count=-1
         reviews=sampledata1['CleanedText'].values
         topn_class1 = sorted(zip(clu.labels , reviews))
         feature =[]
         for coef,feat in topn class1:
                 if coef == count:
                     feature.append(feat)
                 else:
                     a=againcleaning(feature)
                     print(" cluster =", count)
                     from wordcloud import WordCloud, STOPWORDS
                     import matplotlib.pyplot as plt
                     word cloud=WordCloud(background_color='black',stopwords=sto
         p,width=1200,height=1200).generate(a)
                     plt.imshow(word cloud)
                     plt.axis("off")
                     plt.show()
                     count = count + 1
```

cluster = -1







Differentiating noise from imp reviews cluster -1 is noise

Conclusion

In Kmeans i have made them in to 20 clusters, where i can really find the differences between the clusters clearly... as it was said... In Agglomerative clustering where we used silhouette_score and got no. of clusters when it is 2 we have high silhouette_score so we used that.. For eps in dbscan , I took it as per sensitivity analysis it will easily seperate noise from imp reviws.....