SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

Procedure:

- Take top 2000 or 3000 features from tf-idf vectorizers using idf_ score.
- You need to calculate the co-occurrence matrix with the selected features (Note: X.X^T doesn't give the co-occurrence matrix, it returns the covariance matrix, check these bolgs blog-1, blog-2 for more information)
- You should choose the n_components in truncated svd, with maximum explained variance. Please search on how to choose that and implement them. (hint: plot of cumulative explained variance ratio)
- After you are done with the truncated svd, you can apply K-Means clustering and choose the best number of clusters based on elbow method.
- Print out wordclouds for each cluster, similar to that in previous assignment.
- You need to write a function that takes a word and returns the most similar words using cosine similarity between the vectors(vector: a row in the matrix after truncatedSVD)

In [1]:
```
# importing required libraries
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import nltk
import string

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer


import pickle
from tqdm import tqdm
import os
from collections import Counter

# ============================== loading libraries ===========================================
from sklearn.preprocessing import StandardScaler
from sklearn.feature_extraction.text import CountVectorizer
import itertools
from wordcloud import WordCloud, STOPWORDS

import wordcloud
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import DBSCAN
```

In [2]:
```
# Loading preprocessed final df
final = pickle.load(open('preprocessed_final', 'rb'))
```

In [4]:
```
X = final['CleanedText'].values
```

SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

[5.1] Taking top features from TFIDF, SET 2

Take top 2000 or 3000 features from tf-idf vectorizers using idf_ score.

In [5]:
```
# ss
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features= 3000)
tf_idf_vect.fit(X)

# we use the fitted CountVectorizer to convert the text to vector
X_train_tfidf = tf_idf_vect.transform(X)

print("After vectorizations")
print(X_train_tfidf.shape)
print(type(X_train_tfidf))
```

```
After vectorizations
(87773, 3000)
<class 'scipy.sparse.csr.csr_matrix'>
```

In [5]:
```
print(X_train_tfidf.shape)
```

```
(87773, 3000)
```

In [6]:
```
length = X_train_tfidf.shape[1]
print(length)
```

```
3000
```

In [7]:
```
# Get feature names from tfidf vectorizer and not the matrix
tfidf_features = tf_idf_vect.get_feature_names()

# feature weights based on idf score
tfidf_coeff = tf_idf_vect.idf_
```

In [9]:
```
type(tfidf_features)
```

Out[9]:
```
list
```

In [10]:
```
len(tfidf_features)
```

Out[10]:
```
3000
```

[5.2] Calulation of Co-occurrence matrix

You need to calculate the co-occurrence matrix with the selected features (Note: X.X^T doesn't give the co-occurrence matrix, it returns the covariance matrix, check these bolgs blog-1, blog-2 for more information)

In [8]:
```
# We declare a empty zero matrix with the dimension of length of features
coocr_matrix = np.zeros((length,length))
```

In [9]:
```
# let us define the window size
context_window_size = 5
```

In [10]:
```
for sentece in X:
    words = sentece.split()
    for index,word in enumerate(words):
        if word in tfidf_features:
            for j in range(max(index - context_window_size, 0),min(index + context_window_size, len(
words)-1) + 1):
                if words[j] in tfidf_features:
                    coocr_matrix[tfidf_features.index(word),tfidf_features.index(words[j])] += 1
                else:
                    continue
        else:
            continue
```

In [11]:
```
coocr_matrix
```

Out[11]:
```
array([[2.553e+03, 0.000e+00, 0.000e+00, ..., 0.000e+00, 2.000e+00,
        1.000e+00],
       [0.000e+00, 0.000e+00, 0.000e+00, ..., 0.000e+00, 0.000e+00,
        0.000e+00],
       [0.000e+00, 0.000e+00, 0.000e+00, ..., 0.000e+00, 0.000e+00,
        0.000e+00],
       ...,
       [0.000e+00, 0.000e+00, 0.000e+00, ..., 5.620e+02, 0.000e+00,
        2.000e+00],
       [2.000e+00, 0.000e+00, 0.000e+00, ..., 0.000e+00, 5.070e+02,
        0.000e+00],
       [1.000e+00, 0.000e+00, 0.000e+00, ..., 2.000e+00, 0.000e+00,
        2.830e+02]])
```

In [12]:
```
filename = 'co_occurence_matrix.sav'
pickle.dump(coocr_matrix, open(filename, 'wb'))
```

In [12]:
```
coocr_matrix = pickle.load(open(filename, 'rb'))
```

In [13]:
```
# TrucatedSVD
from sklearn.decomposition import TruncatedSVD
truncated_svd = TruncatedSVD(n_components = 500)
truncated_svd_data = truncated_svd.fit(coocr_matrix)
```

In [14]:
```
# List of explained variances
truncated_svd_data_explained_var_ratio = truncated_svd_data.explained_variance_ratio_
```

You should choose the n_components in truncated svd, with maximum explained variance. Please search on how to choose that and implement them. (hint: plot of cumulative explained variance ratio)

[5.3] Finding optimal value for number of components (n) to be retained.

In [15]:
```
# Code referenced: https://chrisalbon.com/machine_learning/feature_engineering/select_best_number_of
_components_in_tsvd

def select_n_components(var_ratio, goal_var: float) -> int:
    """This function tells us the number of components that explains the desired percentage of expla
ined variance"""
    # Set initial variance explained so far
    total_variance = 0.0

    # Set initial number of features
    n_components = 0

    # For the explained variance of each feature:
    for explained_variance in var_ratio:

        # Add the explained variance to the total
        total_variance += explained_variance

        # Add one to the number of components
        n_components += 1

        # If we reach our goal level of explained variance
        if total_variance >= goal_var:
            # End the loop
            break

    # Return the number of components
    return n_components
```

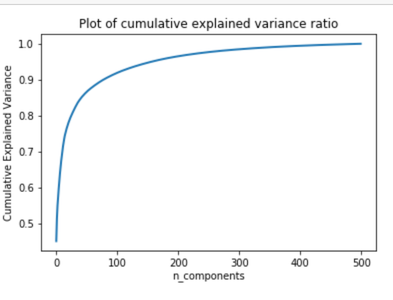
In [16]:
```
# We want to select the number of n_components that explains about 90% of the variance
select_n_components(truncated_svd_data_explained_var_ratio, .90)
```

Out[16]:
```
94
```

In [17]:
```
percentage_var_explained = truncated_svd_data.explained_variance_ / np.sum(truncated_svd_data.explai
ned_variance_)

cum_var_explained = np.cumsum(percentage_var_explained)

plt.plot(cum_var_explained, linewidth = 2)
plt.title('Plot of cumulative explained variance ratio')
plt.xlabel('n_components')
plt.ylabel('Cumulative Explained Variance')
plt.show()
```



Observation: We observe that 90% of variance is explained for n_components = 94.

In [18]:
```
svd_cls = TruncatedSVD(n_components = 94)
svd_data = svd_cls.fit_transform(coocr_matrix)
```

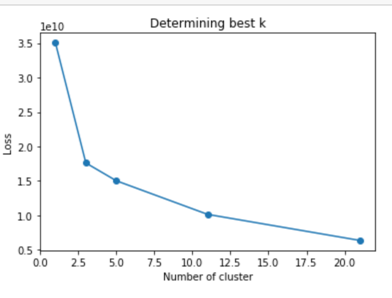
After you are done with the truncated svd, you can apply K-Means clustering and choose the best number of clusters based on elbow method.

[5.4] Applying k-means clustering

In [19]:
```
def getKmeansBestK(X_data):

    """
    This function takes in the vectorizer data, iterates over a set of k values and draws a elbow pl
ot.
    The y axis represents the sum of distances of samples to their closest cluster center.
    """
    k_values = [1, 3, 5, 11, 21]
    sse = {}    # score
    for k in k_values:
        kmeans = KMeans(n_clusters=k).fit(X_data)
        sse[k] = kmeans.inertia_
    plt.figure()
    plt.plot(list(sse.keys()), list(sse.values()), marker='o')
    plt.title("Determining best k")
    plt.xlabel("Number of cluster")
    plt.ylabel("Loss")
    plt.show()
```

In [20]:
```
getKmeansBestK(svd_data)
```



Observation: We can see a sharp fall at k = 3. So we will take value of k = 3.

In [21]:
```
# Implementing k-means
kmeans_tfidf = KMeans(n_clusters= 3, n_jobs=-1, random_state= 507).fit(svd_data)
```

In [22]:
```
result = zip(X , kmeans_tfidf.labels_)
```

In [23]:
```
result_df = pd.DataFrame(result)
result_df.rename(columns={0: "CleanedText", 1: "labels"}, inplace= True)
result_df.head()
```

Out[23]:

	CleanedText	labels
0	bought apartment infested fruit flies hours tr...	0
1	really good idea final product outstanding use...	0
2	received shipment could hardly wait try produc...	0
3	nothing product bother link top page buy used ...	0
4	love stuff sugar free not rot gums tastes good...	0

In [53]:
```
# Number of reviews for each label
result_df['labels'].value_counts()
```

Out[53]:
```
0    2996
1       3
2       1
Name: labels, dtype: int64
```

[5.5] Wordclouds of clusters obtained in the above section

In [24]:
```
reviews = result_df['CleanedText'].values

# Creating empty lists to store reviews based on the label
cluster0 = []
cluster1 = []
cluster2 = []

# for every corresponding label, we will append each review to their respecitve cluster list
for i in range(kmeans_tfidf.labels_.shape[0]):
    if kmeans_tfidf.labels_[i] == 0:
        cluster0.append(reviews[i])

    elif kmeans_tfidf.labels_[i] == 1:
        cluster1.append(reviews[i])

    else :
        cluster2.append(reviews[i])

cluster0_str = ('').join(cluster0)
cluster1_str = ('').join(cluster1)
cluster2_str = ('').join(cluster2)

cluster_str = [cluster0_str, cluster1_str, cluster2_str]
```

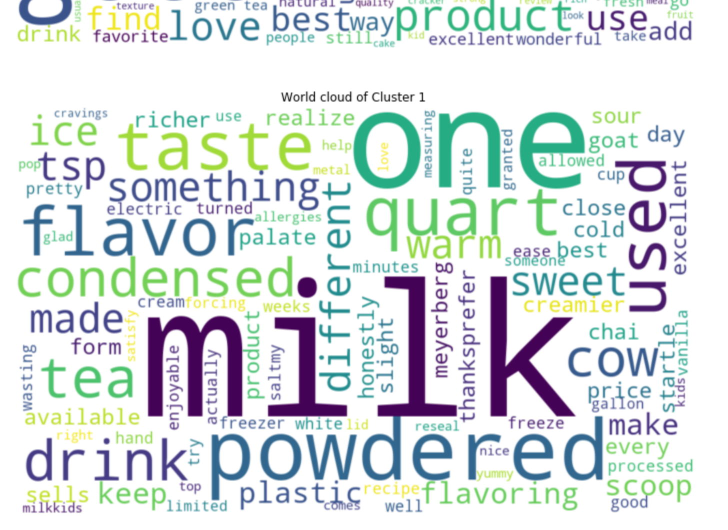
Print out wordclouds for each cluster, similar to that in previous assignment.

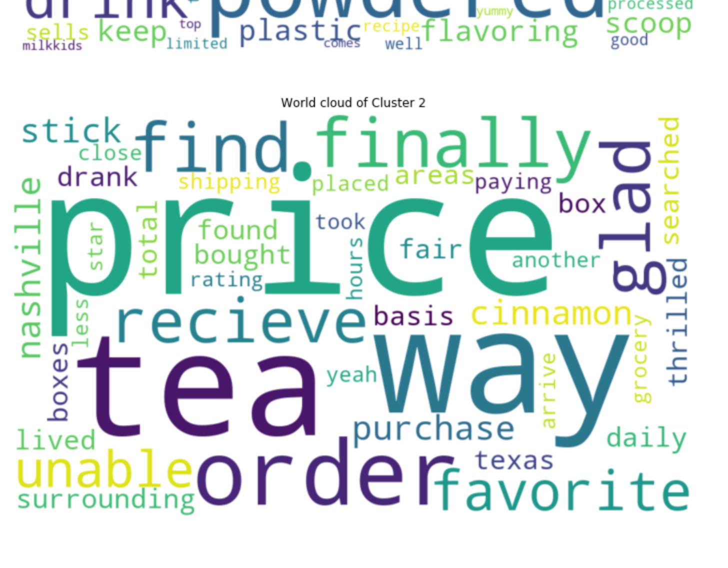
In [60]:
```
def plot_WordCloud(txt, ind):

    """
    This function takes text as string and plots wordcloud. ind here is for the index of the list el
ement
    """
    stopwords = set(STOPWORDS)
    wordcloud = WordCloud(width = 1000, height = 600, background_color ='white', stopwords = stopwor
ds).generate(txt)
    # plot the WordCloud image
    plt.figure(figsize = (10, 8))
    plt.imshow(wordcloud, interpolation = 'bilinear')
    plt.axis("off")
    plt.title("World cloud of Cluster {}".format(ind))
    plt.tight_layout(pad = 0)

    plt.show()
```

In [61]:
```
for ind, cluster in enumerate(cluster_str):
    plot_WordCloud(cluster, ind)
```





[5.6] Function that returns most similar words for a given word.

You need to write a function that takes a word and returns the most similar words using cosine similarity between the vectors (vector: a row in the matrix after truncatedSVD)

In [25]:
```
from sklearn.metrics.pairwise import linear_kernel
```

In [26]:
```
# Code Reference: # Reference code: https://stackoverflow.com/questions/12118720/python-tf-idf-cosin
e-to-find-document-similarity?answertab=votes#tab-top
def get_similar_word(word, n = 5):
    """This function takes a word and returns n similar words"""
    word_index = tfidf_features.index(word)
    cosine_similarities = linear_kernel(svd_data[[word_index]], svd_data).flatten()
    related_docs_indices = cosine_similarities.argsort()[::-1][1:n+1] # skipping 0 because it will r
eturn the same word
    for indices in related_docs_indices:
        print(tfidf_features[indices])
```

In [27]:
```
get_similar_word('happy')
```

```
like
good
product
taste
great
```

Summary

1. We selected **top 3000 features** from Amazon Fine Food reviews using **Tf-idf vectorizer**.
2. We calculated word vectors using co-occurence matrix by condiering **context window size of 5**.
3. We used elbow method to determine **n_components for TruncatedSVD** and the optimal value observed was **94**.