KMeansClustering_amazon_food_review

January 10, 2019

In [1]:
```
# imported necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud, STOPWORDS
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
import sqlite3
con = sqlite3.connect("final.sqlite")
```

In [3]:
```
cleaned_data = pd.read_sql_query("select * from Reviews", con)
```

In [4]:
```
cleaned_data.shape
```

Out[4]:
```
(364171, 12)
```

In [5]:
```
# Sort data based on time
cleaned_data["Time"] = pd.to_datetime(cleaned_data["Time"], unit = "s")
cleaned_data = cleaned_data.sort_values(by = "Time")
#cleaned_data.head()
```

In [6]:
```
cleaned_data["Score"].value_counts()
```

Out[6]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [7]:
```
final = cleaned_data.iloc[:50000,:]
final.shape
```

Out[7]:
```
(50000, 12)
```

1 K-Means Clustering

1.1 Bag of Word

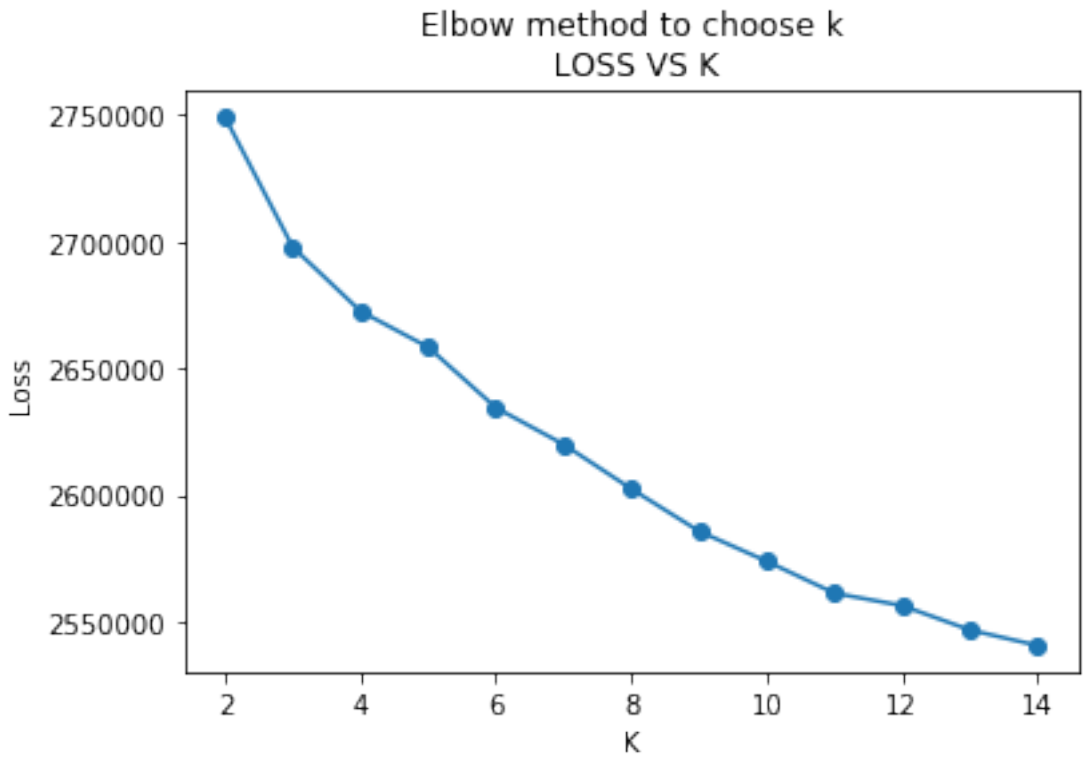
```
In [454]: # 100k data which will use to train model after vectorization
          X = final["CleanedText"]
          print("shape of X:", X.shape)

shape of X: (50000,)


In [455]: # Vectorizor
          bow = CountVectorizer()
          feat = bow.fit_transform(X)
          feat

Out[455]: <50000x27002 sparse matrix of type '<class 'numpy.int64'>'
                  with 1484064 stored elements in Compressed Sparse Row format>

In [456]: # Standardization
          std = StandardScaler(with_mean = False)
          std_feat = std.fit_transform(feat)
          std_feat

Out[456]: <50000x27002 sparse matrix of type '<class 'numpy.float64'>'
                  with 1484064 stored elements in Compressed Sparse Row format>

In [11]: #Plot each cluster features in a cloud
         def plot_cluster_cloud(features, coef):
             coef_df = pd.DataFrame(coef, columns = features)
             print(len(coef_df))
             # Create a figure and set of 15 subplots because our k range is in between
             fig, axes = plt.subplots(5, 3, figsize = (30, 20))
             fig.suptitle("Top 20 words for each cluster ", fontsize = 50)
             cent = range(len(coef_df))
             for ax, i in zip(axes.flat, cent):
                 wordcloud = WordCloud(background_color = "white").generate_from_frequencies(c
                 ax.imshow(wordcloud)
                 ax.set_title("Cluster {} word cloud".format(i+1), fontsize = 30)
                 ax.axis("off")
             plt.tight_layout()
             fig.subplots_adjust(top = 0.90)
             plt.show()

In [253]: # Plot each review of a given cluster based on label
          def plot_word_cloud(txt):
              # store each word from review
              cloud = " ".join(word for word in txt)
              cloud
```

```
            # Remove duplicate words
            stopwords = set(STOPWORDS)
            # call built-in method WordCloud for creating an object for drawing a word cloud
            wordcloud = WordCloud(width = 1000, height = 600, background_color ='white', sto
            # plot the WordCloud image
            plt.figure(figsize = (10, 8))
            plt.imshow(wordcloud, interpolation = 'bilinear')
            plt.axis("off")
            plt.title("World cloud of reviews")
            plt.tight_layout(pad = 0)

            plt.show()
```

In [457]:
```
# Elbow method to find K in k_means clustering
# inertia_ is sum of squared distances of samples to their closest cluster center.
def find_optimal_k(std_data):
    loss = []
    k = list(range(2, 15))
    for noc in k:
        model = KMeans(n_clusters = noc)
        model.fit(std_data)
        loss.append(model.inertia_)
    plt.plot(k, loss, "-o")
    plt.title("Elbow method to choose k")
    plt.xlabel("K")
    plt.ylabel("Loss")
    plt.show()
```

In [13]:
```
# Elbow method to compute K
# This is same as the above function(find_optimal_k)do not confused with this.
%time
loss = []
k = list(range(2, 15))
for noc in k:
    model = KMeans(n_clusters = noc)
    model.fit(feat)
    loss.append(model.inertia_)
plt.plot(k, loss, "-o")
plt.title("Elbow method to choose k\n LOSS VS K")
plt.xlabel("K")
plt.ylabel("Loss")
plt.show()
```

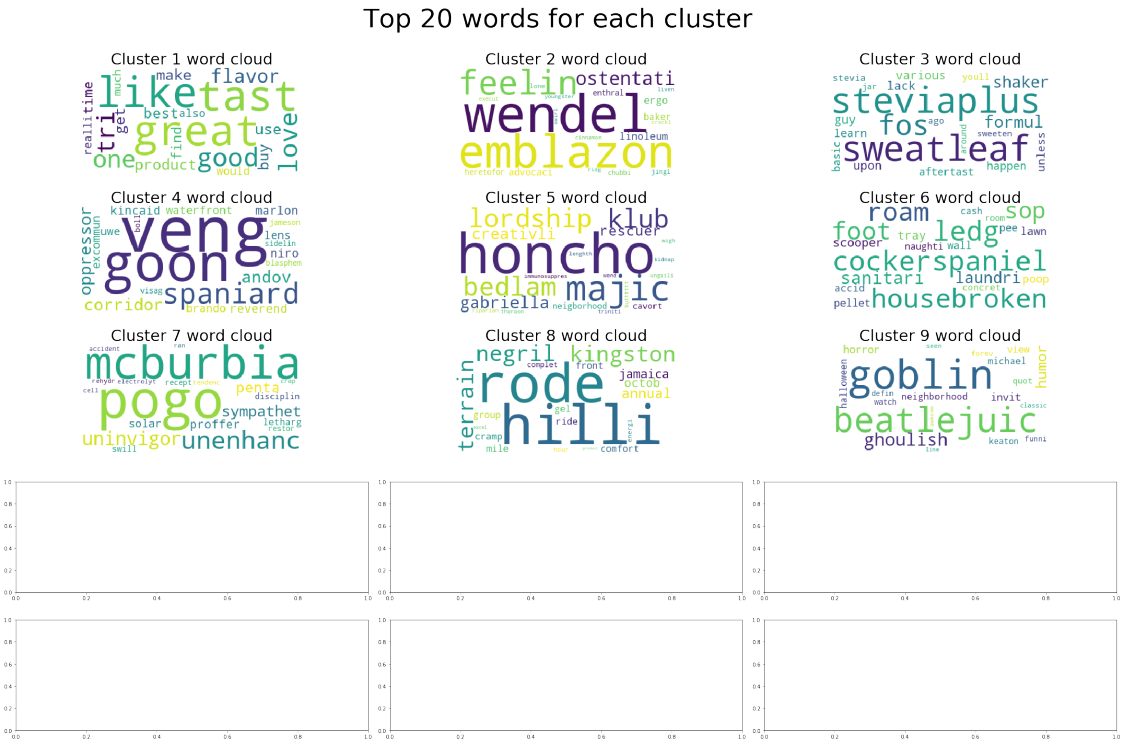
```
Wall time: 0 ns
```



In [14]:
```
# training kmeans
clf = KMeans(n_clusters = 9)
clf.fit(std_feat)
pred = clf.predict(std_feat)
```

In [15]:
```
# getting feature names in features
# and the cluster centers in coef
# Plot the all cluster with their corresponding features
features = bow.get_feature_names()
coef = clf.cluster_centers_
plot_cluster_cloud(features, coef)
```

9

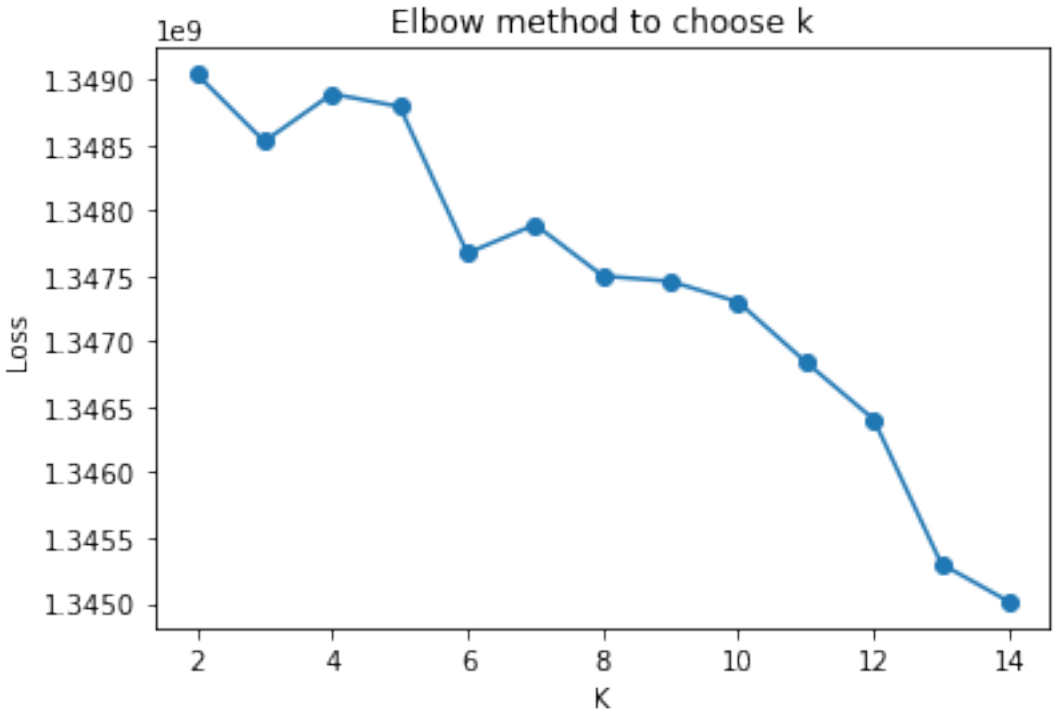


Observations 1. We choose k value using elbow method and found k value to be 9. 2. Applied kmeans on bow and plot each cluster and found that each cluster atleast contains 20 words. 3. As we can see in word cloud, some cluster have nicely group together but some have some other word which are not related at all.

1.2 TF-IDF

```
In [64]: # 5k data-points
         X = final["CleanedText"]

In [65]: # Featurization
         tfidf = TfidfVectorizer()
         feat = tfidf.fit_transform(X)
         feat

Out[65]: <50000x27002 sparse matrix of type '<class 'numpy.float64'>'
                 with 1484064 stored elements in Compressed Sparse Row format>

In [66]: # Standardization
         std = StandardScaler(with_mean = False)
         std_data = std.fit_transform(feat)
         std_data

Out[66]: <50000x27002 sparse matrix of type '<class 'numpy.float64'>'
                 with 1484064 stored elements in Compressed Sparse Row format>
```

In [69]:
```
# Call utility function to get k
find_optimal_k(std_data)
```



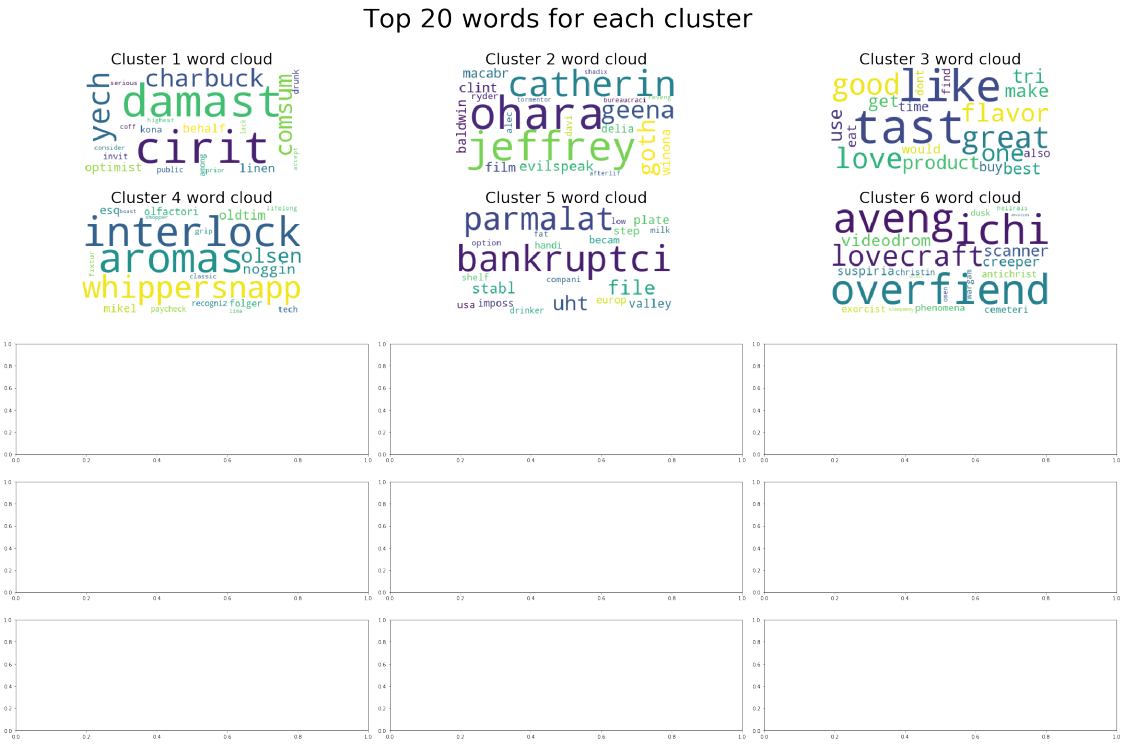
In [70]:
```
# Kmeans to
clf = KMeans(n_clusters = 6)
clf.fit(std_data)
pred = clf.predict(std_data)
```

In [62]:
```
clf.cluster_centers_.shape
```

Out[62]:
```
(11, 27002)
```

In [72]:
```
features = tfidf.get_feature_names()
coef = clf.cluster_centers_
plot_cluster_cloud(features, coef)
```

6



Observations 1. we have total 6 cluster and by looking at the word cloud of each cluster we can say almost none of the cluster have similar meaning of features neither they are related somehow. All cluster have mixed features.

1.3 Word2Vec

```
In [73]: # data
         X = final["Text"]
         X.shape

Out[73]: (50000,)

In [74]: import re
         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 ch
             cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
             cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
             return  cleaned

In [75]: # Train your own Word2Vec model using your own train text corpus
         import gensim
         list_of_sent=[]
```

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

```
In [76]: # Train word2vec model with your own corpus
         w2v_model = gensim.models.Word2Vec(list_of_sent, min_count = 5, size = 50, workers = 4
```

```
In [77]: # Check similar word to like
         w2v_model.wv.most_similar('like')
```

```
Out[77]: [('prefer', 0.6391164064407349),
          ('mean', 0.6134073734283447),
          ('think', 0.5840848088264465),
          ('miss', 0.5640555620193481),
          ('crave', 0.5610888004302979),
          ('awful', 0.5601608753204346),
          ('gross', 0.557422399520874),
          ('love', 0.5546953678131104),
          ('overpower', 0.5535687208175659),
          ('fine', 0.5516911149024963)]
```

```
In [78]: # word2vec vocabulary
         w2v = w2v_model[w2v_model.wv.vocab]
```

```
In [79]: w2v.shape
```

```
Out[79]: (13832, 50)
```

1.3.1 Average Word2Vec

```
In [80]: #Plot each cluster features in a cloud
         def plot_cluster_cloud(features, coef):
             coef_df = pd.DataFrame(coef, columns = features)
             print(len(coef_df))
             fig, axes = plt.subplots(5, 3, figsize = (30, 20))
             fig.suptitle("Top 20 words for each cluster ", fontsize = 50)
             cent = range(len(coef_df))
             for ax, i in zip(axes.flat, cent):
                 wordcloud = WordCloud(background_color = "white").generate_from_frequencies(co
                 ax.imshow(wordcloud)
                 ax.set_title("Cluster {} word cloud".format(i+1), fontsize = 30)
                 ax.axis("off")
```

```
            plt.tight_layout()
            fig.subplots_adjust(top = 0.90)
            plt.show()
```

In [81]:
```
def plot_word_cloud(txt):
    # store each word from review
    cloud = " ".join(word for word in txt)
    cloud
    # Remove duplicate words
    stopwords = set(STOPWORDS)
    # call built-in method WordCloud for creating an object for drawing a word cloud
    wordcloud = WordCloud(width = 1000, height = 600, background_color ='white', stopw
    # plot the WordCloud image
    plt.figure(figsize = (10, 8))
    plt.imshow(wordcloud, interpolation = 'bilinear')
    plt.axis("off")
    plt.title("World cloud of top words")
    plt.tight_layout(pad = 0)

    plt.show()
```

In [82]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = [] # the avg-w2v for each sentence/review is stored in this list
for sent in 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/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

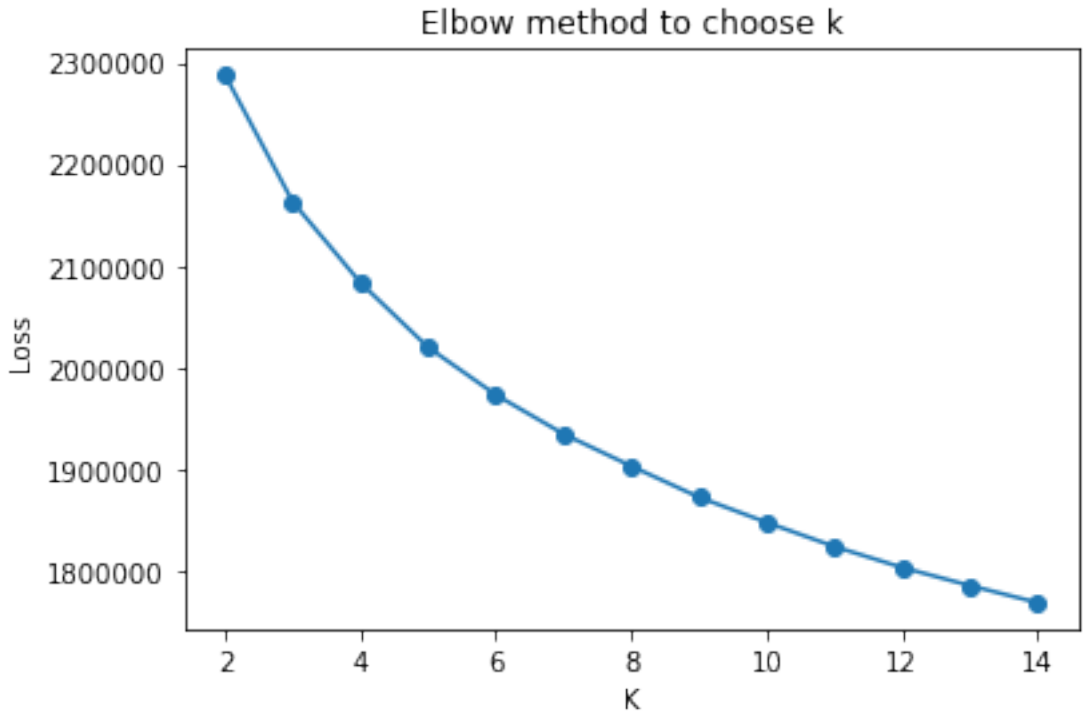
```
50000
50
```

In [84]:
```
# Convert data list to an array
X = np.array(sent_vectors)
X.shape
```

Out[84]:
```
(50000, 50)
```

In [85]:
```
# Standardization
std = StandardScaler(with_mean = False)
std_data = std.fit_transform(X)
```

In [86]:
```
# Find k
find_optimal_k(std_data)
```



In [87]:
```
# KMeans Clustering
clf = KMeans(n_clusters = 10)
clf.fit(std_data)
```

Out[87]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=10, n_init=10, n_jobs=None, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
```

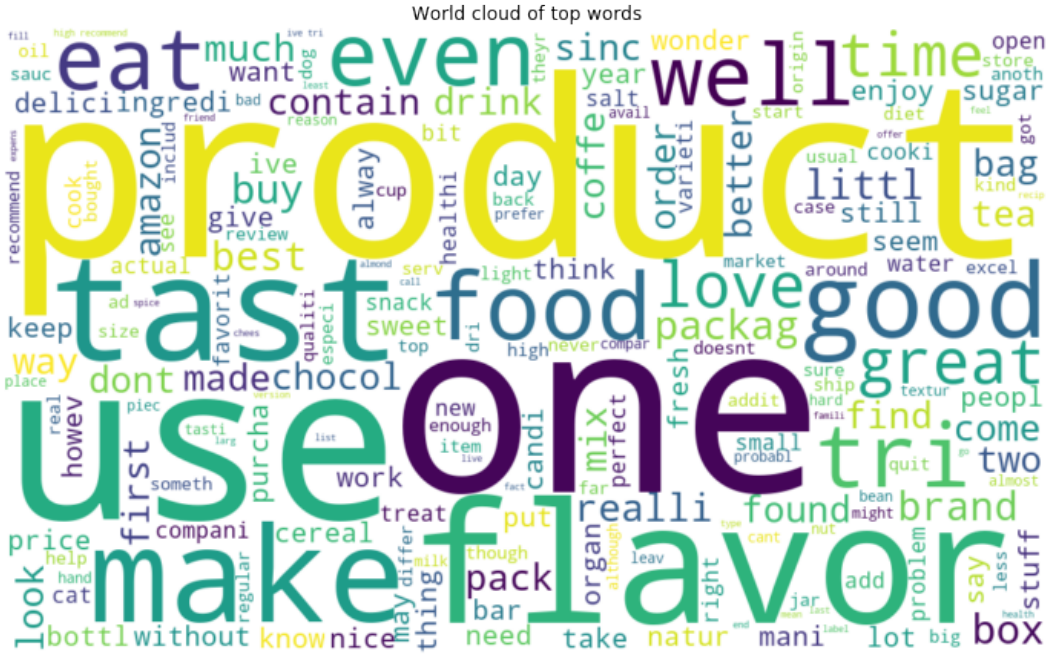
In [ ]:
```
# Assign each review to its cluster label
# i.e. Which review belongs to which cluster
final["cluster_label"] = clf.labels_
```

In [91]:
```
# For each cluster, group with its corresponding label.
for i in range(clf.n_clusters):
    l = list()
    label = final.groupby(["cluster_label"]).groups[i]
    # For each label get the total review and put into a list(l)
```

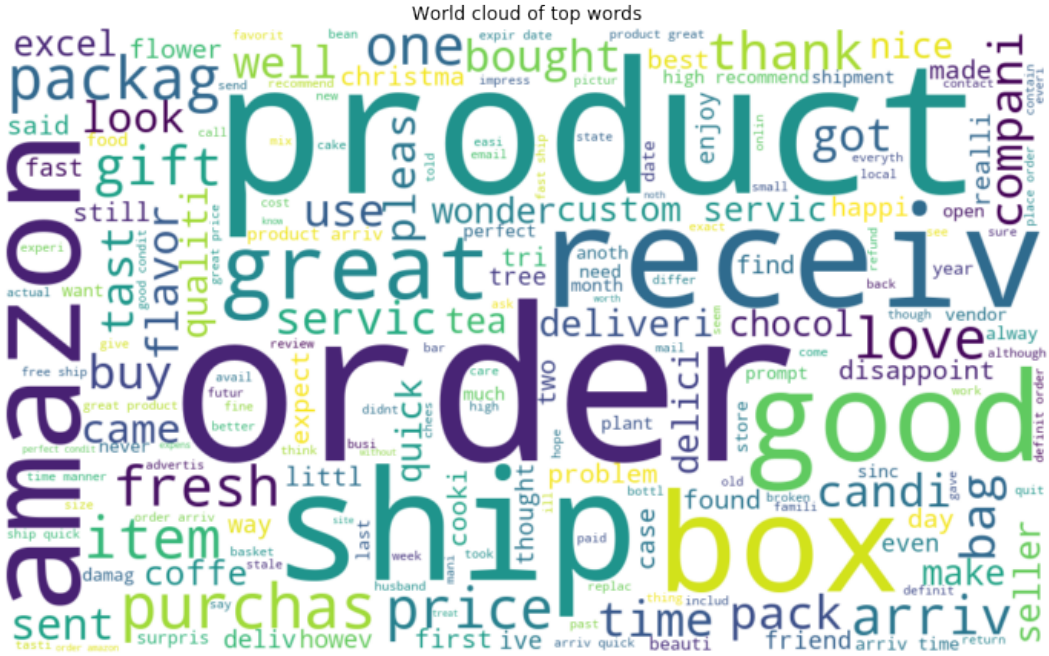
```
        for j in range(len(label)):
            l.append(final.loc[label[j]]["CleanedText"].decode())
        print("Total number of review in cluster {} is: {}".format(i, len(label)))
        # Call plot_word_cloud method to plot review in each cluster
        plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 5039
```


```
Total number of review in cluster 1 is: 7190
```



Total number of review in cluster 2 is: 2603



Total number of review in cluster 3 is: 7157

Total number of review in cluster 4 is: 5800

Total number of review in cluster 5 is: 3455

Total number of review in cluster 6 is: 4051

Total number of review in cluster 7 is: 4985

Total number of review in cluster 8 is: 5334

Total number of review in cluster 9 is: 4386

Observations 1. We applied kmeans on word2vec and choose optimal number of cluster using elbow method. 2. We can not get features directly from word2vec so we get lebel after training of kmeans and assign labels to its corresponding review and plotted wordcloud. We have total 10 cluster and most word in word cloud is somehow related.

1.3.2 TFIDF Word2Vec

```
In [93]: # TF-IDF weighted Word2Vec
         tfidf_feat = tfidf.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

         tfidf_sent_vectors = [] # the tfidf-w2v for each sentence/review is stored in this li
         row=0
         for sent in 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/review
             for word in sent: # for each word in a review/sentence
                 try:
                     vec = w2v_model.wv[word]
                     # obtain the tf_idfidf of a word in a sentence/review
                     tf_idf = X[row, tfidf_feat.index(word)]
                     sent_vec += (vec * tf_idf)
                     weight_sum += tf_idf
                 except:
                     pass
             sent_vec /= weight_sum
             tfidf_sent_vectors.append(sent_vec)
             row += 1
```

```
In [94]: print(len(tfidf_sent_vectors))
         print(len(tfidf_sent_vectors[0]))
```

```
50000
50
```

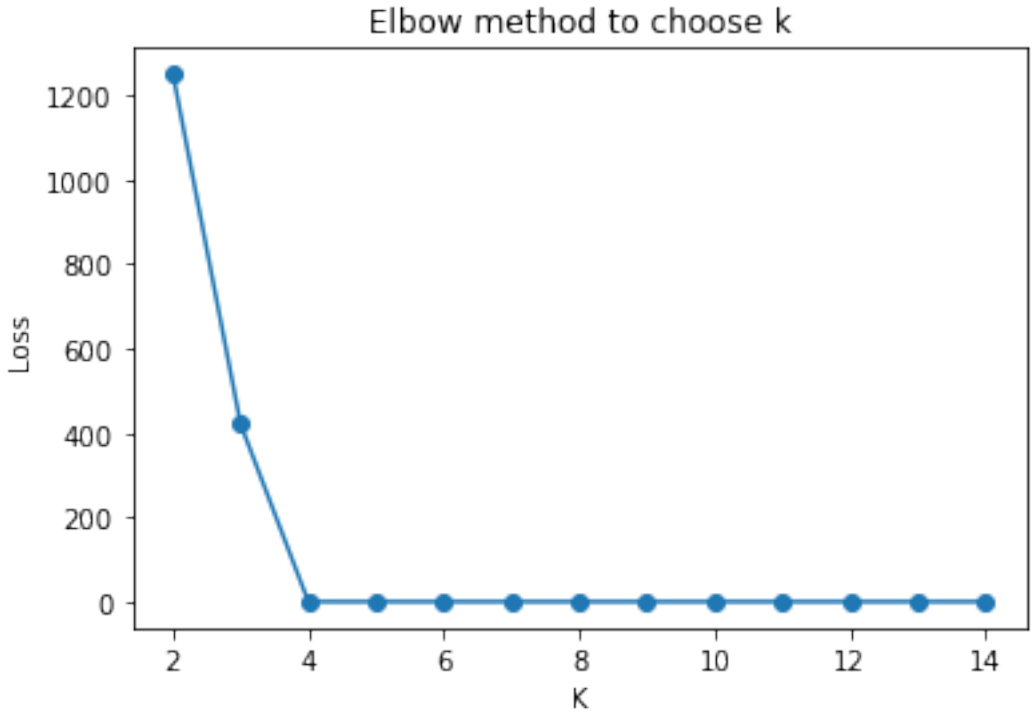
```
In [95]: # Convert list of data to an array
         X = np.array(tfidf_sent_vectors)
         X.shape
```

```
Out[95]: (50000, 50)
```

```
In [96]: # Standardization
         std = StandardScaler(with_mean = False)
         std_data = std.fit_transform(X)
```

```
In [97]: # Convert nan or infinite float to number
         std_data = np.nan_to_num(std_data)
```

In [98]:
```
# Find k using elbow method
find_optimal_k(std_data)
```



In [99]:
```
# KMeans Clustering
clf = KMeans(n_clusters = 3)
clf.fit(std_data)
```

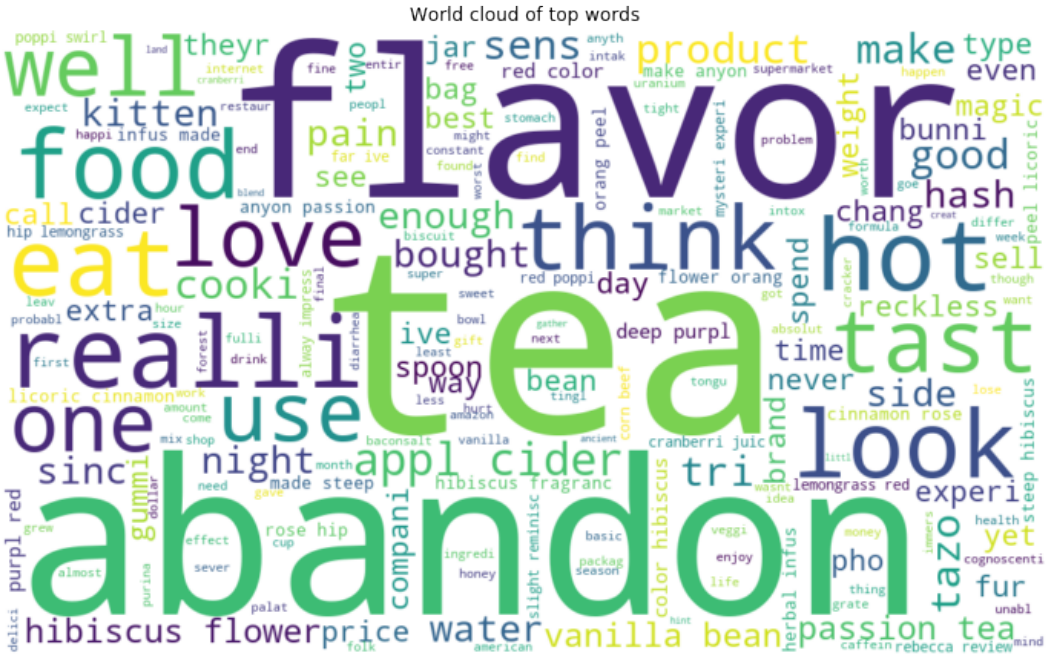
Out[99]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
```

In [ ]:
```
final["cluster_label"] = clf.labels_
```

In [103]:
```
# Same as the average word2vec of k means clustering
# Although we can create a function to print wordcloud but let it be for now
for i in range(clf.n_clusters):
    l = list()
    label = final.groupby(["cluster_label"]).groups[i]
    for j in range(len(label)):
        l.append(final.loc[label[j]]["CleanedText"].decode())
        #print(l)
    print("Total number of review in cluster {} is: {}".format(i, len(label)))
    plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 49975
```


```
Total number of review in cluster 1 is: 13
```



```
Total number of review in cluster 2 is: 12
```

Observations 1. We have total 3 cluster and some words are mixed with other cluster.

2 Hierarchical Clustering

2.1 Bag of Word

```
In [254]: # Take first 5k data poits because agglomerative cluster is computational very expen
          # We can take more than this in high config system
          df = cleaned_data.iloc[:5000,:]
          df.shape

Out[254]: (5000, 12)

In [255]: # Text that we will work on
          X = df["CleanedText"]
          X.shape

Out[255]: (5000,)

In [256]: # Vectorization
          bow = CountVectorizer()
```

```
bow_feat = bow.fit_transform(X)
bow_feat
```

Out[256]:
```
<5000x11508 sparse matrix of type '<class 'numpy.int64'>'
        with 179435 stored elements in Compressed Sparse Row format>
```

In [257]:
```
# Standardization
std = StandardScaler(with_mean = False)
std_feat = std.fit_transform(bow_feat)
std_feat = std_feat.toarray()
```

In [259]:
```
# There is no appropiate method to choose number of cluster, so we can just give a t
# Somewhere dendogram is used to choose number of cluster for hirarchical clustering
# When number of cluster is 2
# using euclidean distance as affinity to compute distances b/w clusters
# and linkage is ward that minimizes the variance of the clusters being merged and i
# We can use any linkage and affinity but ward is recommended
clf = AgglomerativeClustering(n_clusters = 2, affinity = "euclidean", linkage = "ward
labels = clf.fit_predict(std_feat)
```

In [260]:
```
clf.labels_.shape
```

Out[260]:
```
(5000,)
```

In [261]:
```
# Assign each review to its cluster label in dataframe
df["cluster_label"] = clf.labels_
```

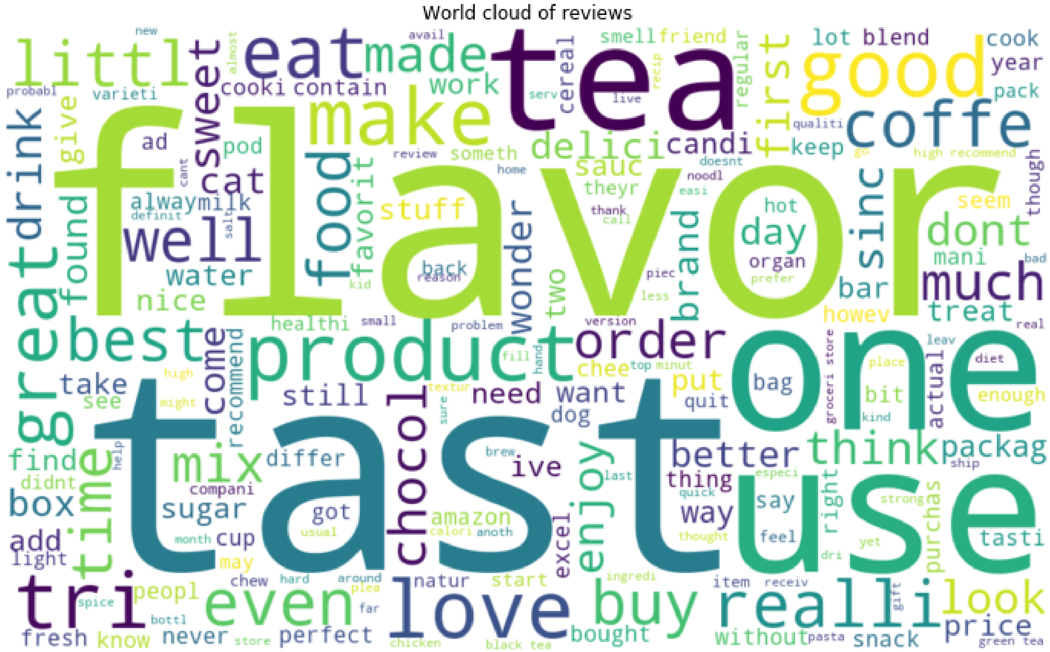
In [266]:
```
# same as average word2vec of k means clustering
for i in range(clf.n_clusters):
    l = list()
    label = df.groupby(["cluster_label"]).groups[i]
    for j in range(len(label)):
        l.append(df.loc[label[j]]["CleanedText"].decode())
    print("Total number of review in cluster {} is: {}".format(i, len(label)))
    plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 2
```

World cloud of reviews

Total number of review in cluster 1 is: 4998

World cloud of reviews

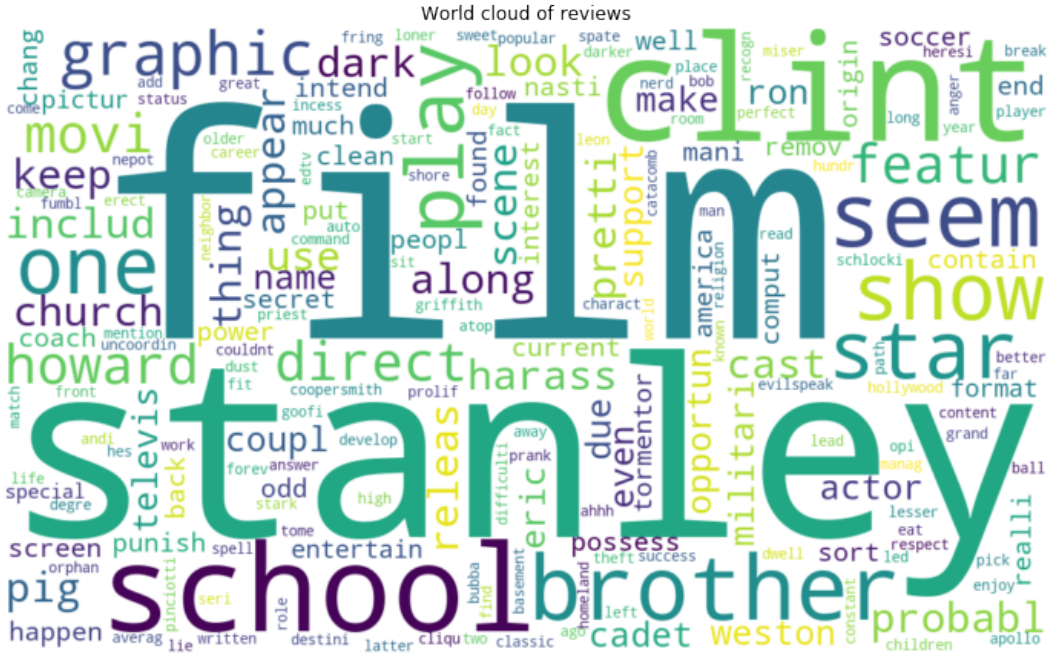


```
In [267]: # Agglomerative clustering with 5 cluster
          clf = AgglomerativeClustering(n_clusters = 5, affinity = "euclidean", linkage = "war
          labels = clf.fit_predict(std_feat)

In [269]: # Assign cluster labels to each review in the data-points
          df["cluster_label"] = clf.labels_

In [270]: # Same as average word2vec k means clustering
          for i in range(clf.n_clusters):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
              for j in range(len(label)):
                  l.append(df.loc[label[j]]["CleanedText"].decode())
              print("Total number of review in cluster {} is: {}".format(i, len(label)))
              plot_word_cloud(l)
```

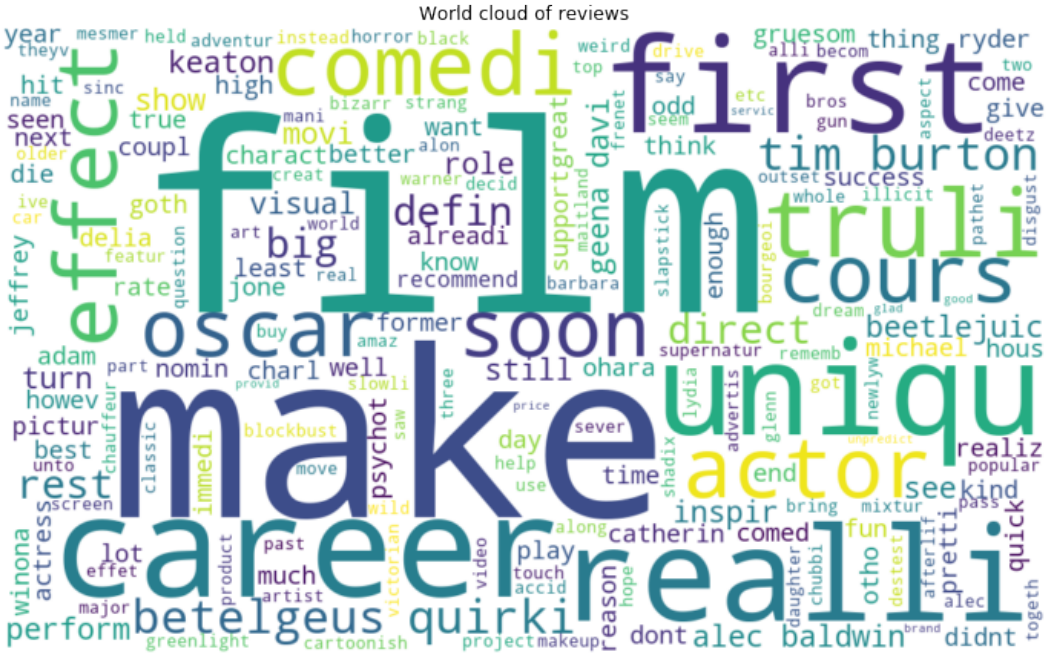
```
Total number of review in cluster 0 is: 4996
```


```
Total number of review in cluster 1 is: 1
```

Total number of review in cluster 2 is: 1



```
Total number of review in cluster 3 is: 1
```




```
Total number of review in cluster 4 is: 1
```

1. We applied agglomerative clustering with 3 and 5 cluster and found that some cluster are common for both 2 and 5 cluster, even some words are common, when we took 5 number of cluster.
2. We assign cluster label for each data points and plotted wordcloud of given text of corresponding class label.
3. As we can see words are grouped nicely in almost all cluster.

2.2 TF-IDF

```
In [271]: # Data
          X = df["CleanedText"]
          X.shape

Out[271]: (5000,)

In [272]: # Featurization
          tfidf = TfidfVectorizer()
          feat = tfidf.fit_transform(X)
          feat

Out[272]: <5000x11508 sparse matrix of type '<class 'numpy.float64'>'
                  with 179435 stored elements in Compressed Sparse Row format>

In [273]: # Standardization
          std = StandardScaler(with_mean = False)
          std_data = std.fit_transform(feat)
          std_data = std_data.toarray()

In [274]: # When number of cluster is 2
          clf = AgglomerativeClustering(n_clusters = 2, affinity = "euclidean", linkage = "ward
          labels = clf.fit_predict(std_data)

In [275]: # Cluster labels shape
          clf.labels_.shape

Out[275]: (5000,)

In [ ]: # Assign each cluster label corresponding to its data-points
        df["cluster_label"] = clf.labels_

In [278]: # Same as average word2vec k means clustering
          for i in range(clf.n_clusters):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
              for j in range(len(label)):
                  l.append(df.loc[label[j]]["CleanedText"].decode())
              print("Total number of review in cluster {} is: {}".format(i, len(label)))
              plot_word_cloud(l)
```

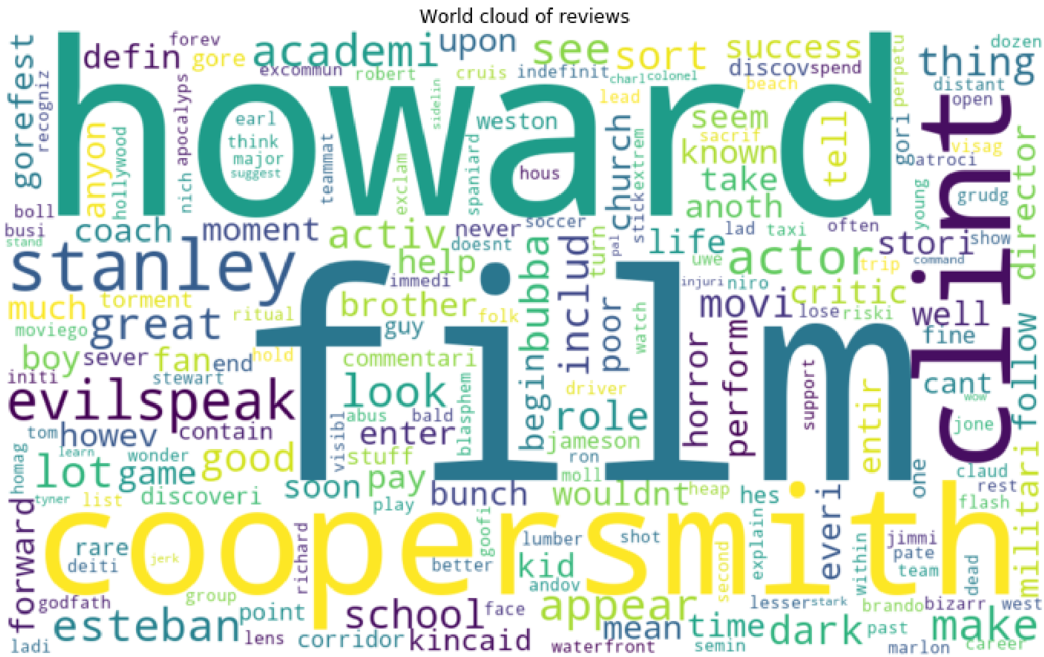
```
Total number of review in cluster 0 is: 2
```


```
Total number of review in cluster 1 is: 4998
```

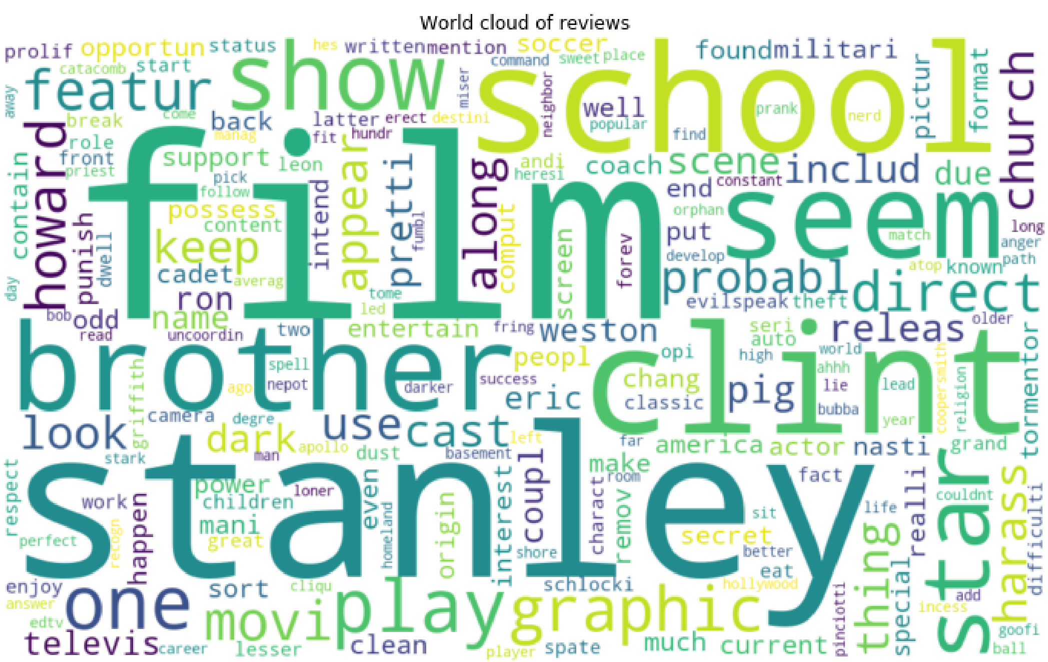
```
In [279]: # When number of cluster is 5
          clf = AgglomerativeClustering(n_clusters = 5, affinity = "euclidean", linkage = "war
          labels = clf.fit_predict(std_data)

In [280]: # cluster labels shape
          clf.labels_.shape

Out[280]: (5000,)

In [283]: # Assign each data-points corresponding to its cluster label
          df["cluster_label"] = clf.labels_

In [284]: # Same as the previous one
          for i in range(clf.n_clusters):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
              for j in range(len(label)):
                  l.append(df.loc[label[j]]["CleanedText"].decode())
              print("Total number of review in cluster {} is: {}".format(i, len(label)))
              plot_word_cloud(l)
```

Total number of review in cluster 0 is: 4996

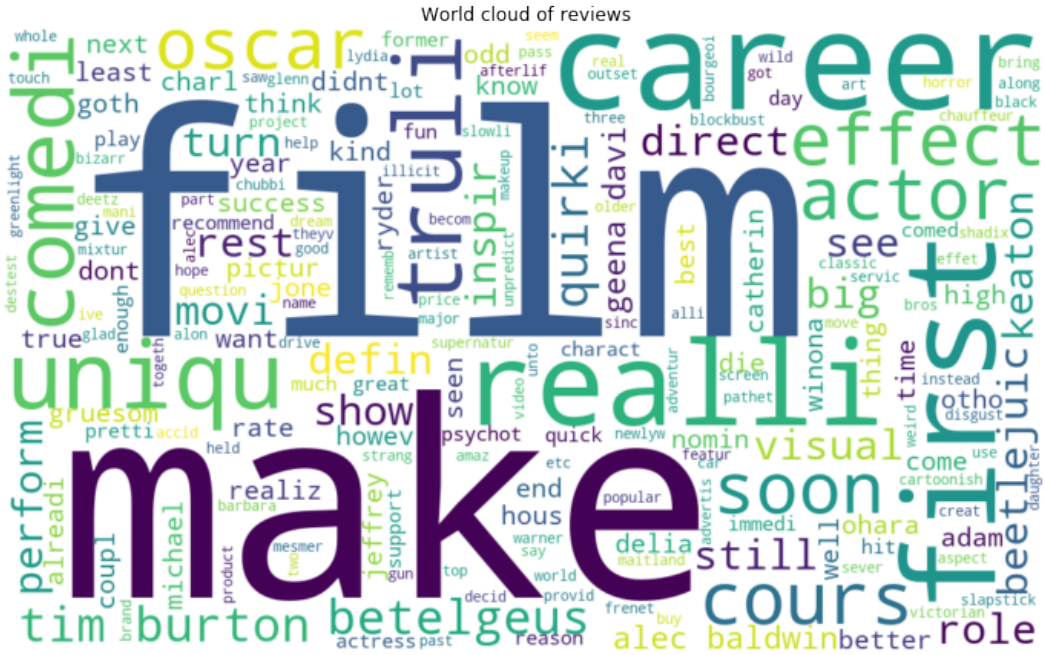
Total number of review in cluster 1 is: 1



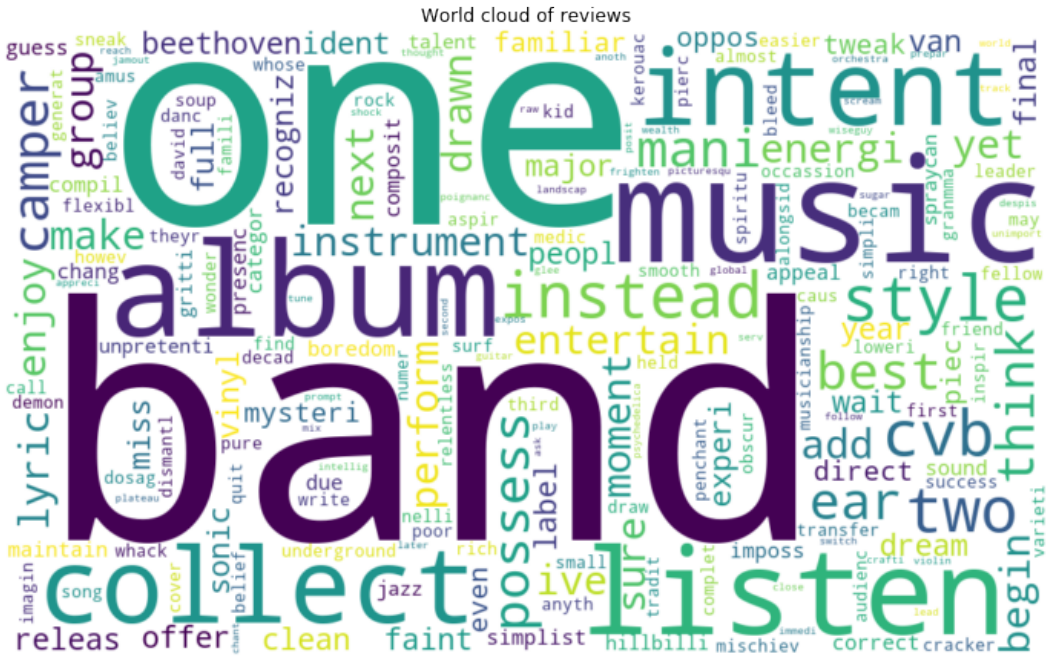
Total number of review in cluster 2 is: 1



Total number of review in cluster 3 is: 1



Total number of review in cluster 4 is: 1



Observations 1. We took 2 and 5 number of cluster and applied agglomerative clustering and observe that words that contain similar intent are grouped together.

2.3 Word2Vec

```
In [286]: # data
          X = df["Text"]
          X.shape

Out[286]: (5000,)

In [287]: # Utility function for cleaning tags and punctuations
          import re
          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 c
              cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
              cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
              return  cleaned

In [288]: # Train your own Word2Vec model using your own train text corpus
          import gensim
          list_of_sent=[]
          #for sent in final_40k['Text'].values:
```

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

```
In [289]: # Word2vec model
          w2v_model = gensim.models.Word2Vec(list_of_sent, min_count = 5, size = 50, workers =
```

```
In [290]: # Get most_similar word like like
          w2v_model.wv.most_similar('like')
```

```
Out[290]: [('but', 0.8052593469619751),
           ('really', 0.791375994682312),
           ('taste', 0.7891703844070435),
           ('think', 0.780022382736206),
           ('real', 0.7688242197036743),
           ('tastes', 0.759600043296814),
           ('too', 0.7508002519607544),
           ('raise', 0.7461390495300293),
           ('overly', 0.7456965446472168),
           ('texture', 0.7441191673278809)]
```

```
In [291]: # word2vec vocabulary
          w2v = w2v_model[w2v_model.wv.vocab]
```

```
In [292]: # Shape of word2vec vocabulary
          w2v.shape
```

```
Out[292]: (5127, 50)
```

2.3.1 Average Word2Vec

```
In [293]: # average Word2Vec
          # compute average word2vec for each review.
          sent_vectors = [] # the avg-w2v for each sentence/review is stored in this list
          for sent in 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/review
              for word in sent: # for each word in a review/sentence
                  try:
                      vec = w2v_model.wv[word]
                      sent_vec += vec
                      cnt_words += 1
```

```
                except:
                    pass
            sent_vec /= cnt_words
            sent_vectors.append(sent_vec)
        print(len(sent_vectors))
        print(len(sent_vectors[0]))
```

```
5000
50
```

In [294]:
```
# Convert list of sent_vectors to an array
X = np.array(sent_vectors)
X.shape
```

Out[294]: (5000, 50)

In [295]:
```
# Standardization
std = StandardScaler(with_mean = False)
std_data = std.fit_transform(X)
```

In [296]:
```
# When number of cluster is 2
clf = AgglomerativeClustering(n_clusters = 2, affinity = "euclidean", linkage = "ward
labels = clf.fit_predict(std_data)
```

In [297]:
```
# Cluster labels shape
clf.labels_.shape
```

Out[297]: (5000,)

In [299]:
```
# Assign each data points to its corresponding cluster
df["cluster_label"] = clf.labels_
```

In [300]:
```
# Same as average word2vec of k means clustering
for i in range(clf.n_clusters):
    l = list()
    label = df.groupby(["cluster_label"]).groups[i]
    for j in range(len(label)):
        l.append(df.loc[label[j]]["CleanedText"].decode())
    print("Total number of review in cluster {} is: {}".format(i, len(label)))
    plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 3076
```

Total number of review in cluster 1 is: 1924

```
In [301]: # When number of cluster is 5
          clf = AgglomerativeClustering(n_clusters = 5, affinity = "euclidean", linkage = "war
          labels = clf.fit_predict(std_data)
```

```
In [302]: # cluster labels shape
          clf.labels_.shape
```

```
Out[302]: (5000,)
```

```
In [304]: # Assign each review to its corresponding cluster label
          df["cluster_label"] = clf.labels_
```

```
In [305]: # Same as average word2vec of k means clustering
          for i in range(clf.n_clusters):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
              for j in range(len(label)):
                  l.append(df.loc[label[j]]["CleanedText"].decode())
              print("Total number of review in cluster {} is: {}".format(i, len(label)))
              plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 972
```


```
Total number of review in cluster 1 is: 1357
```


```
Total number of review in cluster 2 is: 747
```

Total number of review in cluster 3 is: 1368

Total number of review in cluster 4 is: 556

Observations 1. Many words are common in each cluster and some that intent is same are nicely grouped together.

2.3.2 TFIDF Word2Vec

```
In [308]: # TF-IDF weighted Word2Vec
          tfidf_feat = tfidf.get_feature_names() # tfidf words/col-names
          # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfid
          tfidf_sent_vectors = [] # the tfidf-w2v for each sentence/review is stored in this l
          row=0
          for sent in 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/review
              for word in sent: # for each word in a review/sentence
                  try:
                      vec = w2v_model.wv[word]
                      # obtain the tf_idfidf of a word in a sentence/review
                      tf_idf = X[row, tfidf_feat.index(word)]
                      sent_vec += (vec * tf_idf)
                      weight_sum += tf_idf
                  except:
                      pass
              sent_vec /= weight_sum
              tfidf_sent_vectors.append(sent_vec)
              row += 1
```

```
In [309]: print(len(tfidf_sent_vectors))
          print(len(tfidf_sent_vectors[0]))
```

```
5000
50
```

```
In [312]: # Assign each data-points to its corresponding cluster label
          X = np.array(tfidf_sent_vectors)
          X.shape
```

```
Out[312]: (5000, 50)
```

```
In [315]: # Standardization
          std = StandardScaler(with_mean = False)
          std_data = std.fit_transform(X)
```

```
In [318]: # Nan, infinite float to number
          std_data = np.nan_to_num(std_data)
```

```
In [319]: # When number of cluster is 2
          clf = AgglomerativeClustering(n_clusters = 2, affinity = "euclidean", linkage = "ward
          labels = clf.fit_predict(std_data)
```

```
In [320]: # shape of cluster labels
          clf.labels_.shape
```

```
Out[320]: (5000,)
```

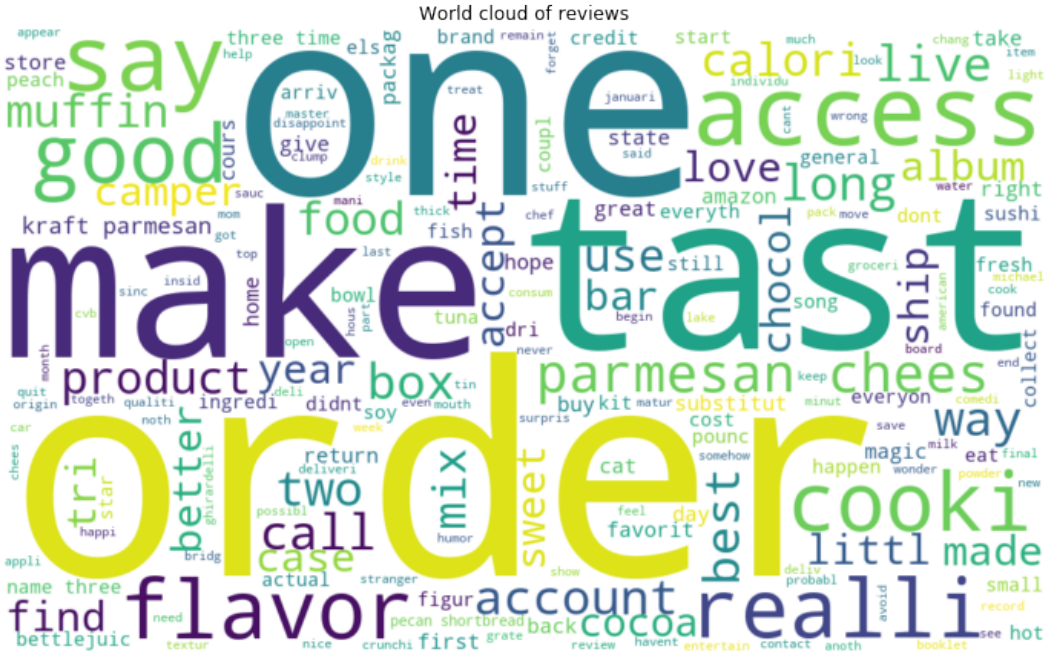
```
In [322]: # Assign each data-points to its corresponding cluster label
          df["cluster_label"] = clf.labels_
```

```
In [323]: # Same as average word2vec of k means clustering.
          for i in range(clf.n_clusters):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
              #print(label)
              #print(len(label))
              for j in range(len(label)):
                  l.append(df.loc[label[j]]["CleanedText"].decode())
                  #print(l)
              print("Total number of review in cluster {} is: {}".format(i, len(label)))
              plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 40
```


```
Total number of review in cluster 1 is: 4960
```

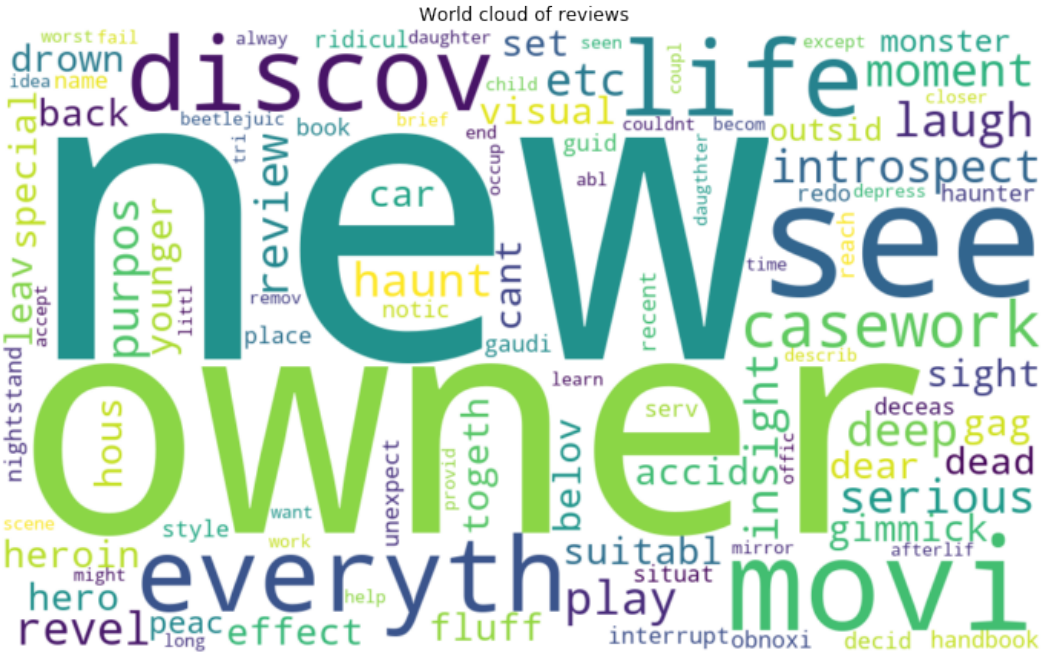

```
In [324]: # When number of cluster is 5
          clf = AgglomerativeClustering(n_clusters = 5, affinity = "euclidean", linkage = "ward
          labels = clf.fit_predict(std_data)

In [325]: clf.labels_.shape

Out[325]: (5000,)

In [327]: df["cluster_label"] = clf.labels_

In [328]: # same as previous one
          for i in range(clf.n_clusters):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
              #print(label)
              #print(len(label))
              for j in range(len(label)):
                  l.append(df.loc[label[j]]["CleanedText"].decode())
                  #print(l)
              print("Total number of review in cluster {} is: {}".format(i, len(label)))
              plot_word_cloud(l)

Total number of review in cluster 0 is: 19
```



Total number of review in cluster 1 is: 8

Total number of review in cluster 2 is: 13

Total number of review in cluster 3 is: 1



```
Total number of review in cluster 4 is: 4959
```

Observations 1. In this clustering, we observe that words are differnet from the previous cluster and most of the cluster are sparse. i.e. Cluster label belongs to more points is very less.

3 DBSCAN

3.1 Bag of Word

```
In [596]: # Take first 5k data-points
          df = cleaned_data.iloc[:5000,:]
          df.shape

Out[596]: (5000, 12)

In [597]: # Take cleanedtext out of other features
          X = df["CleanedText"]
          X.shape

Out[597]: (5000,)

In [598]: # Vectorizor
          bow = CountVectorizer()
```

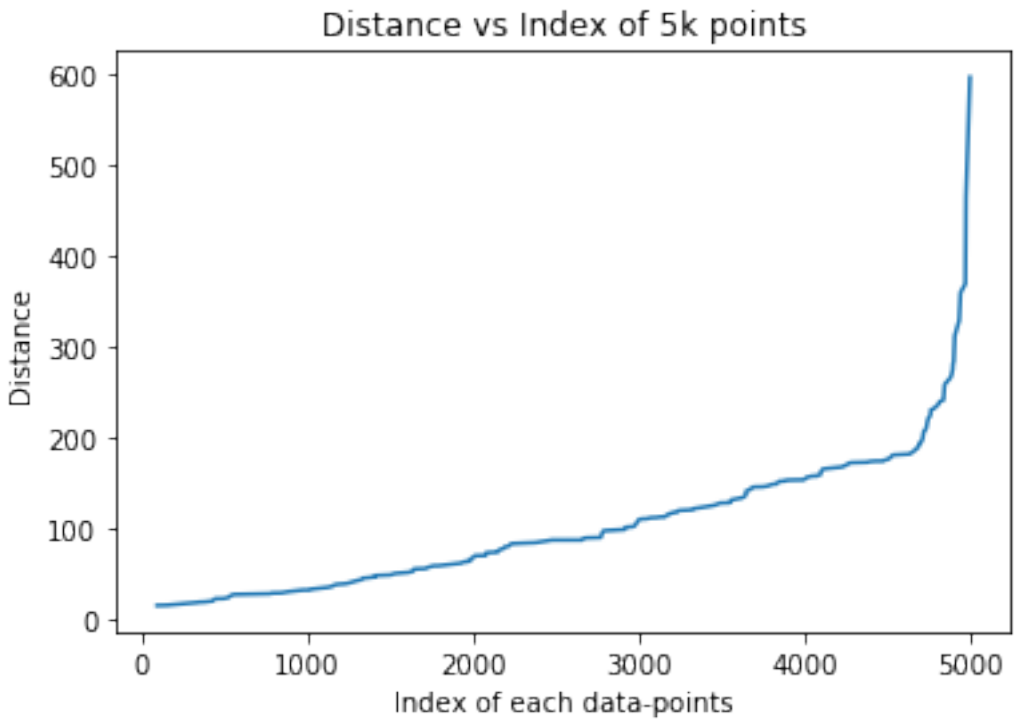
```
feat = bow.fit_transform(X)
feat
```

```
Out[598]: <5000x11508 sparse matrix of type '<class 'numpy.int64'>'
        with 179435 stored elements in Compressed Sparse Row format>
```

```
In [599]: # Standardization
std = StandardScaler(with_mean = False)
std_feat = std.fit_transform(feat)
std_feat
```

```
Out[599]: <5000x11508 sparse matrix of type '<class 'numpy.float64'>'
        with 179435 stored elements in Compressed Sparse Row format>
```

```
In [600]: # Elbow method to choose eps(epsilon)
# To compute distance from each data-points to its 50th neighbors
from sklearn.neighbors import NearestNeighbors
# As the Rule of thumb is to take 2 * d(dimension) for minpts but we are not taking
# Variable with minpts equal to 50
minpts = 50
# Dictionary to store distance and index
d = {}
# sklearn Nearest neighbors classifier with number of neighbors = minpts(50)
clf = NearestNeighbors(n_neighbors = minpts, metric = "euclidean")
# Fitting classifier
clf.fit(std_feat)
# Find the k neighbors(in our case it is 50) of each xi and will return distance to
dist_idx = clf.kneighbors(n_neighbors = minpts, return_distance = True)
dist_idx = np.array(dist_idx)
# Get the distance and indices of the last neighbor
for dist, idx in zip(dist_idx[0], dist_idx[1]):
    d[idx[-1]] = dist[-1]
# Sort distances according to ascending order
sorted_d = sorted((value,key) for (key, value) in d.items())
distance = []
index = []
# Get the index and distance and store it in two different variable
for d, i in sorted_d:
    distance.append(d)
    index.append(i)
# Plot index on x-axis and distance on y-axis
plt.plot(sorted(index), distance)
plt.title("Distance vs Index of 5k points")
plt.xlabel("Index of each data-points")
plt.ylabel("Distance")
plt.show()
```




```
In [601]: # DBSCAN with eps 300 and min_sample 50
          # Typically, We choose min_points is equal to the 2 times of dimension of the data-p
          # If we have noisy data then we take large min_points or according to the domain exp
          # We choose hyperparameter eps(epsilon) by calculaing the distance from each points
          # https://stats.stackexchange.com/questions/88872/a-routine-to-choose-eps-and-minpts
          # https://stats.stackexchange.com/questions/79470/how-to-compare-dbscan-clusters-cho
          clf = DBSCAN(eps = 150, min_samples = 50)
          clf.fit(std_feat)

Out[601]: DBSCAN(algorithm='auto', eps=150, leaf_size=30, metric='euclidean',
              metric_params=None, min_samples=50, n_jobs=None, p=None)

In [602]: # -1 denotes it is noisy points
          print("Total number of cluster with label -1 is: ", list(clf.labels_).count(-1))
          print("total number of cluster with label 0 is: ", list(clf.labels_).count(0))

Total number of cluster with label -1 is:  630
total number of cluster with label 0 is:  4370


In [603]: # Assign each datapoints to its corresponding cluster
          df["cluster_label"] = clf.labels_

In [604]: # Same as average word2vec of k-means clustering
          for i in range(len(set(clf.labels_)) - 1):
```

```
        l = list()
        label = df.groupby(["cluster_label"]).groups[i]
        for j in range(len(label)):
                l.append(df.loc[label[j]]["CleanedText"].decode())
        print("Total number of review in cluster {} is: {}".format(i, len(label)))
        plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 4370
```

Observations 1. By applying epsilon 150 and min_sample 50 we found that only two cluster where each points belongs to either of one cluster. The cluster label is -1 and 0 where -1 represents noisy points, so basically we have only one cluster. 2. As we can see this cluster is also same as the previous one, where not all words are same intent but they are somehow related in some context.

3.2 Tf-Idf

```
In [605]: # data
          X = df["CleanedText"]
          X.shape
```

```
Out[605]: (5000,)
```

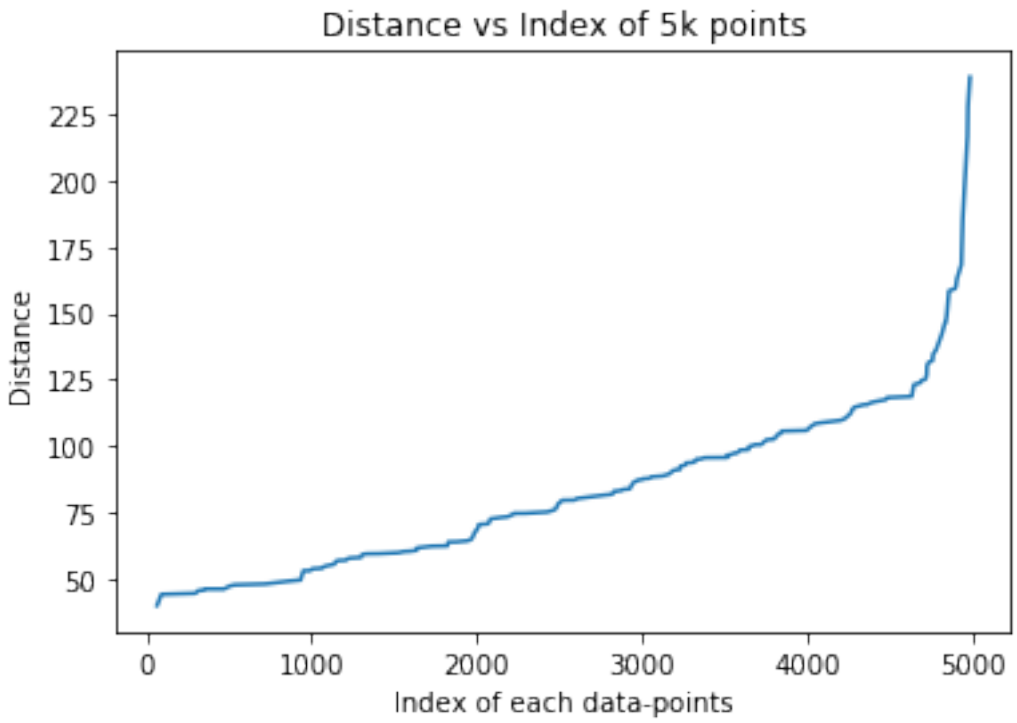
```
In [606]: # TFIDF
          tfidf = TfidfVectorizer()
          tfidf_vect = tfidf.fit_transform(X)
          tfidf_vect
```

Out[606]: <5000x11508 sparse matrix of type '<class 'numpy.float64'>'
with 179435 stored elements in Compressed Sparse Row format>

In [607]:
```
# Standardization
std = StandardScaler(with_mean = False)
std_data = std.fit_transform(tfidf_vect)
```

In [608]:
```
# Elbow method to choose eps(epsilon)
# As the Rule of thumb is to take 2 * d(dimension) for minpts but we are not taking
# To compute distance from its 50th neighbors
# Look at the DBSCAN implementation on bow representation.
from sklearn.neighbors import NearestNeighbors
minpts = 50
d = {}
clf = NearestNeighbors(n_neighbors = minpts, metric = "euclidean")
clf.fit(std_data)
dist_idx = clf.kneighbors(n_neighbors = minpts, return_distance = True)
dist_idx = np.array(dist_idx)
print(dist_idx[0].shape)
print(dist_idx[1].shape)
for dist, idx in zip(dist_idx[0], dist_idx[1]):
    d[idx[-1]] = dist[-1]
sorted_d = sorted((value,key) for (key, value) in d.items())
distance = []
index = []
for d, i in sorted_d:
    distance.append(d)
    index.append(i)
plt.plot(sorted(index), distance)
plt.title("Distance vs Index of 5k points")
plt.xlabel("Index of each data-points")
plt.ylabel("Distance")
plt.show()
```

```
(5000, 50)
(5000, 50)
```



In [609]:
```
# DBSCAN
# For how to choose eps and min_sample? please look at the bag-of-words implementati
db = DBSCAN(eps = 120, min_samples = 50)
db.fit(std_feat)
label = db.labels_
```

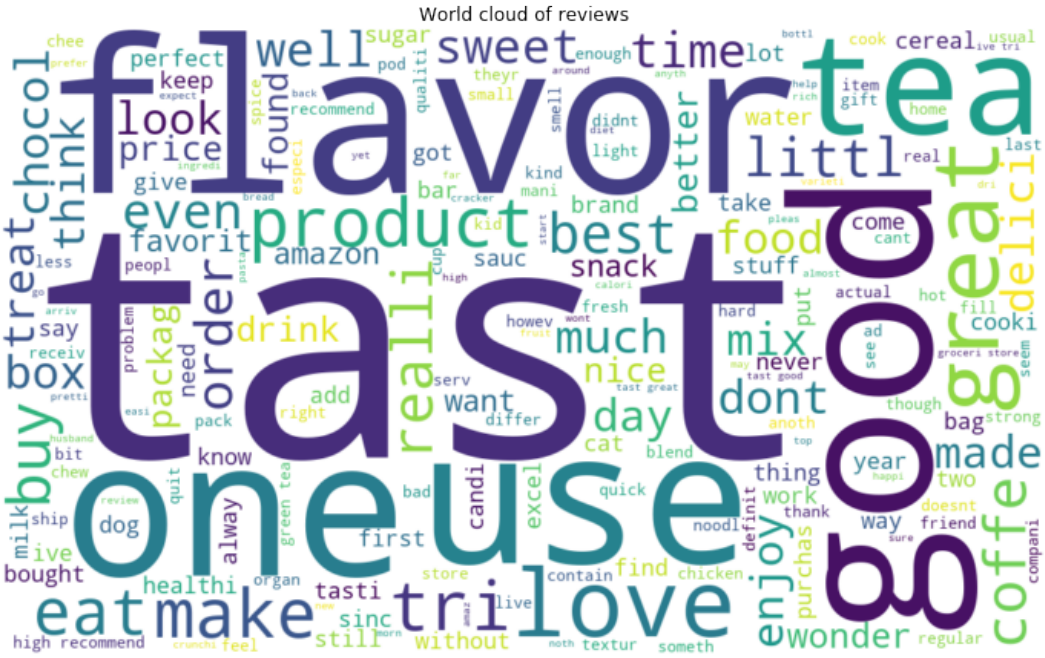
In [610]:
```
# Total number of cluster with -1 label(noisy points) and 0 label
print(list(label).count(-1))
print(list(label).count(0))
```

```
1107
3893
```

In [611]:
```
# Assigning each cluster label to it's data-points
df["cluster_label"] = db.labels_
```

In [612]:
```
# Same as average word2vec of k-means clustering
for i in range(len(set(label)) - 1):
    l = list()
    label = df.groupby(["cluster_label"]).groups[i]
    for j in range(len(label)):
        l.append(df.loc[label[j]]["CleanedText"].decode())
    print("Total number of review in cluster {} is: {}".format(i, len(label)))
    plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 3893
```



Observations 1. look at the bow observations and read each comments across the notebook for clarification. 2. In this clustering we found that only 3893 review out of 5k with cluster label 0 others are noisy points. 3. Some most important word based on frequency have somehow same intent.

3.3 Word2vec

```
In [613]: # data
          X = df["Text"]
          X.shape

Out[613]: (5000,)

In [614]: # Utlity function, cleaning html tag and punctuation from text data
          import re
          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 c
              cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
              cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
              return  cleaned
```

```
In [615]: # Train your own Word2Vec model using your own train text corpus
          import gensim
          list_of_sent=[]
          for sent in X:
              filtered_sentence=[]
              sent=cleanhtml(sent)
              for w in sent.split():
                  for cleaned_words in cleanpunc(w).split():
                      if(cleaned_words.isalpha()):
                          filtered_sentence.append(cleaned_words.lower())
                      else:
                          continue
              list_of_sent.append(filtered_sentence)

In [616]: # Word2vec model
          w2v_model = gensim.models.Word2Vec(list_of_sent, min_count = 5, size = 50, workers =

In [617]: w2v_model.wv.most_similar('like')

Out[617]: [('dig', 0.7873243093490601),
           ('prefer', 0.7846037149429321),
           ('think', 0.7621347904205322),
           ('really', 0.7593311071395874),
           ('enjoy', 0.7527710199356079),
           ('real', 0.7491886615753174),
           ('but', 0.7443016767501831),
           ('lover', 0.7342784404754639),
           ('salty', 0.7308362126350403),
           ('thats', 0.7293223142623901)]

In [618]: w2v = w2v_model[w2v_model.wv.vocab]

In [619]: w2v.shape

Out[619]: (5127, 50)
```

3.3.1 Average Word2Vec

```
In [620]: # average Word2Vec
          # compute average word2vec for each review.
          sent_vectors = [] # the avg-w2v for each sentence/review is stored in this list
          for sent in 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/review
              for word in sent: # for each word in a review/sentence
                  try:
                      vec = w2v_model.wv[word]
                      sent_vec += vec
                      cnt_words += 1
```

```
                except:
                    pass
            sent_vec /= cnt_words
            sent_vectors.append(sent_vec)
        print(len(sent_vectors))
        print(len(sent_vectors[0]))
```

```
5000
50
```

In [622]:
```
# Convert list of sentene vector to a numpy array
X = np.array(sent_vectors)
X.shape
```

Out[622]: (5000, 50)

In [623]:
```
# Standardization
std = StandardScaler()
std_data = std.fit_transform(X)
std_data
```

Out[623]:
```
array([[-0.69691078,  1.40028207, -1.58341538, ..., -0.56981647,
         0.02264965,  0.66096866],
       [-0.92889669,  2.29276107, -2.16649166, ..., -0.70314666,
         0.16503233,  1.23771203],
       [-0.19175687, -0.28948908, -1.07915148, ..., -0.09286748,
         1.6555249 ,  0.29510069],
       ...,
       [-2.17941495, -2.49529037,  1.73894397, ..., -1.88506795,
         1.3805718 , -1.34770072],
       [-0.33675432, -1.77728296,  0.67852954, ..., -0.50716577,
         1.63709842,  0.0651854 ],
       [-0.06948653, -1.39221758,  0.71253417, ..., -0.16654918,
        -0.17237851, -1.22497782]])
```

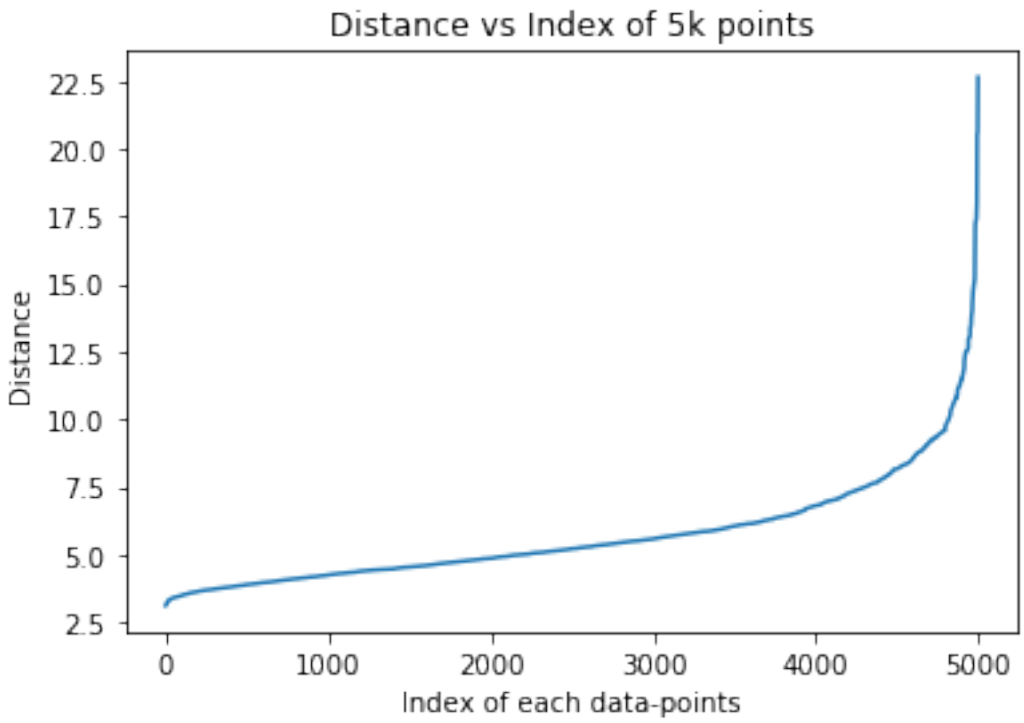
In [624]:
```
std_data = np.nan_to_num(std_data)
std_data
```

Out[624]:
```
array([[-0.69691078,  1.40028207, -1.58341538, ..., -0.56981647,
         0.02264965,  0.66096866],
       [-0.92889669,  2.29276107, -2.16649166, ..., -0.70314666,
         0.16503233,  1.23771203],
       [-0.19175687, -0.28948908, -1.07915148, ..., -0.09286748,
         1.6555249 ,  0.29510069],
       ...,
       [-2.17941495, -2.49529037,  1.73894397, ..., -1.88506795,
         1.3805718 , -1.34770072],
       [-0.33675432, -1.77728296,  0.67852954, ..., -0.50716577,
```

```
         1.63709842,  0.0651854 ],
       [-0.06948653, -1.39221758,  0.71253417, ..., -0.16654918,
        -0.17237851, -1.22497782]])
```

In [625]:
```
# Elbow method to choose epsilon(eps) with min_points = 2 * dimension of data
# Look at the bow representation for more info
from sklearn.neighbors import NearestNeighbors
minpts = 100
d = {}
clf = NearestNeighbors(n_neighbors = minpts, metric = "euclidean")
clf.fit(std_data)
dist_idx = clf.kneighbors(n_neighbors = minpts, return_distance = True)
dist_idx = np.array(dist_idx)
print(dist_idx[0].shape)
print(dist_idx[1].shape)
for dist, idx in zip(dist_idx[0], dist_idx[1]):
    d[idx[-1]] = dist[-1]
sorted_d = sorted((value,key) for (key, value) in d.items())
distance = []
index = []
for d, i in sorted_d:
    distance.append(d)
    index.append(i)
plt.plot(sorted(index), distance)
plt.title("Distance vs Index of 5k points")
plt.xlabel("Index of each data-points")
plt.ylabel("Distance")
plt.show()
```

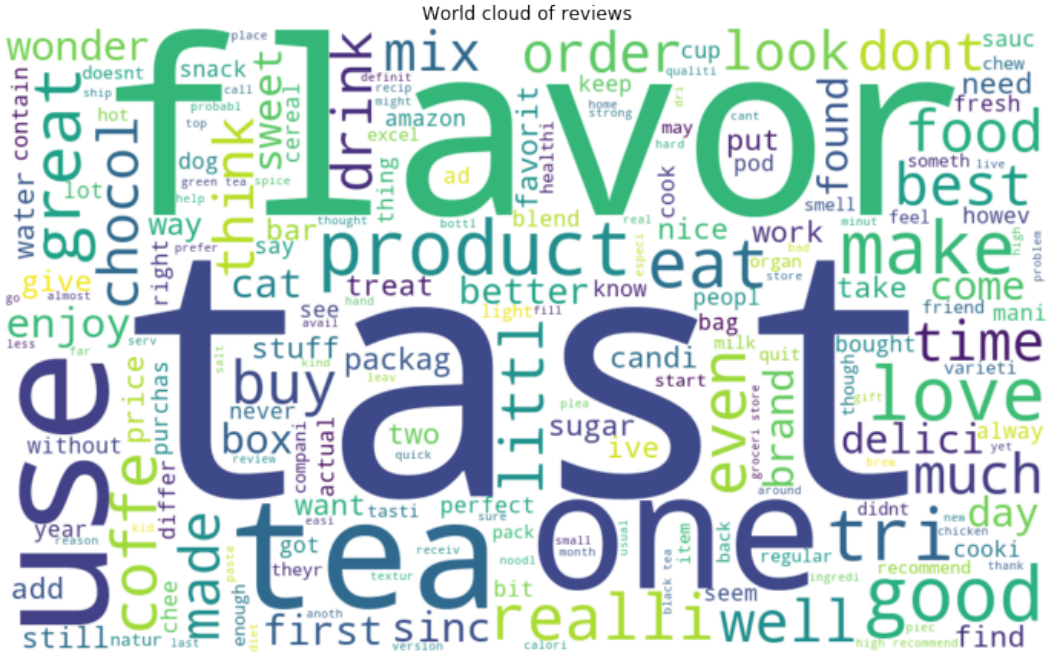
```
(5000, 100)
(5000, 100)
```




```
In [626]: # DBSCAN
          db = DBSCAN(eps = 10, min_samples = 100)
          db.fit(std_data)
          label = db.labels_
          label

Out[626]: array([0, 0, 0, ..., 0, 0, 0], dtype=int64)

In [627]: # Total number of data-points from each cluster
          # -1 shows it is noisy data-points
          print(list(label).count(0))
          print(list(label).count(-1))

4983
17


In [629]: # Put each cluster label with their corresponding data-points.
          df["cluster_label"] = db.labels_

In [630]: # Same as average word2vec of k means clustering
          for i in range(len(set(label)) - 1):
              l = list()
              label = df.groupby(["cluster_label"]).groups[i]
```

```
            for j in range(len(label)):
                l.append(df.loc[label[j]]["CleanedText"].decode())
            print("Total number of review in cluster {} is: {}".format(i, len(label)))
            plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 4983
```



Observations 1. We plotted distance vs index for each datapoints and found the knee and selected as the eps value with min_pts is 100 as the rule of thumb. 2. Wordcloud shows very less points are noisy points and except that all points belongs to cluster label 0 which means agglomerative clustering is not doing good job.

3.3.2 TFIDF Word2Vec

```
In [631]: # TF-IDF weighted Word2Vec
          tfidf_feat = tfidf.get_feature_names() # tfidf words/col-names
          # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfid
          tfidf_sent_vectors = [] # the tfidf-w2v for each sentence/review is stored in this l
          row=0
          for sent in 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/review
              for word in sent: # for each word in a review/sentence
                  try:
                      vec = w2v_model.wv[word]
```

```
                    # obtain the tf_idfidf of a word in a sentence/review
                    tf_idf = tfidf_vect[row, tfidf_feat.index(word)]
                    sent_vec += (vec * tf_idf)
                    weight_sum += tf_idf
                except:
                    pass
            sent_vec /= weight_sum
            tfidf_sent_vectors.append(sent_vec)
            row += 1
```

```
In [632]: len(tfidf_sent_vectors)
```

```
Out[632]: 5000
```

```
In [633]: # List of elemetns to numpy array
          X = np.array(tfidf_sent_vectors)
          X.shape
```

```
Out[633]: (5000, 50)
```

```
In [634]: # Standardization
          from sklearn.preprocessing import StandardScaler
          std = StandardScaler(with_mean = False)
          std_data = std.fit_transform(X)
          std_data
```

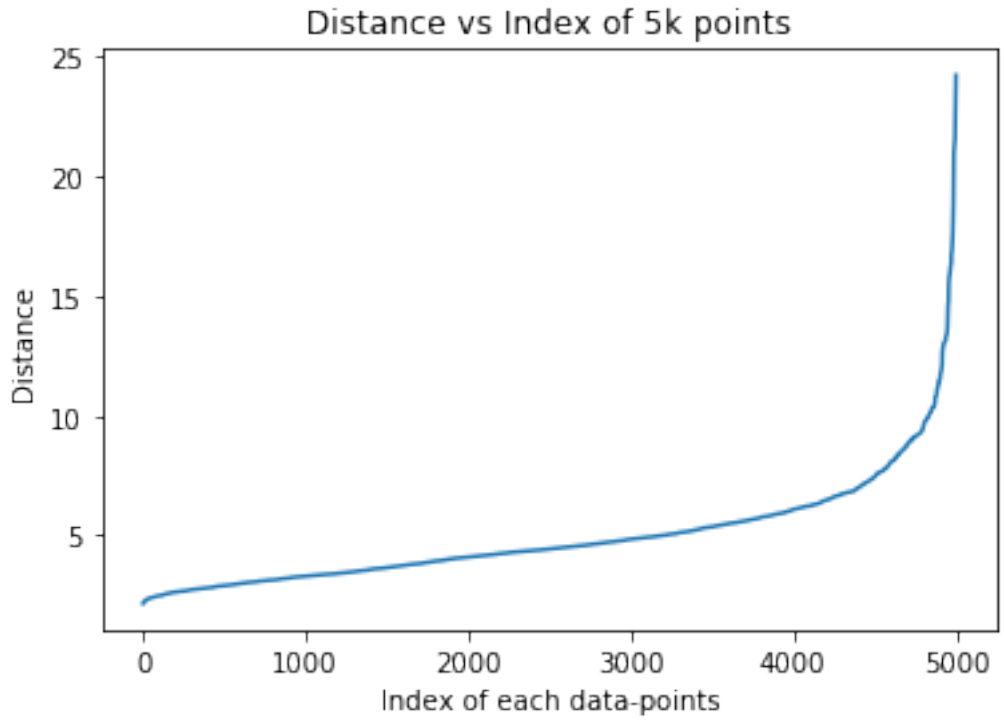
```
Out[634]: array([[ 0.33110273, -3.3025755 ,  0.39343792, ..., -0.55934574,
                   0.39930076,  0.03369972],
                 [ 0.05662162, -2.86168218,  0.43007384, ..., -0.80944147,
                   0.45715373,  0.62104666],
                 [ 0.59087849, -1.24242262,  0.13701192, ...,  0.27001521,
                  -0.37446743, -0.56639055],
                 ...,
                 [ 0.55293135, -4.45874217,  2.08530745, ..., -0.62187385,
                   1.29781151, -1.7490451 ],
                 [ 0.88850653, -5.83081859,  2.56206238, ..., -1.00131159,
                   2.40239991, -0.73359261],
                 [ 2.2438872 , -4.78716444,  1.75880202, ...,  1.0458991 ,
                   1.73119511, -1.15331779]])
```

```
In [635]: std_data = np.nan_to_num(std_data)
```

```
In [636]: # Elbow method to choose eps(epsilon) with minpts = 2 * dimension of data
          from sklearn.neighbors import NearestNeighbors
          minpts = 100
          d = {}
          clf = NearestNeighbors(n_neighbors = minpts, metric = "euclidean")
          clf.fit(std_data)
          dist_idx = clf.kneighbors(n_neighbors = minpts, return_distance = True)
```

```
        dist_idx = np.array(dist_idx)
        print(dist_idx[0].shape)
        print(dist_idx[1].shape)
        for dist, idx in zip(dist_idx[0], dist_idx[1]):
            d[idx[-1]] = dist[-1]
        sorted_d = sorted((value,key) for (key, value) in d.items())
        distance = []
        index = []
        for d, i in sorted_d:
            distance.append(d)
            index.append(i)
        plt.plot(sorted(index), distance)
        plt.title("Distance vs Index of 5k points")
        plt.xlabel("Index of each data-points")
        plt.ylabel("Distance")
        plt.show()
```

```
(5000, 100)
(5000, 100)
```




```
In [637]: # DBSCAN
          db = DBSCAN(eps = 9, min_samples = 100)
          db.fit(std_data)
```

```
label = db.labels_
label
```

Out[637]: array([0, 0, 0, ..., 0, 0, 0], dtype=int64)

In [638]:
```
# Total number of cluster with 0 and -1 labels, where -1 represents it is noisy poin
print(list(label).count(0))
print(list(label).count(-1))
```

```
4963
37
```

In [639]:
```
# Assigning each data-points to its corresponding labels
df["cluster_label"] = db.labels_
```

In [640]:
```
# This is same as average word2vec of k means clustering
for i in range(len(set(label)) - 1):
    l = list()
    label = df.groupby(["cluster_label"]).groups[i]
    for j in range(len(label)):
        l.append(df.loc[label[j]]["CleanedText"].decode())
    print("Total number of review in cluster {} is: {}".format(i, len(label)))
    plot_word_cloud(l)
```

```
Total number of review in cluster 0 is: 4963
```

Observations 1. As we can see only 37 reviews are noisy except that all belongs to cluster 0. 2. As we are getting reviews belongs to any one of the cluster and we are getting all review clustered together which means all review have same intent. Looks like bias cluster.

Conclusions 1. We use kmeans clustering with 50k datapoints and DBSCAN with 5k data-points on 4 set of techniques and for each featurization, choose k value and eps using elbow method respectively and also used agglomerative clustering with 5k data-points and just choose two different number of cluster(2 and 5) and plotted word cloud of all review, for all clustering technique. 2. We observe that in kmeans and agglomerative clustering, average word2vec perform slightely well. We are saying this just by looking at the cloud cluster because we did not apply any technique to check performence of kmeans or agglomerative clustering. In DBSCAN we can say that it not good as it clustered everything in a single cluster and as the review given by user is not same type of review. 3. I have written comment in each section of each technique please go through comments.