10_Amazon_Food_Reviews_Clustering

April 14, 2019

1 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.

2 K-Means, Agglomerative & DBSCAN Clustering

```
<li><strong>Apply K-means Clustering on these feature sets:</strong>
    <ul>
<li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors using (B
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
```

```
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
<li>Find the best k using the elbow-knee method (plot k vs inertia_)</li>
<li>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.

```
    </ul>
</li>
<br>
<li><strong>Apply Agglomerative Clustering on these feature sets:</strong>
    <ul>
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
<li>Apply agglomerative algorithm and try a different number of clusters like 2,5 etc.</li>
<li>Same as that of K-means, plot word clouds for each cluster and summarize in your own words w
        <li>You can take around 5000 reviews or so(as this is very computationally expensive one
    </ul>
</li>
<br>
<br>
<li><strong>Apply DBSCAN Clustering on these feature sets:</strong>
    <ul>
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
<li>Find the best Eps using the <a href='https://stackoverflow.com/questions/12893492/choosing-e
<li>Same as before, plot word clouds for each cluster and summarize in your own words what that
        <li>You can take around 5000 reviews for this as well.</li>
    </ul>
</li>
```

2.1 [A] K-Means Clustering

3 Import Required Packages

In [1]:
```python
import os
from datetime import datetime
import pandas as pd
import numpy as np

# package for reading from database
import sqlite3

# visualization related packages
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

# data prerocessing related
```

```
from sklearn.preprocessing import StandardScaler

# for computing distances betweeen data points
from sklearn.metrics import pairwise_distances

# import model related packages
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
from sklearn.metrics import silhouette_score

# visualization related packages
from wordcloud import WordCloud
from prettytable import PrettyTable
```

4 UTIL Functions

4.1 Data Preprocessing related Functions

```
In [2]: def preprocess_data(config_dict, scaling=True, dim_reduction=False):
            """
            This function does preprocessing of data such as column standardization and
            dimensionality reduction using Truncated SVD
            """

            # Read train, test data frames & truncate it as needed
            train_df = pd.read_csv(config_dict['train_csv_path'], index_col=False)
            train_df = train_df.iloc[0:config_dict['train_size']]

            # print the statisics of train, test df
            print('Train df shape',train_df.shape)

            # separate features and labels
            id_values = train_df['Id']
            train_features = train_df.drop(['Label', 'Id'], axis=1)

            # get feature names as list
            feature_name_list = train_features.columns.values.tolist()

            # If Scaling is opted scale the train, test data
            if scaling:
                standard_scaler = StandardScaler()
                standard_scaler.fit(train_features)
                # scale the features
                train_features = pd.DataFrame(standard_scaler.transform(train_features),
                                              columns=feature_name_list)

            train_features['Id'] =  id_values
            print('Shape of ->  train features :%d,%d '%train_features.shape)
```

```
        # if dim reduction is opted, reduce the dimension
        if dim_reduction:
            # create an SVD object
            truc_svd = TruncatedSVD(n_components=train_features.shape[1]-1, n_iter=8, algori

            # fit to data
            truc_svd.fit(train_features)
            # get explained variance ratio of each component
            explained_var_ratios = truc_svd.explained_variance_ratio_
            # get cummulative ratio list for selecting the number of components
            cumulative_ratios = np.cumsum(explained_var_ratios)

            # plot the #components vs captured variance in the data
            plt.title('SVD Decomposition')
            plt.xlabel('Number of components')
            plt.ylabel('Cumulative Percentage Ratio')
            plt.plot(range(1,train_features.shape[1]), cumulative_ratios)
            plt.show()

            # set a threshold for stopping selection of components.
            svd_thesh = 0.001
            # select the number of components as the first component for which the differenc
            #  very less (less than svd thresh) compared with the very next component
            selected_dim = list(filter(lambda x : x[1] < svd_thesh, enumerate(np.diff(cumula
            print('Num dimensions selected by SVD', selected_dim)
            print('Total variance captured:%f'%(cumulative_ratios[selected_dim]))

            # create an object for selecting the components
            truc_svd = TruncatedSVD(n_components=selected_dim, n_iter=8, algorithm='randomiz
            # refit with the desired number of components
            truc_svd.fit(train_features)

            # reduce the number of dimensions to selected number of components
            train_features = pd.DataFrame(truc_svd.transform(train_features))

            # get the shape of final data frame and print it
            print('Shape of train df:(%d,%d)'%train_features.shape)


        return train_features
```

4.2 Model training and evaluation related functions

```
In [3]: def find_best_hyperparameter(config_dict, train_features):

        """
        This function helps to find the best hyper parameter for the clustering algorithm.
```

```
All set of hyper param values using which the model to be evaluated can be passed to
list hyperparam_list. It also takes algo_type which can be one among k-means, agglom
or DBSCAN.
"""

print('='*100)

hyperparam_list = config_dict['hyperparam_list']
algo_type = config_dict['algo_type']

# set the input for training
X_train = train_features.drop(['Id'], axis=1)

hyper_param_score_list = list()
inertia_score_list = list() # for k-means algorithm

for hyp_vals in hyperparam_list:

    # Model defined here
    if algo_type == 'kmeans':

        # create an object of clustering algorithm
        clustering_model = KMeans(n_clusters=hyp_vals, init='k-means++', n_init=10)

        # fit on data
        clustering_model.fit(X_train)
        # get the inertia value as score
        inertia_val = clustering_model.inertia_

        # get the silhouytte score for this clustering
        if len(set(clustering_model.labels_)) == 1:
            sil_score = -1
        else:
            sil_score = silhouette_score(X_train, clustering_model.labels_)

        # append hyper param scores
        inertia_score_list.append((hyp_vals, inertia_val,))
        hyper_param_score_list.append((hyp_vals, sil_score,))

    elif algo_type == 'agglomerative':

        # create clustering algorithm object
        clustering_model = AgglomerativeClustering(n_clusters=hyp_vals)
        # fit on data
        clustering_model.fit(X_train)

        # get the silhouytte score for this clustering
        if len(set(clustering_model.labels_)) == 1:
```

```
                sil_score = -1
            else:
                sil_score = silhouette_score(X_train, clustering_model.labels_)

            sil_score = silhouette_score(X_train, clustering_model.labels_)

            # append hyper param scores
            hyper_param_score_list.append((hyp_vals, sil_score,))

        elif algo_type == 'dbscan':

            # hyper params in the order (eps, min_samples,)
            clustering_model = DBSCAN(eps=hyp_vals[0], min_samples=hyp_vals[0], metric='
            # fit on data
            clustering_model.fit(X_train)
            # get the inertia value as score

            if len(set(clustering_model.labels_)) == 1:
                sil_score = -1 # minimum possible silhoutte score

            else:
                sil_score = silhouette_score(X_train, clustering_model.labels_)

            # append hyper param scores
            hyper_param_score_list.append((hyp_vals, sil_score,))

        else:
            print('Invalid choice')

    # plot inertia vs k for k-means clustering
    if algo_type == 'kmeans':
        # plot k versus inertia
        inertia_values_list = [item[1] for item in inertia_score_list]
        plt.plot(hyperparam_list, inertia_values_list)
        plt.xlabel('Number of Clusters')
        plt.ylabel('Inertia Value')
        plt.title('Elbow Method')
        plt.show()

    return hyper_param_score_list
```

```
In [4]: def get_cluster_id(config_dict, score_list, train_features):

            """
            This function fit a model based on best hyper parameter values got and
            assign cluster id to each data point.
            """
```

```python
# get the best hyperparams from the list
hyp_vals, hyp_score = max(score_list, key=lambda x: x[1])

# get configuration values
hyperparam_list = config_dict['hyperparam_list']
algo_type = config_dict['algo_type']

# Model defined here
if algo_type == 'kmeans':
    print('Best hyper param selected n_clusters : %d '%hyp_vals)
    print('Best silhoutte score for this hyper parameter : %f'%hyp_score)
    clustering_model = KMeans(n_clusters=hyp_vals, init='k-means++', n_init=10)
    # set entry for putting in table
    hyp_str = 'k= '+ str(hyp_vals)

elif algo_type == 'agglomerative':
    print('Best hyper param selected n_clusters : %d'%hyp_vals)
    print('Best silhoutte score score for this hyper parameter : %f'%hyp_score)
    clustering_model = AgglomerativeClustering(n_clusters=hyp_vals)
    # set entry for putting in table
    hyp_str = 'k= '+ str(hyp_vals)

elif algo_type == 'dbscan':
    # hyper params in the order (eps, min_samples,)
    print('Best hyper param selected eps:%f,min_samples :%d'%hyp_vals)
    print('Best silhoutte score score for this hyper parameter : %f'%hyp_score)
    clustering_model = DBSCAN(eps=hyp_vals[0], min_samples=hyp_vals[1], metric='eucl

    # set entry for putting in table
    hyp_str = 'eps= %.4f, min_pts= %d '%hyp_vals

else:
    print('Invalid choice')

X_train = train_features.drop(['Id'], axis=1)

clustering_model.fit(X_train)

# get the labels for each data point (i.e cluster id)
assigned_cluseter_ids = clustering_model.labels_

# create a data frame with review ID and its predicted cluster
pred_df = pd.DataFrame({'Id': train_features['Id'],
                        'Cluster' : assigned_cluseter_ids},
                       index=range(train_features.shape[0]))

# set the clustering size info as a string
cluster_info = str(dict(pred_df['Cluster'].value_counts()))
```

```
        # form a table entry to insert into pretty table
        table_entry = [cluster_info, hyp_str, '{0:.4f}'.format(hyp_score)]

        return (table_entry, pred_df,)
```

```
In [5]: def get_kdistance_plot(df, k_val):
        """
        This function returns a k-distance plot for a given data frame. It compute all pairw
        and then compute avegare k-distances. It also finds the eps_val for DBSCAN algorithm
        """

        # compute pairwise distances and create a distance data frame
        pair_dist_df = pd.DataFrame(pairwise_distances(df))
        pair_dist_df.shape[0]

        # declare a list for hodling mean k-distances
        mean_k_distance_list = list()

        # for each data point compute the k-mean distance
        for index, row in pair_dist_df.iterrows():

            # drop the distance to the point itself
            temp_entry = row.drop([index])

            # sort the values in ascending order of distance
            temp_entry = temp_entry.sort_values(ascending=True)
            # pick the first k_val points as the k distance
            temp_entry = temp_entry.iloc[0:k_val]

            # compute the mean k distance
            mean_k_distance = temp_entry.mean()

            # save the k mean distance for this point into a list
            mean_k_distance_list.append(mean_k_distance)

        # sort the k-mean distance in descending order
        mean_k_distance_list = sorted(mean_k_distance_list, reverse=True)

        # find eps value by looking into the sudden chnage in distance
        maxima_diff_list = list(filter(lambda x : x > 0.005, abs(np.diff(mean_k_distance_lis
        eps_val = mean_k_distance_list[len(maxima_diff_list)]

        # plot the k-mean distances in a figure
        plt.plot(range(1, pair_dist_df.shape[0] + 1), mean_k_distance_list)
        plt.xlabel('Data Points')
        plt.ylabel('K distance')
```

```
    plt.title('K distance plot -> k:%d, eps:%f'%(k_val, eps_val,))
    plt.show()

    return (mean_k_distance_list, eps_val,)
```

4.3 Functions for preparing word cloud of each cluster

```
In [6]: def read_from_DB(id_list):
            """
            This function reads the Cleaned Review Text and its id into a data frame and returns
            """

            # create a connection object for connecting with DB
            con = sqlite3.connect('/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/fina

            #
            df = pd.read_sql_query('SELECT Id, CleanedText, Summary, Label from Reviews', con)

            # get only the selected id and the correspondig CleanedText
            df = df[df['Id'].isin(id_list)]
            df = df[['Id', 'CleanedText', 'Label']]

            # close the connection
            con.close()

            return df

In [7]: def get_cluster_wordcloud(pred_cluster_df, review_id_df):
            """
            This function shows the word cloud for each cluster given the predicted cluster info
            """

            # create a word cloud template for each cluster word cloud
            wc = WordCloud(background_color='white', width=800, height=800)

            # do word cloud for each cluster
            for gid, gdf in pred_cluster_df.groupby(['Cluster']):

                print('='*100)

                # get id of each data point in this cluster
                id_list = gdf['Id'].tolist()

                # filter only the selected id reviews
                selected_rev_df = review_id_df[review_id_df['Id'].isin(id_list)]
                # get the class (+ve, -ve) of each ID
                val_counts_dict = dict(selected_rev_df['Label'].value_counts())
```

```
            # get the majority class for this cluster
            num_pos_rev = val_counts_dict[1]
            num_neg_rev = val_counts_dict[0]
            majority_class = 'Positive' if num_pos_rev > num_neg_rev else 'Negative'

            # print a table containing information about this cluster
            Pret_table_c = PrettyTable()
            Pret_table_c.field_names = ['Cluster_ID', 'Num Data Points', '# +ve Reviews',
                                        '# -ve Reviews', 'Majority Class']
            Pret_table_c.title = 'Cluster %d Info'%(gid,)

            Pret_table_c.add_row([gid, gdf.shape[0], val_counts_dict[1], val_counts_dict[0],
                                  majority_class])
            print(Pret_table_c)


            # initialize a text for this cluster, this will hold all the words that belong t
            cluster_text = str()

            for rev_txt in selected_rev_df['CleanedText']:
                cluster_text += rev_txt

            # generate word cloud for this cluster
            wc_output = wc.generate(cluster_text)

            plt.figure(figsize=(8,8))
            plt.imshow(wc_output)
            plt.axis('off')
            plt.title('Word Cloud for Cluster ID: %d'%(gid,))
            plt.tight_layout(pad=0.0)
            plt.show()

            print('='*100)
```

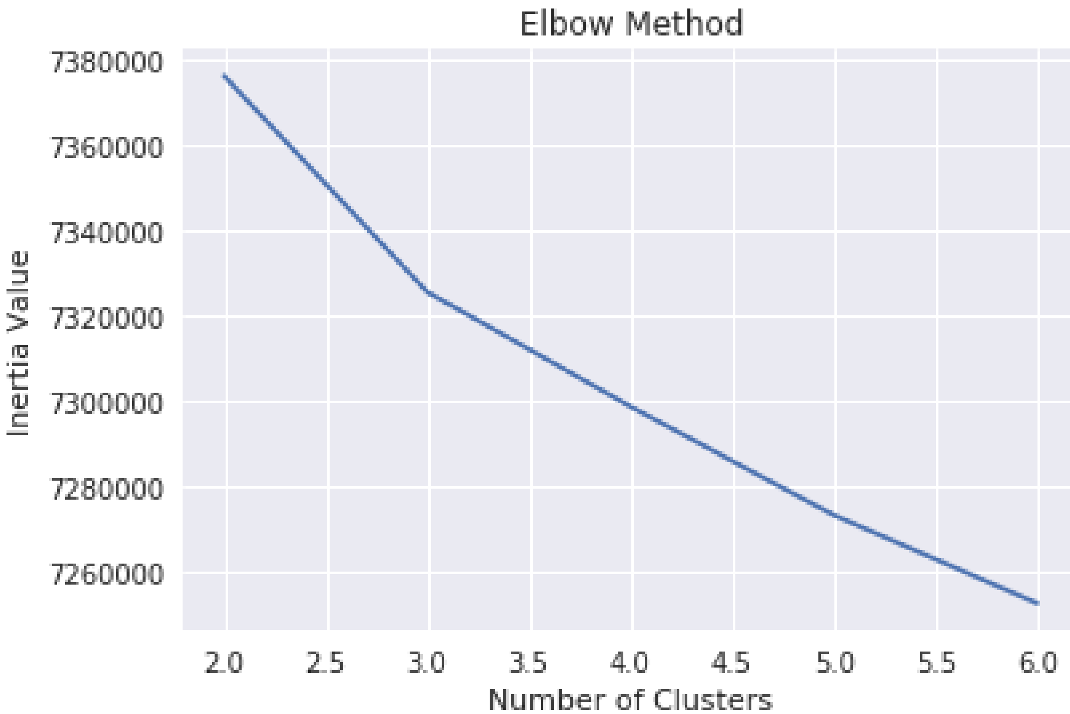
4.3.1 [A.1] Applying K-Means Clustering on BOW, SET 1

```
In [8]: config_dict = {
            'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/BOW/trai
            'train_size' : 15000,
            'hyperparam_list' : [2, 3, 4, 5, 6],
            'algo_type' : 'kmeans'
        }
```

```
In [9]: train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
        score_list = find_best_hyperparameter(config_dict, train_features)
```

```
Train df shape (15000, 503)
Shape of ->  train features :15000,502
```

==




```
In [10]: print('Score list for this clustering :\n', score_list)
```

```
Score list for this clustering :
 [(2, 0.35220317632255554), (3, 0.20534017832980486), (4, 0.1498655129908616), (5, 0.14238491192
```

```
In [11]: ptabe_entry_a1, pred_df = get_cluster_id(config_dict, score_list, train_features)
         pred_df.head()
```

```
Best hyper param selected n_clusters : 2
Best silhoutte score for this hyper parameter : 0.352203
```

Out[11]:

	Id	Cluster
0	456873	1
1	81416	0
2	519340	0
3	340949	0
4	453782	0

4.3.2 [A.2] Wordclouds of clusters obtained after applying k-means on BOW SET 1

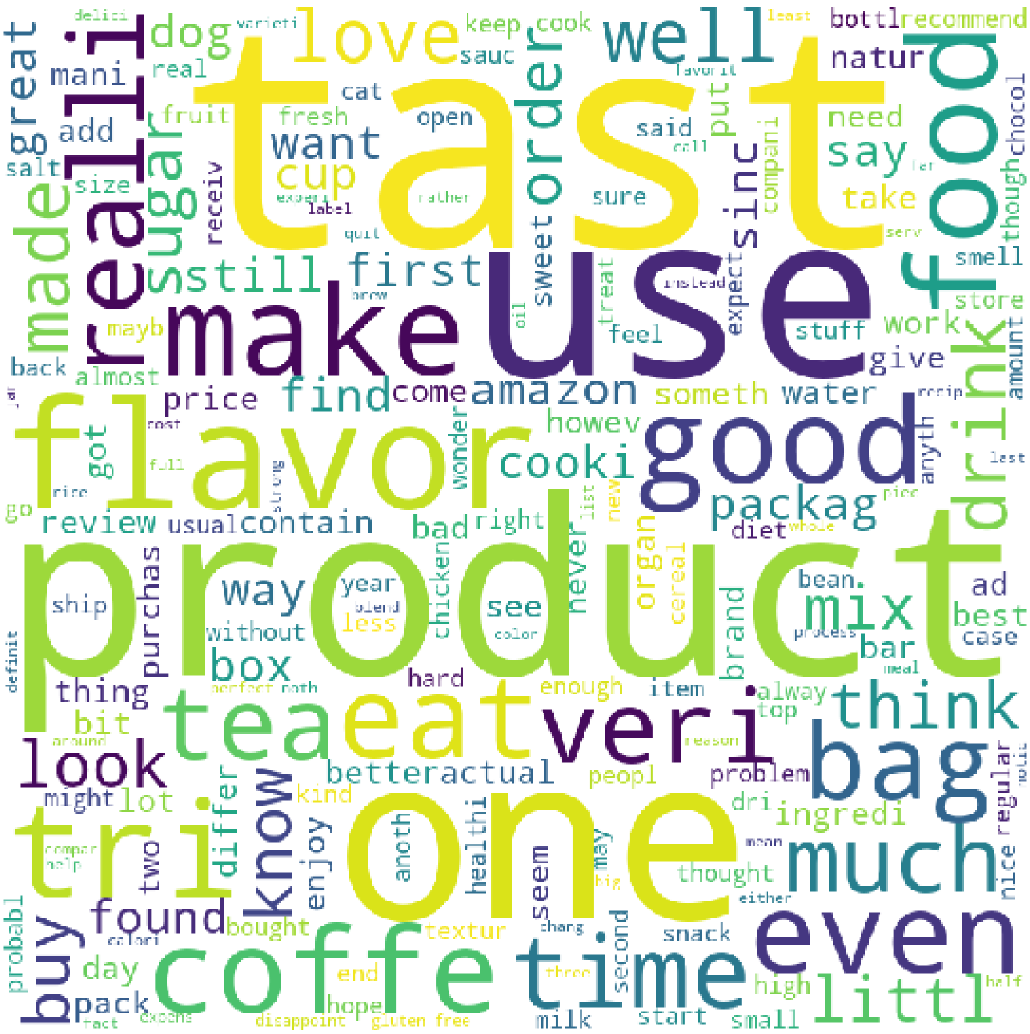
In [12]:
```
# get id of each review in the training data points
id_list = train_features['Id'].tolist()
# get only the reviews which are used for training step
rev_df = read_from_DB(id_list)
# plot the word cloud for every clusters predicted
get_cluster_wordcloud(pred_df, rev_df)
```

```
==============================================================================================
+-----------------------------------------------------------------------------------+
|                                   Cluster 0 Info                                  |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     0      |      13051      |      6551     |      6500     |    Positive    |
+------------+-----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: 0

Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
Cluster 1 Info				
1	1949	873	1076	Negative

Word Cloud for Cluster ID: 1



===

4.4 Observation

Inertia value decreases sharply without any elbow region

Silhouette coefficient can be used to select the number of clusters, in this case k=2 for which we got the best score

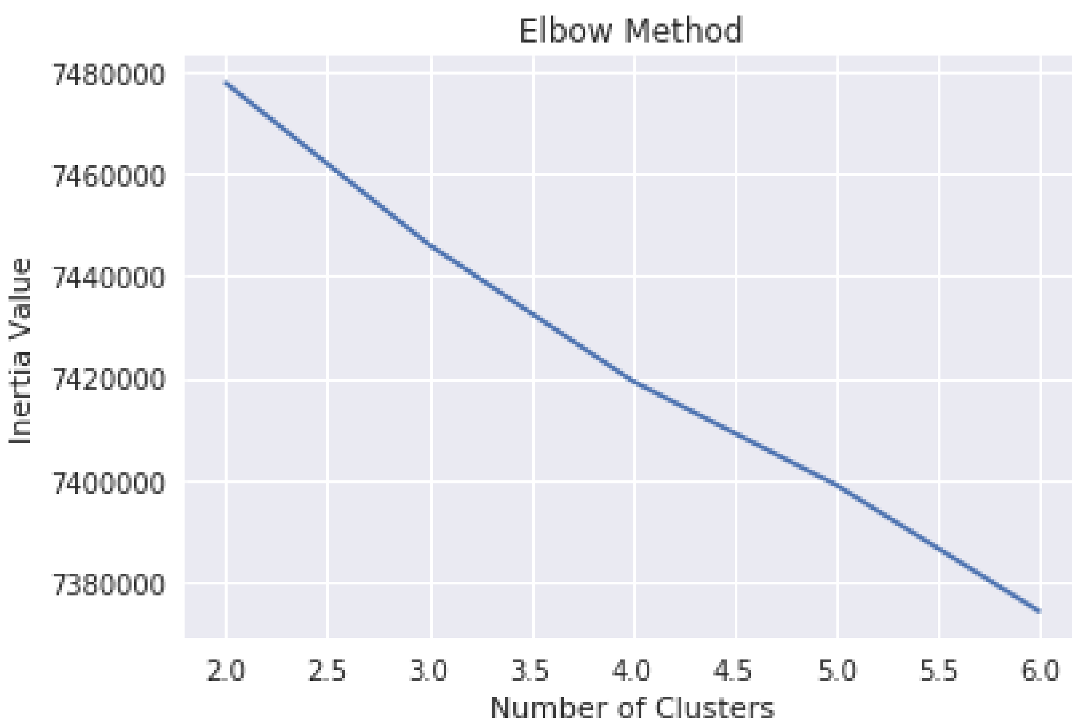
Both clusters have many words in common. This means its not the word but a pattern of word that distinguishes the cluster. We cannot simply relay on just one feature to do clustering

4.4.1 [A.3] Applying K-Means Clustering on TFIDF, SET 2

In [13]:
```
config_dict = {
    'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF/t
    'train_size' : 15000,
    'hyperparam_list' : [2, 3, 4, 5, 6],
    'algo_type' : 'kmeans'
}
```

In [14]:
```
train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
score_list = find_best_hyperparameter(config_dict, train_features)
```

```
Train df shape (15000, 503)
Shape of ->  train features :15000,502
==========================================================================================
```



In [15]:
```
print('Score list for this clustering :\n', score_list)
```

```
Score list for this clustering :
 [(2, 0.005332590945988098), (3, 0.0035891003118323508), (4, 0.0048517343200489595), (5, -0.0100
```

In [16]:
```
ptabe_entry_a2, pred_df = get_cluster_id(config_dict, score_list, train_features)
pred_df.head()
```

```
Best hyper param selected n_clusters : 2
Best silhoutte score for this hyper parameter : 0.005333
```

Out[16]:

	Id	Cluster
0	456873	0
1	81416	0
2	519340	1
3	340949	1
4	453782	0

4.4.2 [A.4] Wordclouds of clusters obtained after applying k-means on TFIDF SET 2

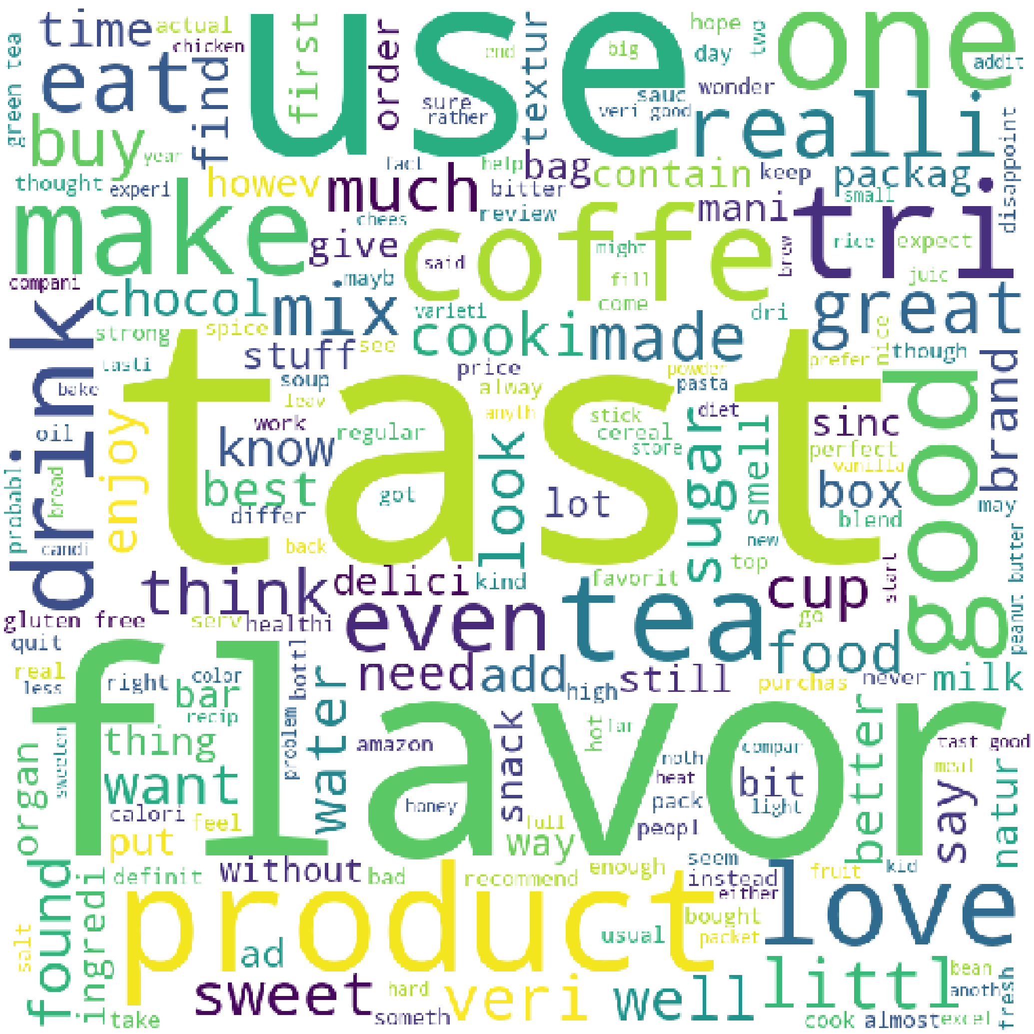
In [17]:
```
# get id of each review in the training data points
id_list = train_features['Id'].tolist()
# get only the reviews which are used for training step
rev_df = read_from_DB(id_list)
# plot the word cloud for every clusters predicted
get_cluster_wordcloud(pred_df, rev_df)
```

```
=======================================================================================================================
+------------------------------------------------------------------------------+
|                                Cluster 0 Info                                |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     0      |       6780      |      2923     |      3857     |    Negative    |
+------------+-----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: 0

Cluster 1 Info				
Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
1	8220	4501	3719	Positive

Word Cloud for Cluster ID: 1



==

4.5 Observation

Inertia value decreases sharply without any elbow region

Silhouette coefficient can be used to select the number of clusters, in this case k=2 for which we got the best score

Both clusters have many words in common. This means it is not the word but a pattern of word that distinguishes the cluster. We cannot simply relay on just one feature to do clustering

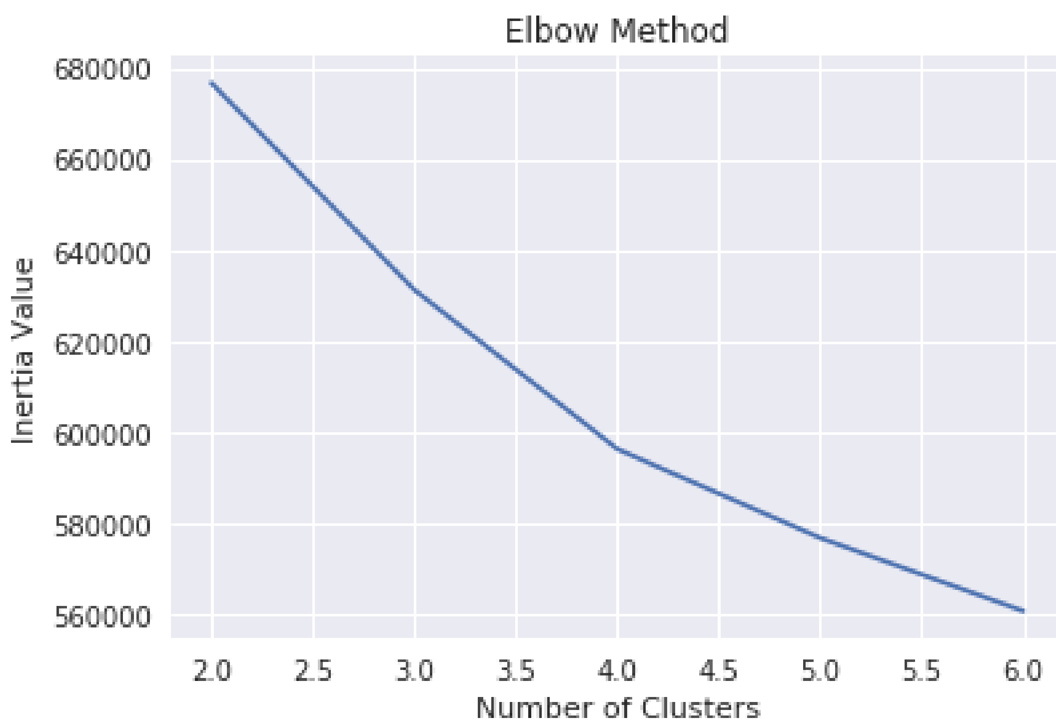
Silhouette score for this clustering is very poor score = 0.05

4.5.1 [A.5] Applying K-Means Clustering on AVG W2V, SET 3

```
In [18]: config_dict = {
             'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/AVG_W2V
             'train_size' : 15000,
             'hyperparam_list' : [2, 3, 4, 5, 6],
             'algo_type' : 'kmeans'
         }
```

```
In [19]: train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
         score_list = find_best_hyperparameter(config_dict, train_features)
```

```
Train df shape (15000, 52)
Shape of ->  train features :15000,51
==========================================================================================
```




```
In [20]: print('Score list for this clustering :\n', score_list)
```

```
Score list for this clustering :
 [(2, 0.09443577923088471), (3, 0.09690401266701287), (4, 0.09556962073504416), (5, 0.0850925880
```

```
In [21]: ptabe_entry_a3, pred_df = get_cluster_id(config_dict, score_list, train_features)
         pred_df.head()
```

```
Best hyper param selected n_clusters : 3
Best silhoutte score for this hyper parameter : 0.096904
```

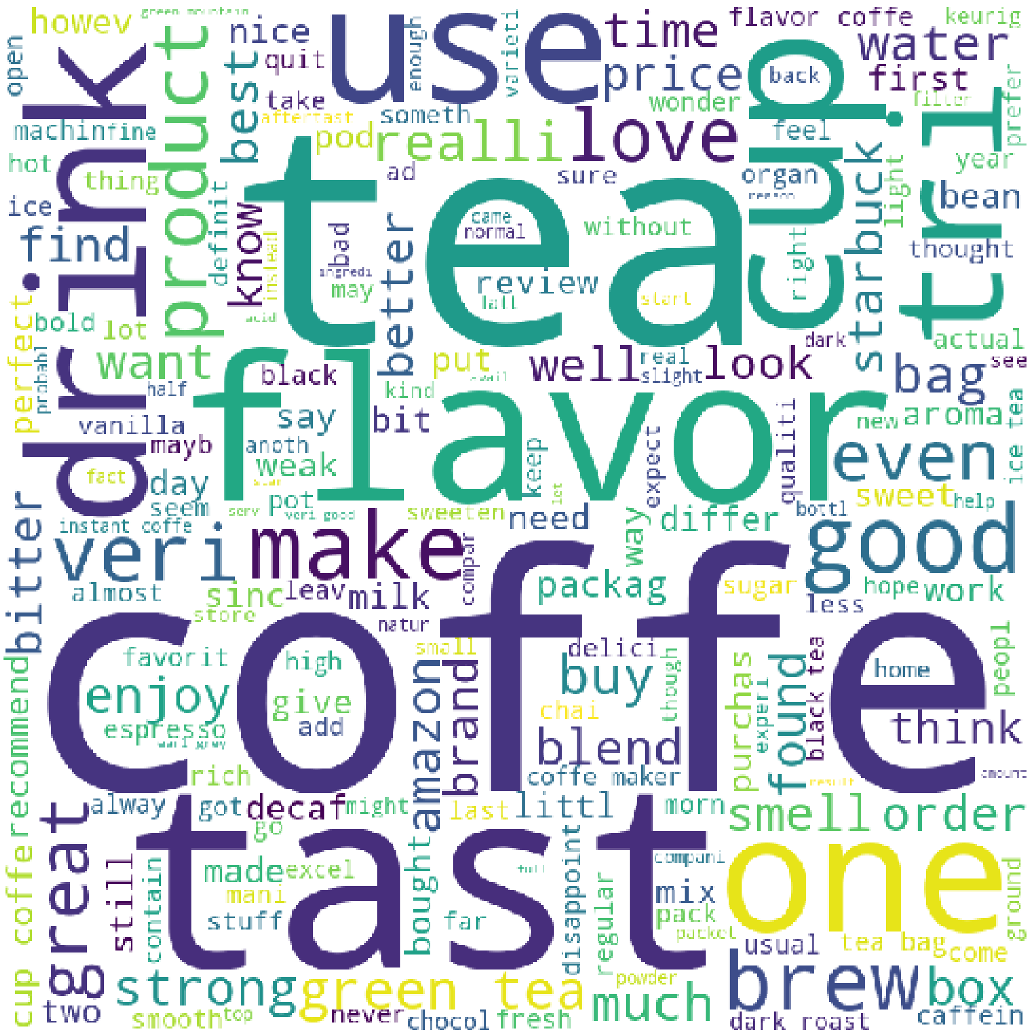
```
Out[21]:        Id  Cluster
         0  456873        1
         1   81416        2
         2  519340        0
         3  340949        1
         4  453782        1
```

4.5.2 [A.6] Wordclouds of clusters obtained after applying k-means on AVG W2V SET 3

```
In [22]: # get id of each review in the training data points
         id_list = train_features['Id'].tolist()
         # get only the reviews which are used for training step
         rev_df = read_from_DB(id_list)
         # plot the word cloud for every clusters predicted
         get_cluster_wordcloud(pred_df, rev_df)
```

```
=================================================================================================
+--------------------------------------------------------------------------------+
|                                 Cluster 0 Info                                 |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     0      |       2393      |      1309     |      1084     |    Positive    |
+------------+-----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: 0




```
================================================================================
================================================================================
```

Cluster 1 Info				
Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
1	5831	2448	3383	Negative

Word Cloud for Cluster ID: 1

Cluster 2 Info				
Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
2	6776	3667	3109	Positive

Word Cloud for Cluster ID: 2

==

4.6 Observation

Inertia value decreases sharply without any elbow region

Silhouette coefficient can be used to select the number of clusters, in this case k=3 for which we got the best score

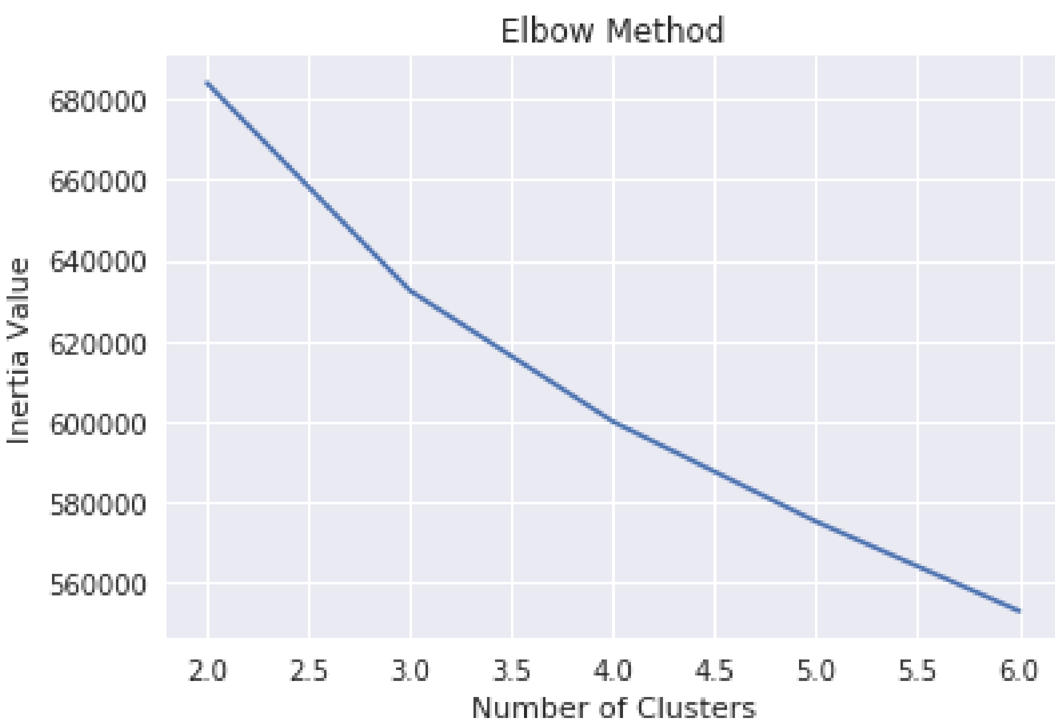
Both clusters have many words in common. This means it s not the word but a pattern of word that distinguishes the cluster. We cannot simply relay on just one feature to do clustering

4.6.1 [A.7] Applying K-Means Clustering on TFIDF W2V, SET 4

```
In [23]: config_dict = {
             'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF_W
             'train_size' : 15000,
             'hyperparam_list' : [2, 3, 4, 5, 6],
             'algo_type' : 'kmeans'
         }
```

```
In [24]: train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
         score_list = find_best_hyperparameter(config_dict, train_features)
```

```
Train df shape (15000, 52)
Shape of ->  train features :15000,51
==========================================================================================
```




```
In [25]: print('Score list for this clustering :\n', score_list)
```

```
Score list for this clustering :
 [(2, 0.15845545839009997), (3, 0.09276123777834097), (4, 0.09837859926179662), (5, 0.0996582982
```

```
In [26]: ptabe_entry_a4, pred_df = get_cluster_id(config_dict, score_list, train_features)
         pred_df.head()
```

```
Best hyper param selected n_clusters : 2
Best silhoutte score for this hyper parameter : 0.158455
```

Out[26]:

	Id	Cluster
0	456873	0
1	81416	0
2	519340	1
3	340949	0
4	453782	0

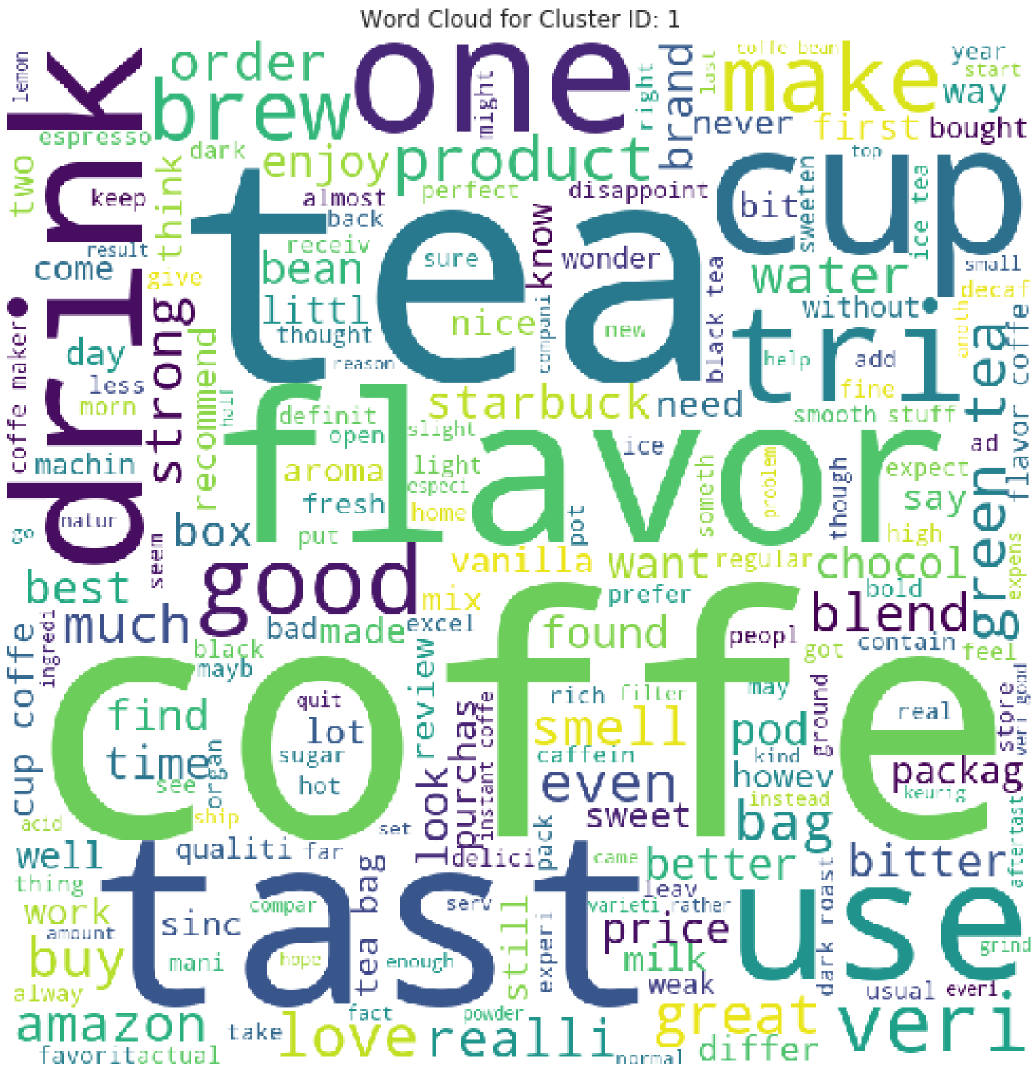
4.6.2 [A.8] Wordclouds of clusters obtained after applying k-means on TFIDF W2V SET 4

In [27]:
```
# get id of each review in the training data points
id_list = train_features['Id'].tolist()
# get only the reviews which are used for training step
rev_df = read_from_DB(id_list)
# plot the word cloud for every clusters predicted
get_cluster_wordcloud(pred_df, rev_df)
```

```
==========================================================================================
+----------------------------------------------------------------------------------+
|                                  Cluster 0 Info                                  |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     0      |      12946      |      6322     |      6624     |    Negative    |
+------------+-----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: 0


```
==========================================================================================
==========================================================================================
+-------------------------------------------------------------------------------+
|                                 Cluster 1 Info                                |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     1      |      2054       |      1102     |      952      |    Positive    |
+------------+-----------------+---------------+---------------+----------------+
```



4.7 Observation

Inertia value decreases sharply without any elbow region

Silhouette coefficient can be used to select the number of clusters, in this case k=2 for which we got the best score

Both clusters have many words in common. This means it is not the word but a pattern of word that distinguishes the cluster. We cannot simply relay on just one feature to do clustering

4.8 [B] Agglomerative Clustering

4.8.1 [B.1] Applying Agglomerative Clustering on AVG W2V, SET 3

```
In [28]: config_dict = {
             'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/AVG_W2V
             'train_size' : 5000,
             'hyperparam_list' : [2, 3, 4, 5, 6],
             'algo_type' : 'agglomerative'
         }
```

```
In [29]: train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
         score_list = find_best_hyperparameter(config_dict, train_features)
```

```
Train df shape (5000, 52)
Shape of ->  train features :5000,51
==================================================================================================
```

```
In [30]: print('Score list for this clustering :\n', score_list)
```

```
Score list for this clustering :
 [(2, 0.06843433509933095), (3, 0.06813809061058529), (4, 0.06849660399005532), (5, 0.0483884027
```

```
In [31]: ptabe_entry_b1, pred_df = get_cluster_id(config_dict, score_list, train_features)
         pred_df.head()
```

```
Best hyper param selected n_clusters : 4
Best silhoutte score score for this hyper parameter : 0.068497
```

Out[31]:

	Id	Cluster
0	456873	1
1	81416	1
2	519340	2
3	340949	3
4	453782	0

4.8.2 [B.2] Wordclouds of clusters obtained after applying Agglomerative Clustering on AVG W2V SET 3

```
In [32]: # get id of each review in the training data points
         id_list = train_features['Id'].tolist()
         # get only the reviews which are used for training step
         rev_df = read_from_DB(id_list)
         # plot the word cloud for every clusters predicted
         get_cluster_wordcloud(pred_df, rev_df)
```

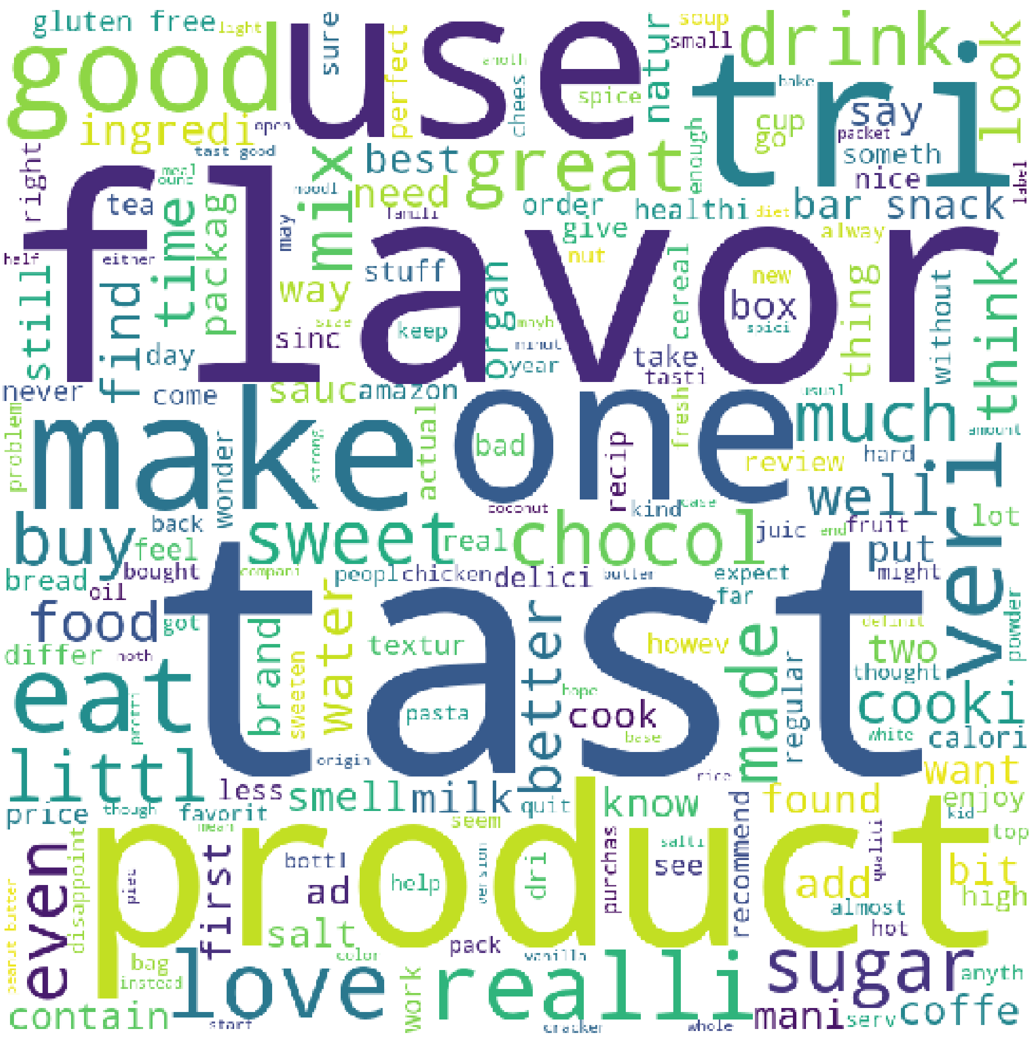
```
==========================================================================================
+--------------------------------------------------------------------------------+
|                                 Cluster 0 Info                                 |
+------------+----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+----------------+---------------+---------------+----------------+
|     0      |      1573      |      722      |      851      |    Negative    |
+------------+----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: 0


```
==========================================================================================
==========================================================================================
+--------------------------------------------------------------------------------+
```

```
|                              Cluster 1 Info                              |
+------------+----------------+--------------+--------------+---------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+----------------+--------------+--------------+---------------+
|     1      |      2177      |     1150     |     1027     |    Positive    |
+------------+----------------+--------------+--------------+---------------+
```

Word Cloud for Cluster ID: 1




```
========================================================================================
========================================================================================
+--------------------------------------------------------------------------+
|                              Cluster 2 Info                              |
+------------+----------------+--------------+--------------+---------------+
```

Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
2	617	341	276	Positive

Word Cloud for Cluster ID: 2

Cluster 3 Info				
Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class

```
|     3      |       633       |      293      |      340      |    Negative    |
+------------+-----------------+---------------+---------------+----------------+
```


```
==========================================================================================
```

4.8.3 [B.3] Applying Agglomerative Clustering on TFIDF W2V, SET 4

```
In [33]: config_dict = {
            'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF_W
            'train_size' : 5000,
            'hyperparam_list' : [2, 3, 4, 5, 6],
```

```
            'algo_type' : 'agglomerative'
        }
```

In [34]:
```
train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
score_list = find_best_hyperparameter(config_dict, train_features)
```

```
Train df shape (5000, 52)
Shape of ->  train features :5000,51
===========================================================================================
```

In [35]:
```
print('Score list for this clustering :\n', score_list)
```

```
Score list for this clustering :
 [(2, 0.13184396652056307), (3, 0.1176629658795971), (4, 0.09243798682890239), (5, 0.09142444357
```

In [36]:
```
ptabe_entry_b2, pred_df = get_cluster_id(config_dict, score_list, train_features)
pred_df.head()
```

```
Best hyper param selected n_clusters : 2
Best silhoutte score score for this hyper parameter : 0.131844
```

Out[36]:

	Id	Cluster
0	456873	0
1	81416	0
2	519340	1
3	340949	1
4	453782	0

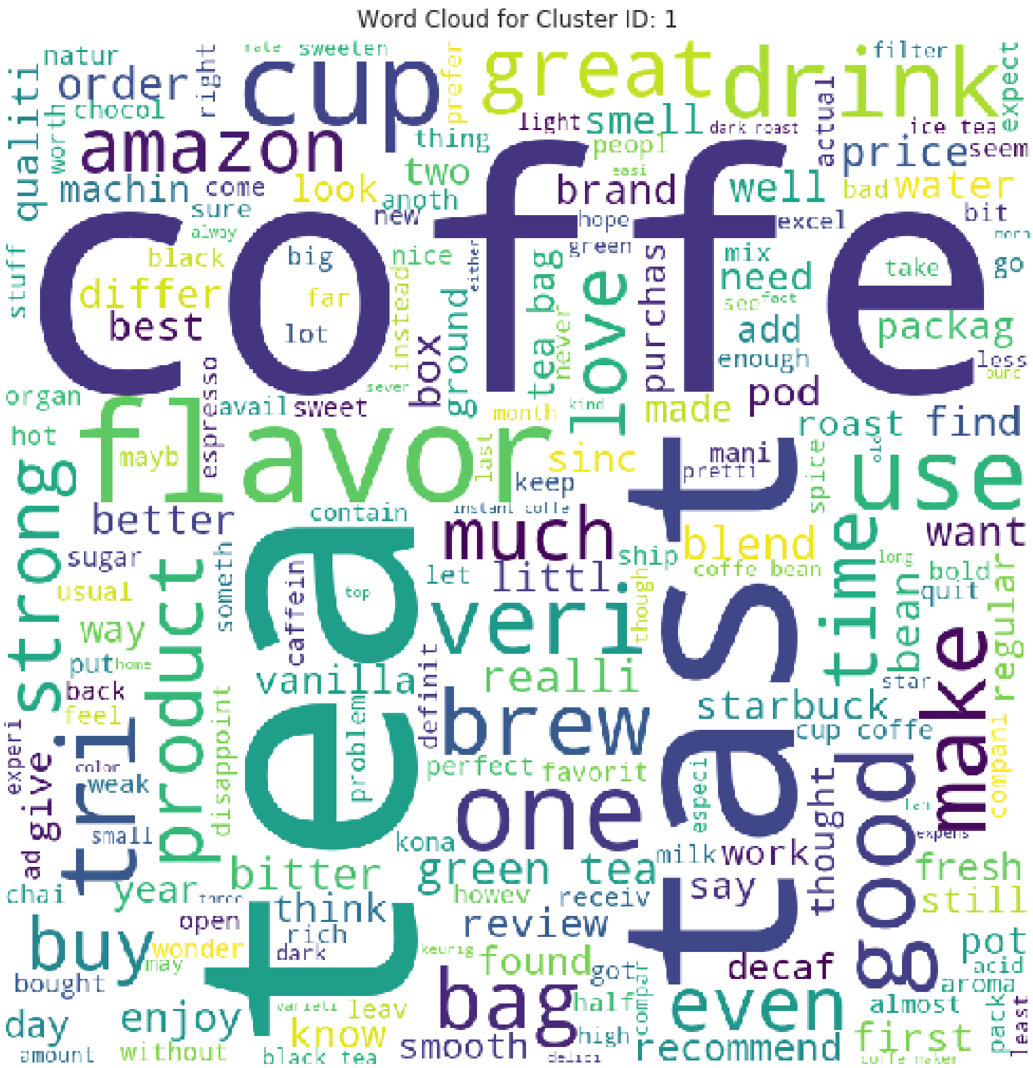
4.8.4 [B.4] Wordclouds of clusters obtained after applying Agglomerative Clustering on TFIDF W2V SET 4

In [37]:
```
# get id of each review in the training data points
id_list = train_features['Id'].tolist()
# get only the reviews which are used for training step
rev_df = read_from_DB(id_list)
# plot the word cloud for every clusters predicted
get_cluster_wordcloud(pred_df, rev_df)
```

```
===========================================================================================
+--------------------------------------------------------------------------------+
|                                 Cluster 0 Info                                 |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     0      |       4383      |      2174     |      2209     |    Negative    |
+------------+-----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: 0


```
==========================================================================================
==========================================================================================
+--------------------------------------------------------------------------------+
|                               Cluster 1 Info                                   |
+------------+-----------------+---------------+---------------+-----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+-----------------+
|     1      |       617       |      332      |      285      |    Positive     |
+------------+-----------------+---------------+---------------+-----------------+
```



==

4.9 Observation for SET 3 & SET 4

Silhouette coefficient can be used to select the number of clusters

The clusters have many words in common. This means its not the word but a pattern of word that distinguishes the cluster. We cannot simply relay on just one feature to do clustering

4.10 [C] DBSCAN Clustering

4.10.1 [C.1] Applying DBSCAN on AVG W2V, SET 3

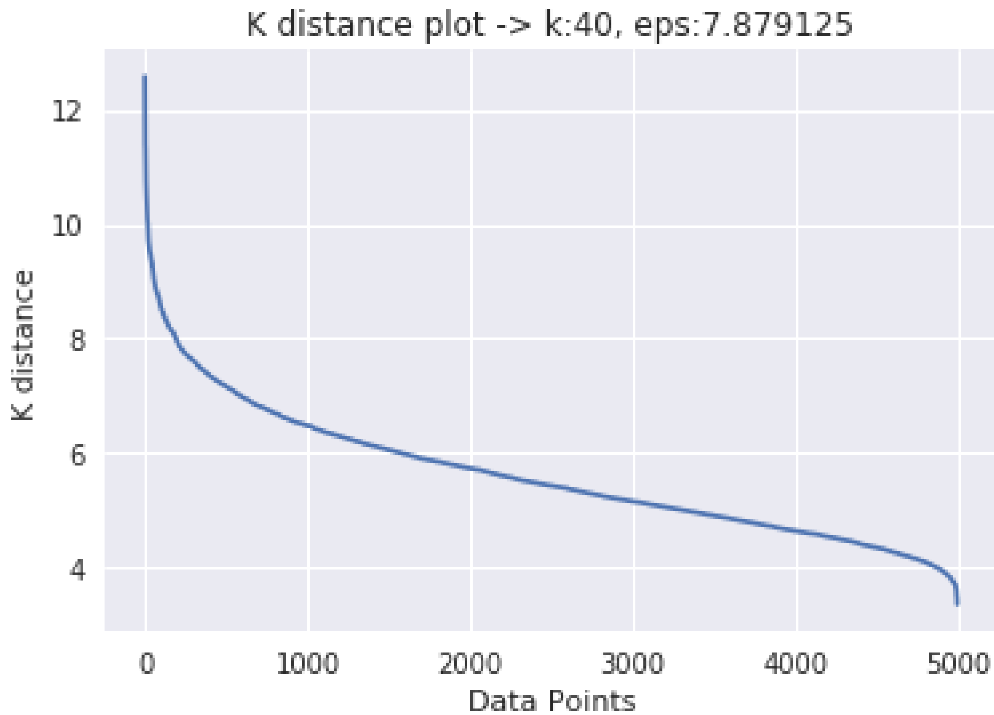
In [38]:
```
config_dict = {
        'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/AVG_W2V
        'train_size' : 5000,
        'min_pts_list' : [40, 60, 80, 100, 120, 150],
        'hyperparam_list' : list(), # initialize this list as empty
        'algo_type' : 'dbscan'
    }
```

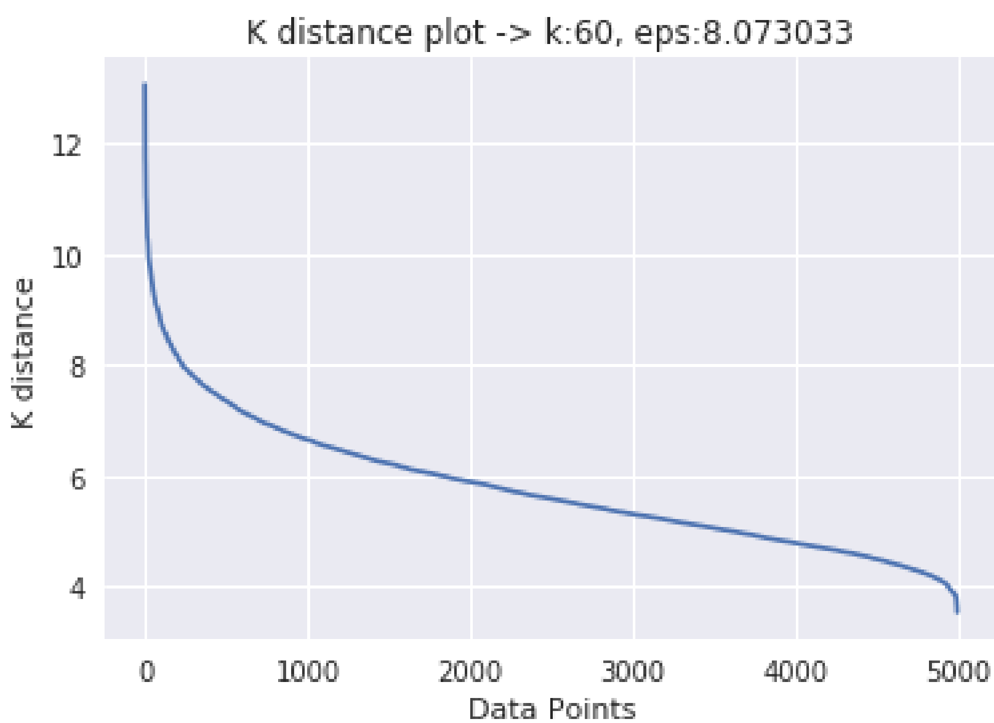
In [39]:
```
train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
```

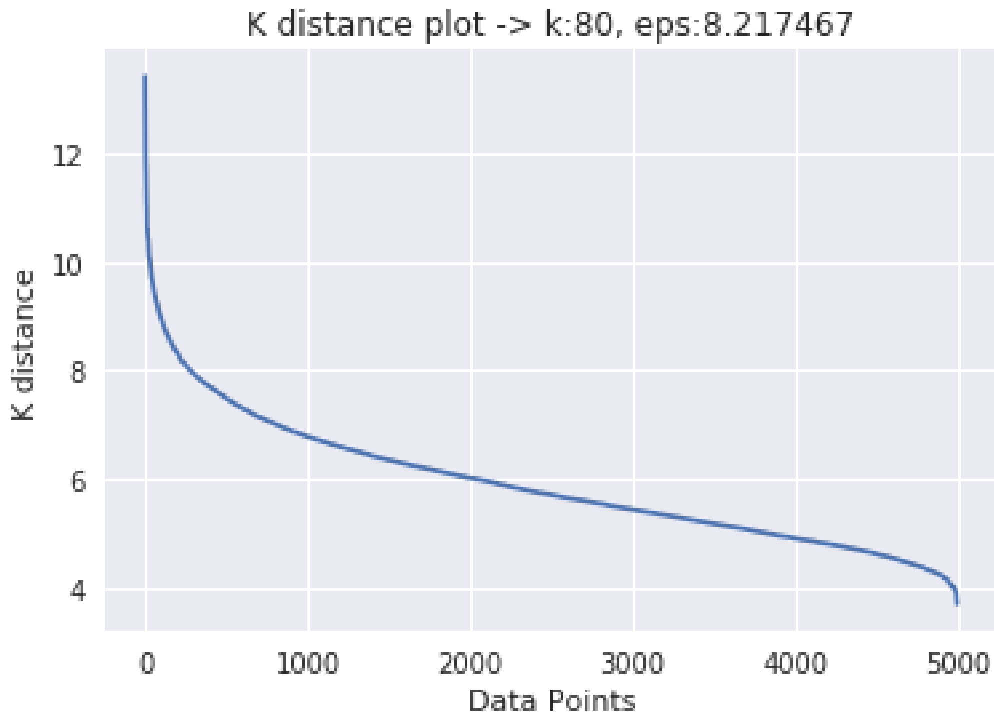
```
Train df shape (5000, 52)
Shape of ->  train features :5000,51
```

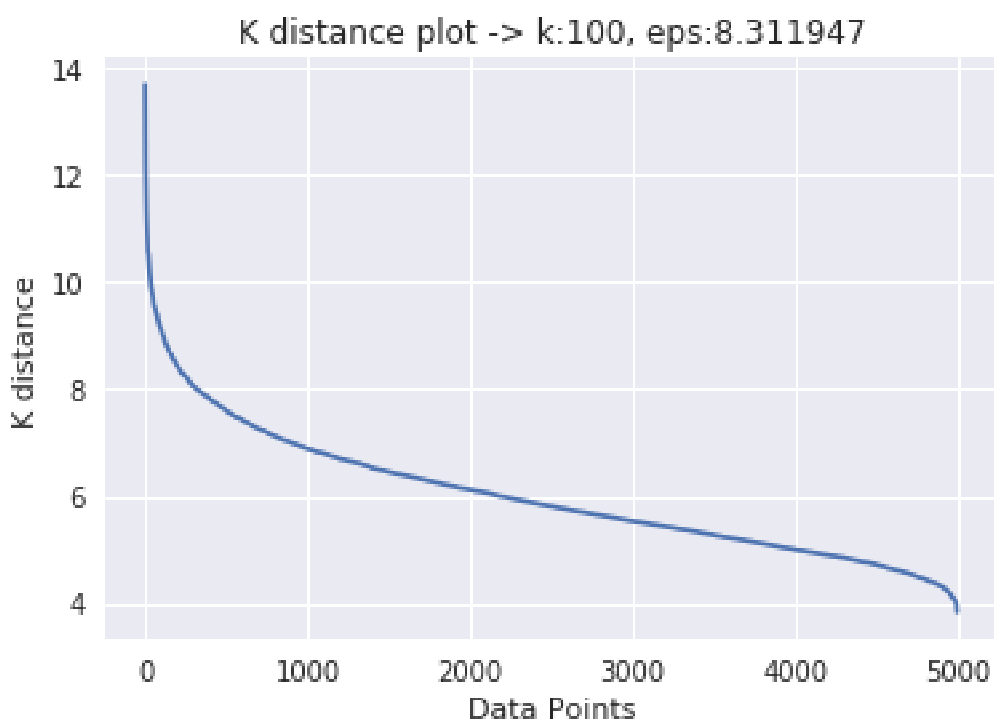
4.10.2 Identify the eps_val using k-distance method

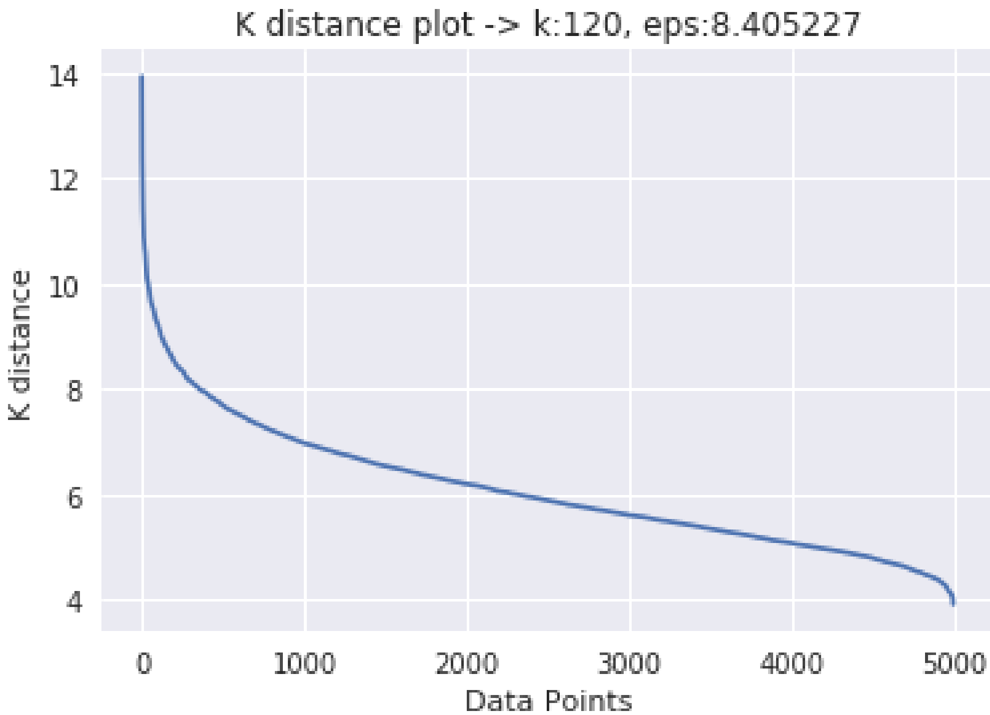
In [40]:
```
dist_input_df = train_features.drop(['Id'], axis=1)

# declare a list to hold all the hyperparams
hyp_param_list = list()

for min_pts in config_dict['min_pts_list']:
    mean_k_distance_list, eps_val, = get_kdistance_plot(dist_input_df, min_pts)
    hyp_param_list.append((eps_val, min_pts,))

# set hyper param in
config_dict['hyperparam_list'] = hyp_param_list
```

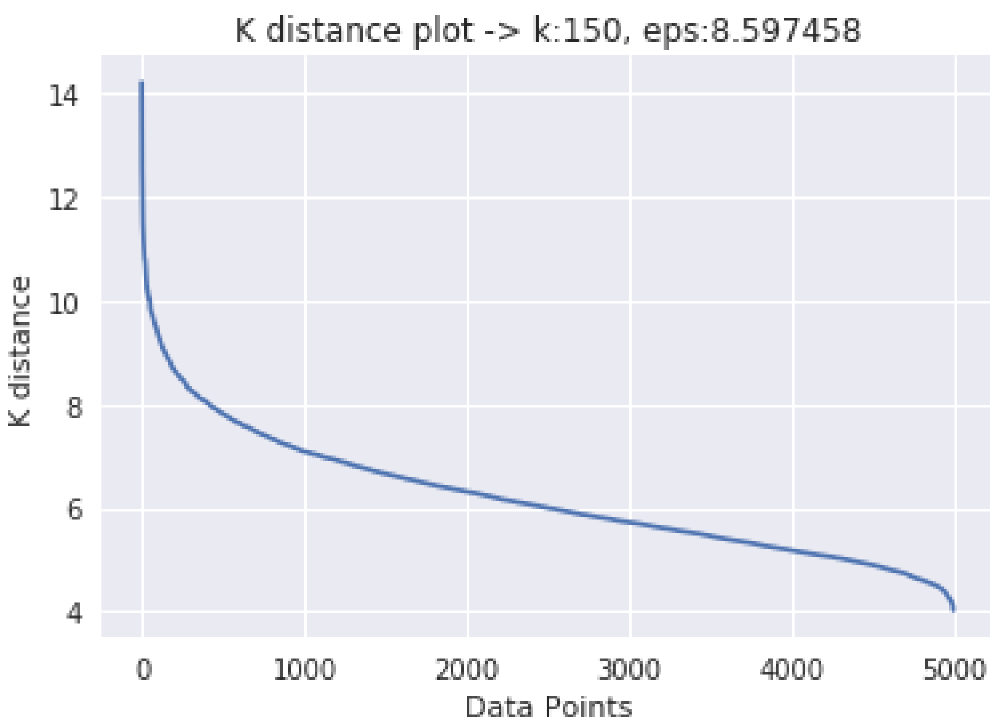

K distance plot -> k:40, eps:7.879125
K distance
Data Points
12
10
8
6
4
0
1000
2000
3000
4000
5000


K distance plot -> k:60, eps:8.073033
K distance
Data Points
12
10
8
6
4
0
1000
2000
3000
4000
5000


K distance plot -> k:80, eps:8.217467
K distance
12
10
8
6
4
0
1000
2000
3000
4000
5000
Data Points


K distance plot -> k:100, eps:8.311947
K distance
14
12
10
8
6
4
0
1000
2000
3000
4000
5000
Data Points


K distance plot -> k:120, eps:8.405227
K distance
Data Points
14
12
10
8
6
4
0
1000
2000
3000
4000
5000


K distance plot -> k:150, eps:8.597458
K distance
Data Points
14
12
10
8
6
4
0
1000
2000
3000
4000
5000

```
In [41]: score_list = find_best_hyperparameter(config_dict, train_features)
         print('Score list for this clustering :\n', score_list)
```

```
==================================================================================================
Score list for this clustering :
 [((7.879124555167806, 40), 0.31914734436834824), ((8.073033236962353, 60), 0.3326226160676315),
```

```
In [42]: ptabe_entry_c1, pred_df = get_cluster_id(config_dict, score_list, train_features)
         pred_df.head()
```

```
Best hyper param selected eps:8.597458,min_samples :150
Best silhoutte score score for this hyper parameter : 0.355103
```

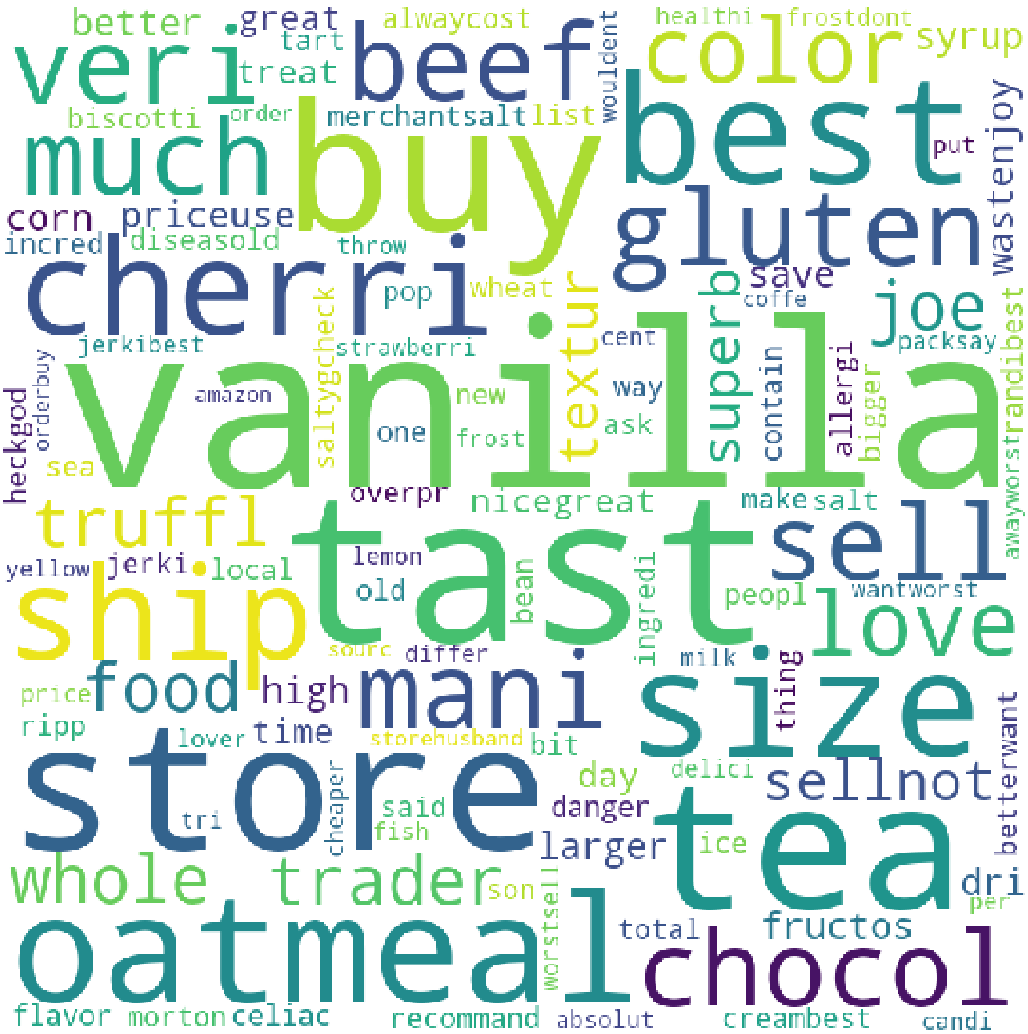
```
Out[42]:        Id  Cluster
         0  456873        0
         1   81416        0
         2  519340        0
         3  340949        0
         4  453782        0
```

4.10.3 [C.2] Wordclouds of clusters obtained after applying DBSCAN on AVG W2V SET 3

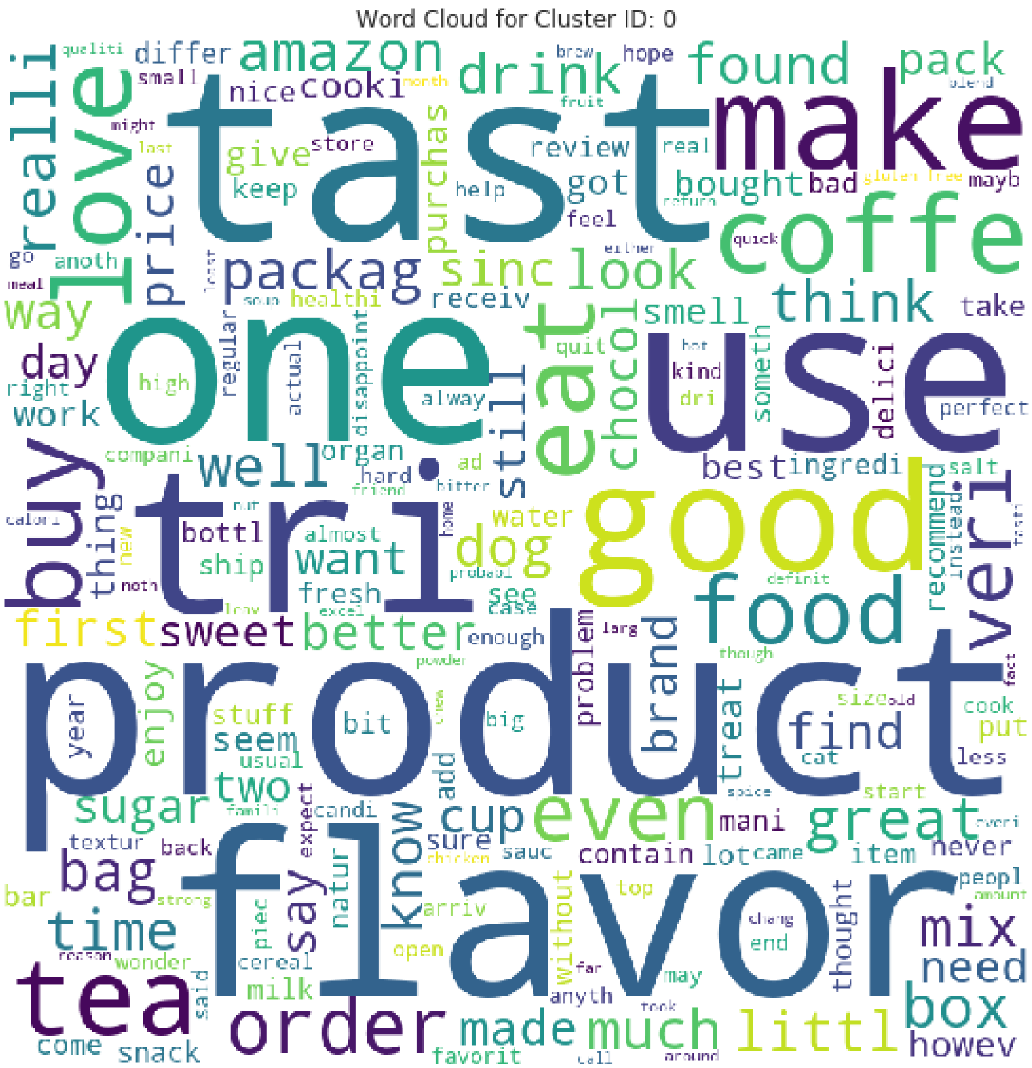
```
In [43]: # get id of each review in the training data points
         id_list = train_features['Id'].tolist()
         # get only the reviews which are used for training step
         rev_df = read_from_DB(id_list)
         # plot the word cloud for every clusters predicted
         get_cluster_wordcloud(pred_df, rev_df)
```

```
==================================================================================================
+--------------------------------------------------------------------------------+
|                                Cluster -1 Info                                 |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     -1     |        21       |       10      |       11      |    Negative    |
+------------+-----------------+---------------+---------------+----------------+
```

Word Cloud for Cluster ID: -1




```
==========================================================================================
==========================================================================================
+-----------------------------------------------------------------------------+
|                               Cluster 0 Info                                |
+------------+-----------------+---------------+---------------+----------------+
| Cluster_ID | Num Data Points | # +ve Reviews | # -ve Reviews | Majority Class |
+------------+-----------------+---------------+---------------+----------------+
|     0      |       4979      |      2496     |      2483     |    Positive    |
+------------+-----------------+---------------+---------------+----------------+
```




```
==========================================================================================
```

4.10.4 [C.3] Applying DBSCAN on TFIDF W2V, SET 4

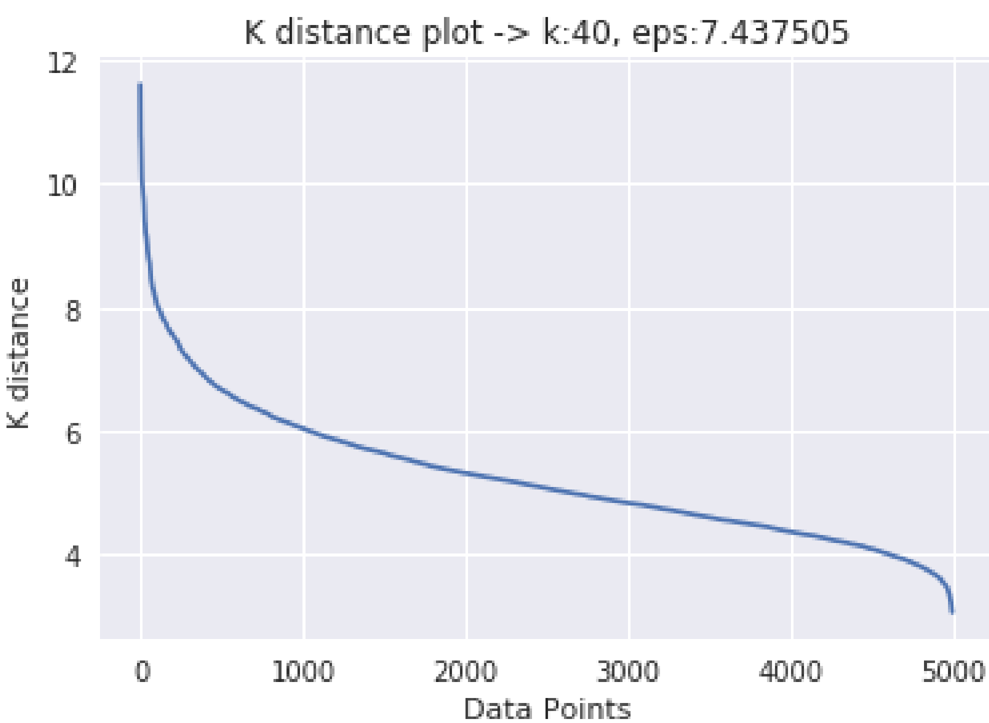
```
In [44]: config_dict = {
             'train_csv_path' :'/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF_W
             'train_size' : 5000,
             'min_pts_list' : [40, 60, 80, 100, 120, 150],
             'hyperparam_list' : list(), # initialize this list as empty
             'algo_type' : 'dbscan'
         }
```

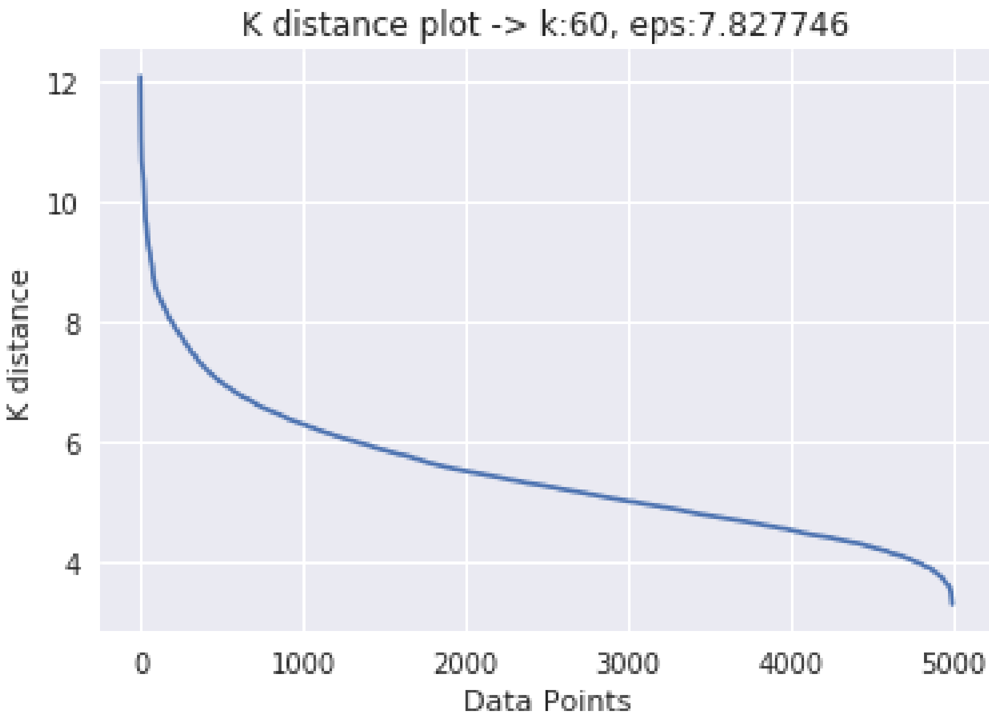
```
In [45]: train_features = preprocess_data(config_dict, scaling=True, dim_reduction=False)
```

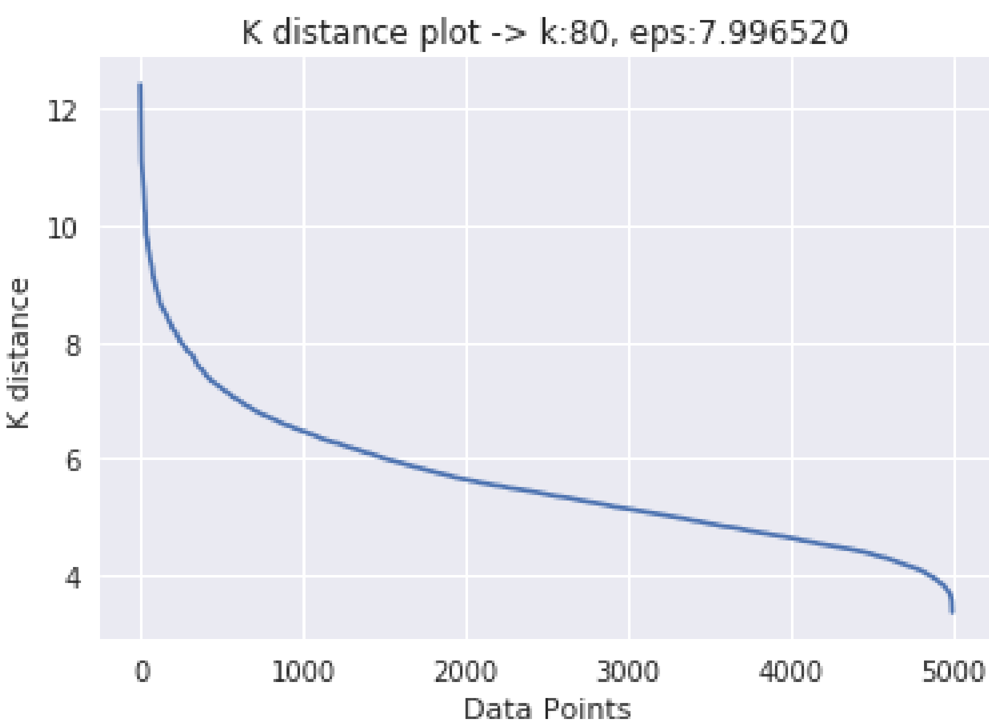
```
Train df shape (5000, 52)
Shape of ->  train features :5000,51
```

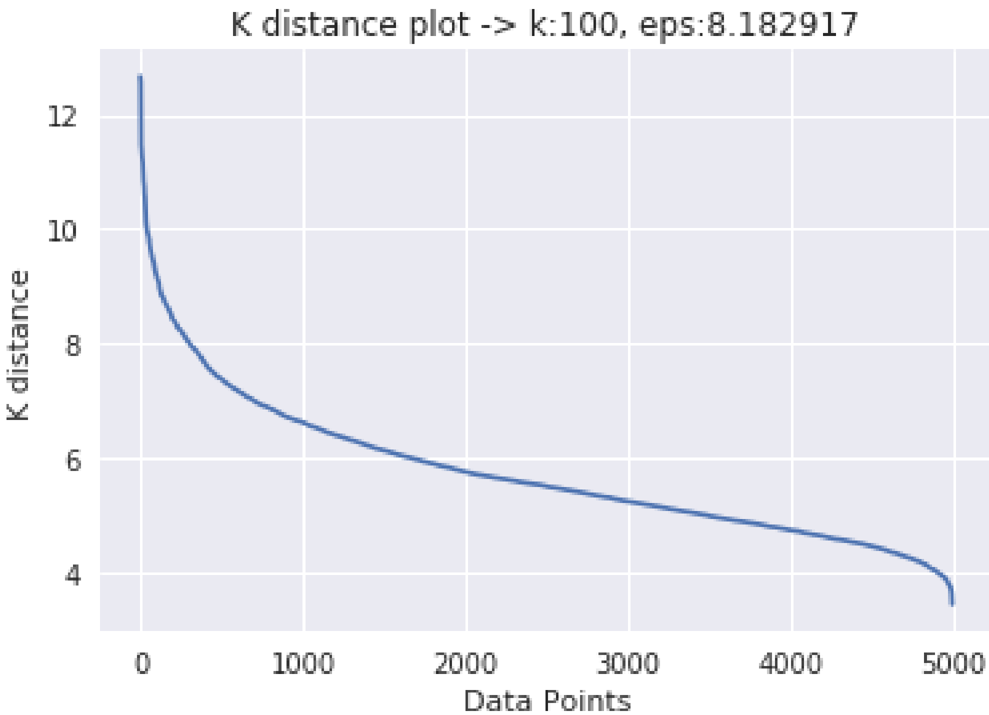
4.10.5 Identify the eps_val using k-distance method

```
In [46]: dist_input_df = train_features.drop(['Id'], axis=1)

         # declare a list to hold all the hyperparams
         hyp_param_list = list()

         for min_pts in config_dict['min_pts_list']:
             mean_k_distance_list, eps_val, = get_kdistance_plot(dist_input_df, min_pts)
             hyp_param_list.append((eps_val, min_pts,))

         # set hyper param in
         config_dict['hyperparam_list'] = hyp_param_list
```

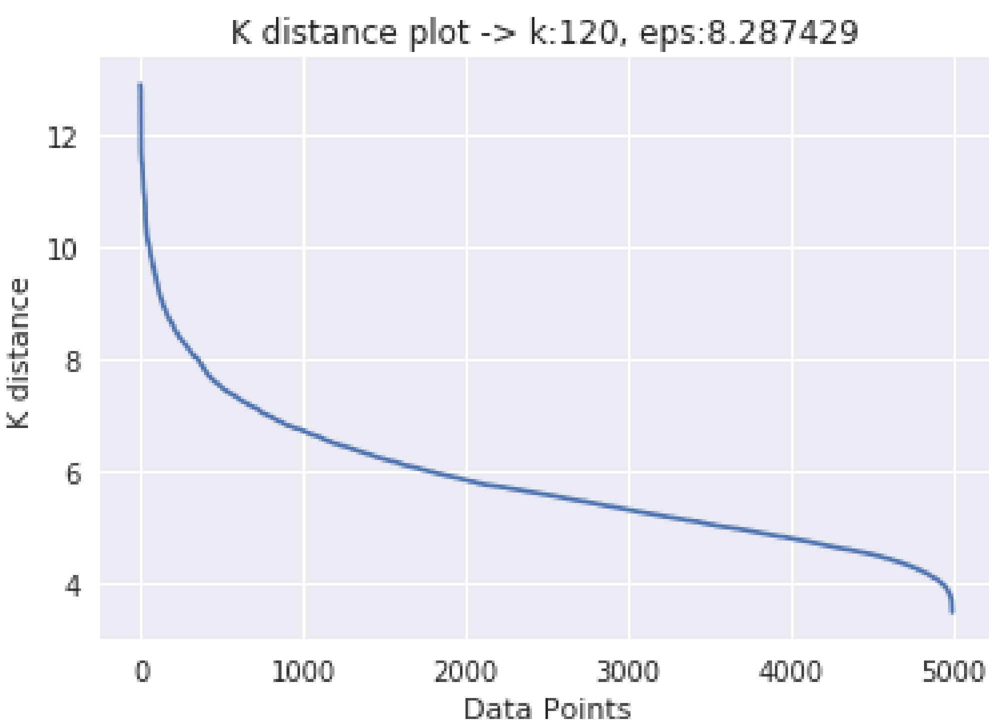



K distance plot -> k:60, eps:7.827746
K distance
Data Points
12
10
8
6
4
0
1000
2000
3000
4000
5000

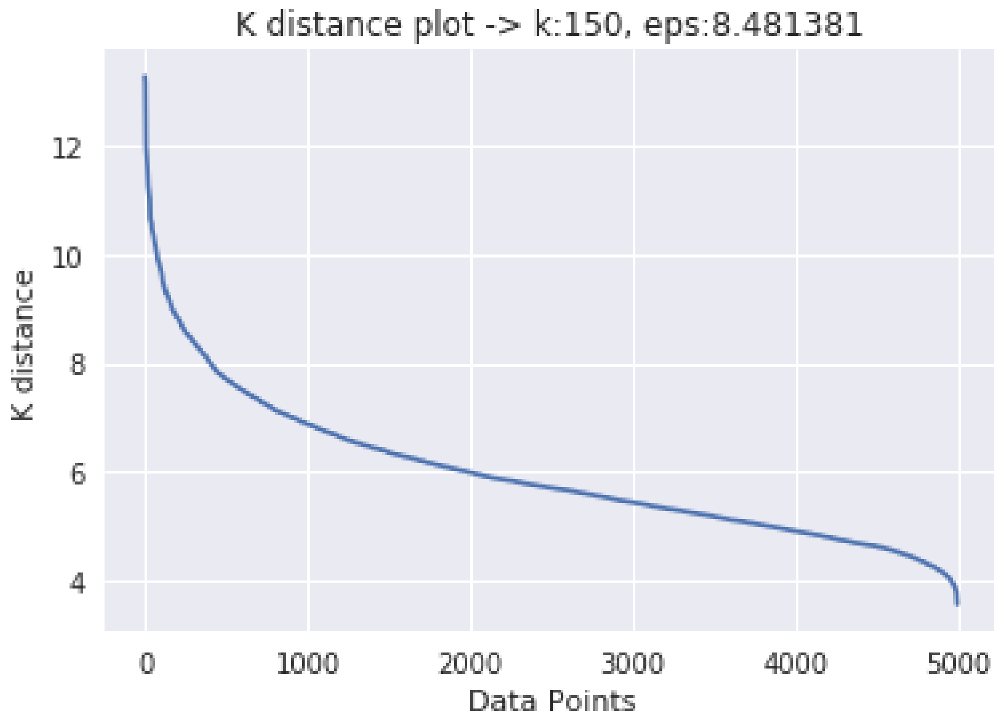

K distance plot -> k:80, eps:7.996520
K distance
Data Points
12
10
8
6
4
0
1000
2000
3000
4000
5000



K distance plot -> k:100, eps:8.182917
K distance
Data Points
12
10
8
6
4
0
1000
2000
3000
4000
5000



K distance plot -> k:120, eps:8.287429
K distance
Data Points
12
10
8
6
4
0
1000
2000
3000
4000
5000




```
In [47]: score_list = find_best_hyperparameter(config_dict, train_features)
         print('Score list for this clustering :\n', score_list)
```

```
==========================================================================================
Score list for this clustering :
 [((7.437505298428046, 40), 0.3000192553249008), ((7.82774585189994, 60), 0.3425005647524928), (
```

```
In [48]: ptabe_entry_c2, pred_df = get_cluster_id(config_dict, score_list, train_features)
         pred_df.head()
```

```
Best hyper param selected eps:8.287429,min_samples :120
Best silhoutte score score for this hyper parameter : 0.386138
```

Out[48]:

	Id	Cluster
0	456873	0
1	81416	0
2	519340	0
3	340949	0
4	453782	0

4.10.6 [C.4] Wordclouds of clusters obtained after applying DBSCAN on TFIDF W2V SET 4

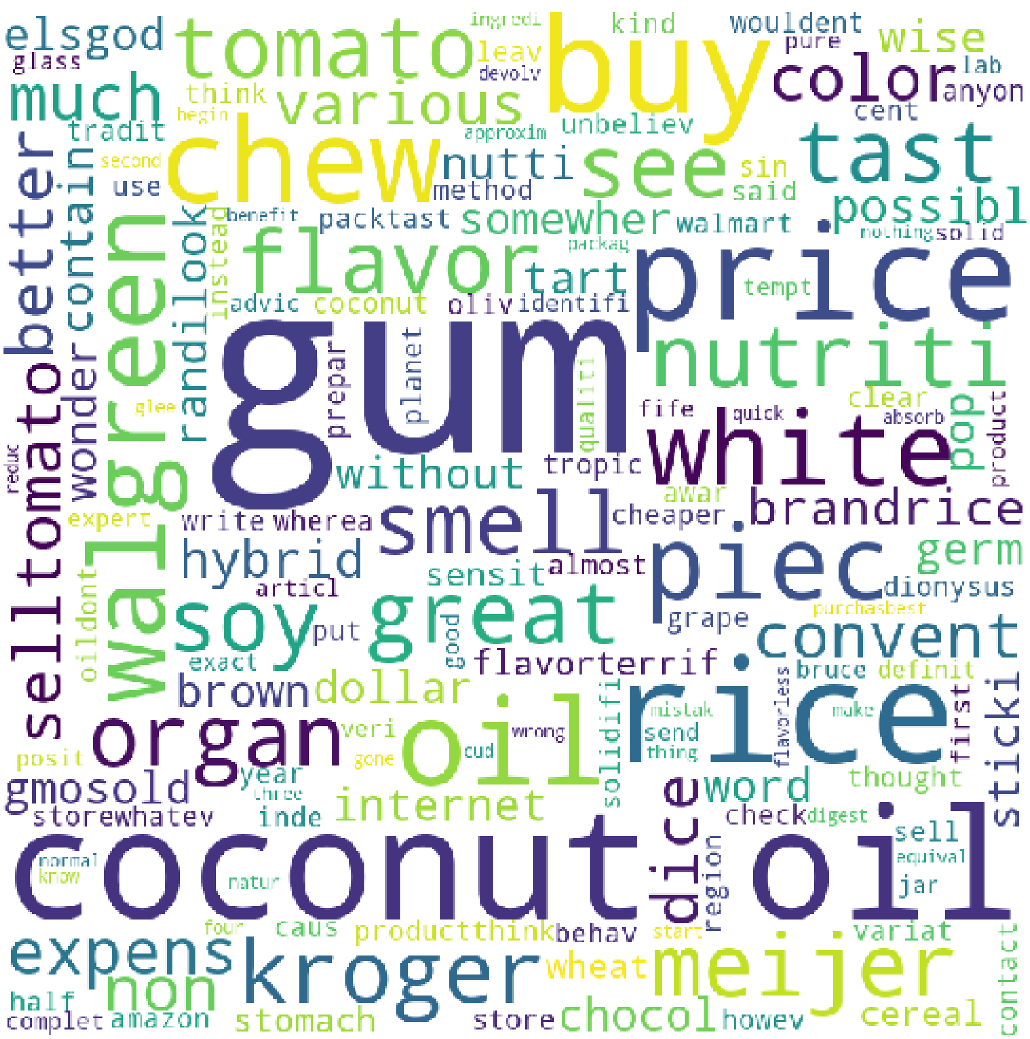
```
In [49]: # get id of each review in the training data points
         id_list = train_features['Id'].tolist()
```

```python
# get only the reviews which are used for training step
rev_df = read_from_DB(id_list)
# plot the word cloud for every clusters predicted
get_cluster_wordcloud(pred_df, rev_df)
```

```
==============================================================================================
```

Cluster -1 Info				
Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
-1	12	4	8	Negative

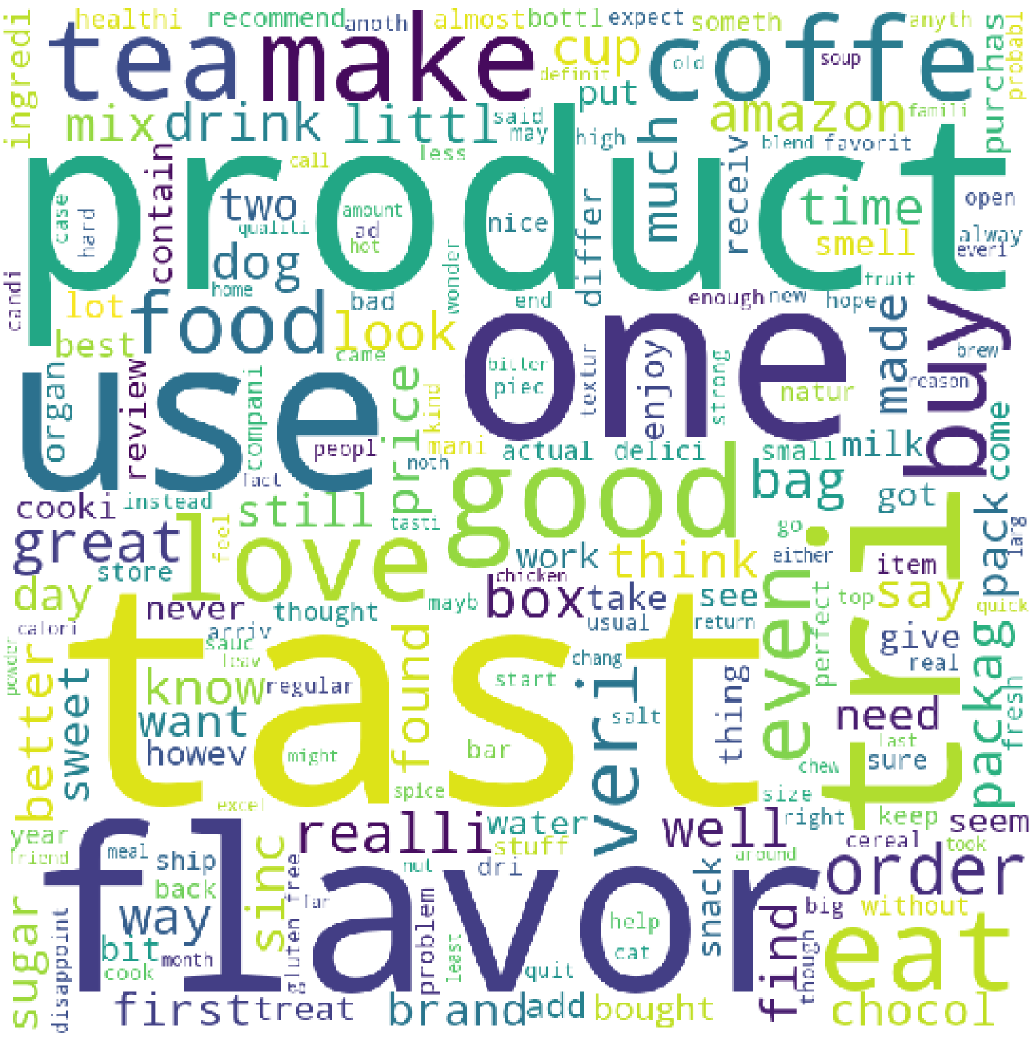
Word Cloud for Cluster ID: -1



Cluster 0 Info

Cluster_ID	Num Data Points	# +ve Reviews	# -ve Reviews	Majority Class
0	4988	2502	2486	Positive

Word Cloud for Cluster ID: 0



4.11 Observation

Silhouette coefficient can be used to select the number of clusters

Cluster ID -1 (Noise Points) has many words which are related to groceries such as rice, cococnut oil, tomato etc.

DBSCAN method identified one nosiy cluster (-1) and one valid cluster (0)

5 Procedure Summary

All the four datasets are column standardized before feeding to clustering algorithm

Best hyper parameter is selected using inertia/silhouette score. In this assignment for all clustering methods the clusters are selected based on the silhouette score

All words in a cluster are displayed using word cloud representation

The min_pts points are set by trial and error method

For DBSCAN the right number of eps value is determined using k-distance plot. From k-distance plot we need to identify the knee point inorder to set the eps value.

6 Results Summary

In [50]:
```
Pret_table = PrettyTable()
Pret_table.field_names = ['Vectorizer', 'Algorithm', 'Cluster Info {id:size}', 'Hyper-P
Pret_table.title = 'Clustering Results Summary'
```

In [51]:
```
# K-means
Pret_table.add_row(['BoW', 'K-means'] + ptabe_entry_a1)
Pret_table.add_row(['TF-IDF', 'K-means'] + ptabe_entry_a2)
Pret_table.add_row(['Avg W2V', 'K-means'] + ptabe_entry_a3)
Pret_table.add_row(['TF-IDF W2V', 'K-means'] + ptabe_entry_a4)

# Agglomerative
Pret_table.add_row(['Avg W2V', 'Agglomerative'] + ptabe_entry_b1)
Pret_table.add_row(['TF-IDF W2V', 'Agglomerative'] + ptabe_entry_b2)

# DBSCAN
Pret_table.add_row(['Avg W2V', 'DBSCAN'] + ptabe_entry_c1)
Pret_table.add_row(['TF-IDF W2V', 'DBSCAN'] + ptabe_entry_c2)
```

In [52]:
```
print(Pret_table)
```

```
+------------------------------------------------------------------------------------------
|                                              Clustering Results Summary
+------------+---------------+-------------------------------------+--------------------------+
| Vectorizer |   Algorithm   |        Cluster Info {id:size}       |        Hyper-Param       |
+------------+---------------+-------------------------------------+--------------------------+
|    BoW     |    K-means    |         {0: 13051, 1: 1949}         |           k= 2           |
|   TF-IDF   |    K-means    |          {1: 8220, 0: 6780}         |           k= 2           |
|  Avg W2V   |    K-means    |    {2: 6776, 1: 5831, 0: 2393}      |           k= 3           |
| TF-IDF W2V |    K-means    |         {0: 12946, 1: 2054}         |           k= 2           |
```

Avg W2V	Agglomerative	{1: 2177, 0: 1573, 3: 633, 2: 617}	k= 4
TF-IDF W2V	Agglomerative	{0: 4383, 1: 617}	k= 2
Avg W2V	DBSCAN	{0: 4979, -1: 21}	eps= 8.5975, min_pts= 150
TF-IDF W2V	DBSCAN	{0: 4988, -1: 12}	eps= 8.2874, min_pts= 120

7 Conclusions

The best clustering obtained is from DBSCAN with silhouette value 0.3861

Many clusters formed have many words in common. This means that we cannot simply relay on words to get proper clustering, rather we need to try with many combination of words .