Assignment - 11 (Computing Word Vectors using TruncatedSVD)

September 14, 2018

1 OBJECTIVE :- Compute Word Vectors using TruncatedSVD

In [2]:
```
# Importing libraries
import warnings
warnings.filterwarnings("ignore")

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

from sklearn.feature_extraction.text import CountVectorizer
from nltk.stem.porter import PorterStemmer

import re

import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

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

2 Loading Data

In [3]:
```
# using the SQLite Table to read data.
con1 = sqlite3.connect('database.sqlite')
```

```
# Eliminating neutral reviews i.e. those reviews with Score = 3
filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
def polarity(x):
    if x < 3:
        return 'negative'
    return 'positive'

# Applying polarity function on Score column of filtered_data
filtered_data['Score'] = filtered_data['Score'].map(polarity)

print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

```
Out[3]:    Id   ProductId          UserId                      ProfileName  \
        0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
        1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
        2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
        3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
        4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

           HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
        0                     1                       1  positive  1303862400
        1                     0                       0  negative  1346976000
        2                     1                       1  positive  1219017600
        3                     3                       3  negative  1307923200
        4                     0                       0  positive  1350777600

                         Summary                                               Text
        0  Good Quality Dog Food  I have bought several of the Vitality canned d...
        1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
        2  "Delight" says it all  This is a confection that has been around a fe...
        3         Cough Medicine  If you are looking for the secret ingredient i...
        4            Great taffy  Great taffy at a great price.  There was a wid...
```

3 Data Cleaning: Deduplication

```
In [4]: #Sorting data according to ProductId in ascending order
        sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals

        #Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
        print(final.shape)
```

```
#Checking to see how much % of data still remains
((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
```

```
(364173, 10)
```

Out[4]: 69.25890143662969

In [5]:
```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

print(final.shape)
final[30:50]
```

```
(364171, 10)
```

Out[5]:

```
            Id   ProductId          UserId  \
138683  150501  0006641040   AJ46FKXOVC7NR
138676  150493  0006641040   AMX0PJKV4PPNJ
138682  150500  0006641040  A1IJKK6Q1GTEAY
138681  150499  0006641040  A3E7R866M94L0C
476617  515426  141278509X   AB1A5EGHHVA9M
22621    24751  2734888454  A1C298ITT645B6
22620    24750  2734888454  A13ISQV0U9GZIC
284375  308077  2841233731  A3QD68O22M2XHQ
157850  171161  7310172001   AFXMWPNS1BLU4
157849  171160  7310172001   A74C7IARQEM1R
157833  171144  7310172001  A1V5MY8V9AWUQB
157832  171143  7310172001  A2SW060IW01VPX
157837  171148  7310172001  A3TFTWTG2CC1GA
157831  171142  7310172001  A2Z01AYFVQYG44
157830  171141  7310172001   AZ40270J4JBZN
157829  171140  7310172001   ADXXVGRCGQQUO
157828  171139  7310172001  A13MS1JQG2ADOJ
157827  171138  7310172001  A13LAE0YTXA11B
157848  171159  7310172001  A16GY2RCF410DT
157834  171145  7310172001  A1L8DNQYY69L2Z

                                      ProfileName  \
138683                         Nicholas A Mesiano
138676                 E. R. Bird "Ramseelbird"
138682                                 A Customer
138681                    L. Barker "simienwolf"
476617                                    CHelmic
22621                            Hugh G. Pritchard
22620                                   Sandikaye
284375                                    LABRNTH
```

157850	H. Sandler
157849	stucker
157833	Cheryl Sapper "champagne girl"
157832	Sam
157837	J. Umphress
157831	Cindy Rellie "Rellie"
157830	Zhinka Chunmee "gamer from way back in the 70's"
157829	Richard Pearlstein
157828	C. Perrone
157827	Dita Vyslouzilova "dita"
157848	LB
157834	R. Flores

	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time \
138683	2	2	positive	940809600
138676	71	72	positive	1096416000
138682	2	2	positive	1009324800
138681	2	2	positive	1065830400
476617	1	1	positive	1332547200
22621	0	0	positive	1195948800
22620	1	1	negative	1192060800
284375	0	0	positive	1345852800
157850	0	0	positive	1229385600
157849	0	0	positive	1230076800
157833	0	0	positive	1244764800
157832	0	0	positive	1252022400
157837	0	0	positive	1240272000
157831	0	0	positive	1254960000
157830	0	0	positive	1264291200
157829	0	0	positive	1264377600
157828	0	0	positive	1265760000
157827	0	0	positive	1269216000
157848	0	0	positive	1231718400
157834	0	0	positive	1243728000

	Summary \
138683	This whole series is great way to spend time w...
138676	Read it once. Read it twice. Reading Chicken S...
138682	It Was a favorite!
138681	Can't explain why
476617	The best drink mix
22621	Dog Lover Delites
22620	made in china
284375	Great recipe book for my babycook
157850	Excellent treats
157849	Sophie's Treats
157833	THE BEST healthy dog treat!
157832	My Alaskan Malamute Loves Them!!

```
157837                                          Best treat ever!
157831            my 12 year old maltese has always loved these
157830                           Dogs, Cats, Ferrets all love this
157829                                                5 snouts!
157828                                       Best dog treat ever
157827                                  Great for puppy training
157848                                                   Great!
157834                                          Terrific Treats

                                                          Text
138683  I can remember seeing the show when it aired o...
138676  These days, when a person says, "chicken soup"...
138682  This was a favorite book of mine when I was a ...
138681  This book has been a favorite of mine since I ...
476617  This product by Archer Farms is the best drink...
22621   Our dogs just love them.  I saw them in a pet ...
22620   My dogs loves this chicken but its a product f...
284375  This book is easy to read and the ingredients ...
157850  I have been feeding my greyhounds these treats...
157849  This is one product that my welsh terrier can ...
157833  This is the ONLY dog treat that my Lhasa Apso ...
157832  These liver treas are phenomenal. When i recei...
157837  This was the only treat my dog liked during ob...
157831  No waste , even if she is having a  day when s...
157830  I wanted a treat that was accepted and well li...
157829  My Westie loves these things!  She loves anyth...
157828  This is the only dog treat that my terrier wil...
157827  New puppy loves this, only treat he will pay a...
157848  My dog loves these treats!  We started using t...
157834  This is a great treat which all three of my do...
```

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

In [6]:
```
final = final[final['ProductId'] != '2841233731']
final = final[final['ProductId'] != '0006641040']
final.shape
```

Out[6]:
```
(364136, 10)
```

4 Text Preprocessing: Stemming, stop-word removal and Lemmatization.

In [7]:
```
#set of stopwords in English
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
words_to_keep = set(('not'))
```

```
stop -= words_to_keep
#initialising the snowball stemmer
sno = nltk.stem.SnowballStemmer('english')

 #function to clean the word of any html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

#function to clean the word of any punctuation or special characters
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [8]:
```
#Code for removing HTML tags , punctuations . Code for removing stopwords . Code for c
# also greater than 2 . Code for stemmimg and also to convert them to lowercase letter
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to descri
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to descri
                else:
                    continue
            else:
                continue

    str1 = b" ".join(filtered_sentence) #final string of cleaned words


    final_string.append(str1)
    i+=1
```

In [9]:
```
#adding a column of CleanedText which displays the data after pre-processing of the re
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
#below the processed review can be seen in the CleanedText Column
print('Shape of final',final.shape)
final.head()
```

```
Shape of final (364136, 11)
```

Out[9]:
```
            Id   ProductId          UserId      ProfileName  \
476617  515426  141278509X   AB1A5EGHHVA9M          CHelmic
22621    24751  2734888454  A1C298ITT645B6  Hugh G. Pritchard
22620    24750  2734888454  A13ISQV0U9GZIC         Sandikaye
157850  171161  7310172001   AFXMWPNS1BLU4       H. Sandler
157849  171160  7310172001   A74C7IARQEM1R          stucker

        HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
476617                     1                       1  positive  1332547200
22621                      0                       0  positive  1195948800
22620                      1                       1  negative  1192060800
157850                     0                       0  positive  1229385600
157849                     0                       0  positive  1230076800

                   Summary                                               Text  \
476617  The best drink mix  This product by Archer Farms is the best drink...
22621    Dog Lover Delites  Our dogs just love them.  I saw them in a pet ...
22620        made in china  My dogs loves this chicken but its a product f...
157850    Excellent treats  I have been feeding my greyhounds these treats...
157849     Sophie's Treats  This is one product that my welsh terrier can ...

                                              CleanedText
476617  product archer farm best drink mix ever mix fl...
22621   dog love saw pet store tag attach regard made ...
22620   dog love chicken product china wont buy anymor...
157850  feed greyhound treat year hound littl finicki ...
157849  one product welsh terrier eat sophi food alerg...
```

RANDOMLY SAMPLING 25K POINTS OUT OF WHOLE DATASET

In [10]:
```
##Sorting data according to Time in ascending order for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, ki

# We will collect different 40K rows without repetition from time_sorted_data datafra
my_final = time_sorted_data.take(np.random.permutation(len(final))[:25000])

sample = my_final['CleanedText'].values
```

5 Defining 'WordVector' Class to compute word vectors using TruncatedSVD

In [12]:
```
# Definition of class
class WordVector:


        # Initialising the max_features and sample_data to pass in TFIDF vectorizer
        def __init__(self, max_feat , sample_data):
            self.max_feat = max_feat # No.of top words
            self.sample_data = sample_data # document to vectorize
            # List of all top max_feat words
            self.top_words = []
            self.freq = []

        # Picking top max_feat words by using TFIDF vextorizer
        def topWords(self):
            tf_idf_vect = TfidfVectorizer(max_features=self.max_feat)
            tfidf_vec = tf_idf_vect.fit_transform(self.sample_data)
            print("the type of count vectorizer :",type(tfidf_vec))
            print("the shape of out text TFIDF vectorizer : ",tfidf_vec.get_shape())
            print("the number of unique words :", tfidf_vec.get_shape()[1])

            # Top 'n' words
            self.top_words = tf_idf_vect.get_feature_names()
            # tfidf frequencies of top 'n' words
            self.freq = tf_idf_vect.idf_

            return tf_idf_vect.get_feature_names()

        # Computing the co-occurrence matrix with value of neighbourhood as neighbour_num
        def cooccurrenceMatrix(self, neighbour_num , list_words):

            # Storing all words with their indices in the dictionary
            corpus = dict()
            # List of all words in the corpus
            doc = []
            index = 0
            for sent in self.sample_data:
                for word in sent.split():
                    doc.append(word)
                    corpus.setdefault(word,[])
                    corpus[word].append(index)
                    index += 1

            # Co-occurrence matrix
            matrix = []
```

```python
        # rows in co-occurrence matrix
        for row in list_words:
            # row in co-occurrence matrix
            temp = []
            # column in co-occurrence matrix
            for col in list_words :
                if( col != row):
                    # No. of times col word is in neighbourhood of row word
                    count = 0
                    # Value of neighbourhood
                    num = neighbour_num
                    # Indices of row word in the corpus
                    positions = corpus[row]
                    for i in positions:
                        if i<(num-1):
                            # Checking for col word in neighbourhood of row
                            if col in doc[i:i+num]:
                                count +=1
                        elif (i>=(num-1)) and (i<=(len(doc)-num)):
                            # Check col word in neighbour of row
                            if (col in doc[i-(num-1):i+1]) and (col in doc[i:i+num]):
                                count +=2
                            # Check col word in neighbour of row
                            elif (col in doc[i-(num-1):i+1]) or (col in doc[i:i+num])
                                count +=1
                        else :
                            if (col in doc[i-(num-1):i+1]):
                                count +=1


                    # appending the col count to row of co-occurrence matrix
                    temp.append(count)
                else:
                    # Append 0 in the column if row and col words are equal
                    temp.append(0)
            # appending the row in co-occurrence matrix
            matrix.append(temp)
        # Return co-occurrence matrix
        return np.array(matrix)


    # Function to draw Cumulative_explained_variance VS n_components plot to find opt
    def plotCumulativeVariance(self, co_occurrence_matrix):
        #Applying TruncatedSVD
        from sklearn.decomposition import TruncatedSVD
        max_features = co_occurrence_matrix.shape[1]-1
        svd = TruncatedSVD(n_components=max_features)
        svd_data = svd.fit_transform(co_occurrence_matrix)
```

```
        percentage_var_explained = svd.explained_variance_ / np.sum(svd.explained_var
        cum_var_explained = np.cumsum(percentage_var_explained)
        # Plot the TrunvatedSVD spectrum
        plt.figure(1, figsize=(6, 4))
        plt.clf()
        plt.plot(cum_var_explained, linewidth=2)
        plt.axis('tight')
        plt.grid()
        plt.xlabel('n_components')
        plt.ylabel('Cumulative_explained_variance')
        plt.title("Cumulative_explained_variance VS n_components")
        plt.show()

    # Function to get matrix of word_vectors U'(n*k matrix) using TruncatedSVD . Here
    # Here pass co-occurrence matrix  and optimal no. of components
    def computeVectors(self, co_occurrence_matrix, num_components):
        from sklearn.decomposition import TruncatedSVD
        svd_trunc = TruncatedSVD(n_components=num_components)
        svd_transform = svd_trunc.fit_transform(co_occurrence_matrix)
        # Returns Transformed matrix of Word-Vectors
        return svd_transform

    # Applying k-means clustering and obtaining all the clusters
    def getClusters(self, num_clusters, matrix_word_vec):
        from sklearn.cluster import KMeans
        kmeans = KMeans(n_clusters=num_clusters, n_jobs=-1).fit(matrix_word_vec)
        index = [i for i in range(len(self.top_words))]
        d = dict()
        for (key, value) in zip(kmeans.labels_, index):
            d.setdefault(key,[])
            d[key].append(value)
        # List of all clusters
        clusters = []
        labels = sorted(list(set(kmeans.labels_)))
        for i in labels:
            temp = []
            for idx in sorted(d[i]):
                temp.append(self.top_words[idx])
            clusters.append(temp)

        # Return the list of clusters
        return clusters

    # Function to generate word cloud
    def generateWordCloud(self, list_of_words):
        from wordcloud import WordCloud, STOPWORDS
        stopwords = set(STOPWORDS)
```

```
        # Dictionary consisting of words as keys and their frequencies as values
        word_dict = {word : self.freq[self.top_words.index(word)] for word in list_of_
        
        # Initialising and generating wordcloud
        wc = WordCloud(background_color='white', stopwords=stopwords, max_words=100, m
        wc.generate_from_frequencies(word_dict)
        
        # Show wordcloud
        plt.figure(figsize = (12, 8), facecolor = None)
        plt.imshow(wc, interpolation="bilinear")
        plt.axis("off")
        plt.tight_layout(pad = 0)
        plt.show()
```

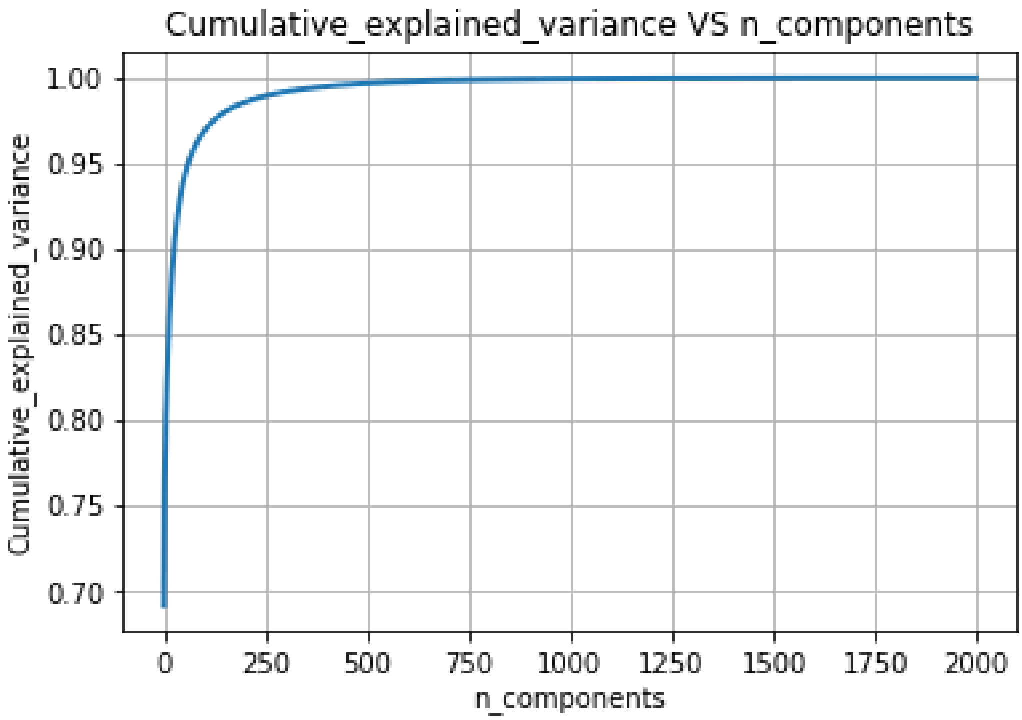
6 (a). Using WordVector class for computing Word Vectors for top 2K words :

```
In [15]: # Creating the object of WordVector class for top 2K words and using 'sample' dataset
         wv = WordVector(2000,sample)
         
         # Picking top 2K words
         words_top = wv.topWords()
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (25000, 2000)
the number of unique words : 2000
```

```
In [16]: # Computing the co-occurrence matrix for 'words_top' with value of neighbourhood = 5
         co_occ_matrix = wv.cooccurrenceMatrix(5, words_top)
         print("Shape of co-occurrence matrix : ",co_occ_matrix.shape )
         print('\n')
         
         # drawing Cumulative_explained_variance VS n_components plot to find optimal number o
         wv.plotCumulativeVariance(co_occ_matrix)
```

```
Shape of co-occurrence matrix :  (2000, 2000)
```



OBSERVATION :- From above we can observe that only 250 components can explain almost 99% of variance . So, it will be good to use only 250 components instead of total 2000 components .

```
In [17]: # Computing word vectors with 250 components
         word_vec_matrix = wv.computeVectors(co_occ_matrix, 250)
         print("Shape of word-vector : ",word_vec_matrix.shape)

         # Applying k-means with no_of_clusters = 50 on 'word_vec_matrix' and get all clusters
         word_cluster = wv.getClusters(50, word_vec_matrix)

Shape of word-vector :  (2000, 250)
```

7 Seeing Words In The Clusters :

```
In [24]: print("Words in Cluster- 1 :\n",word_cluster[0])

Words in Cluster- 1 :
 ['bean', 'bitter', 'black', 'blend', 'brew', 'dark', 'green', 'ice', 'morn', 'rich', 'roast',
```

SUMMARY :- By observing above cluster we can conclude that words in cluster are related to flavours and types of coffee .

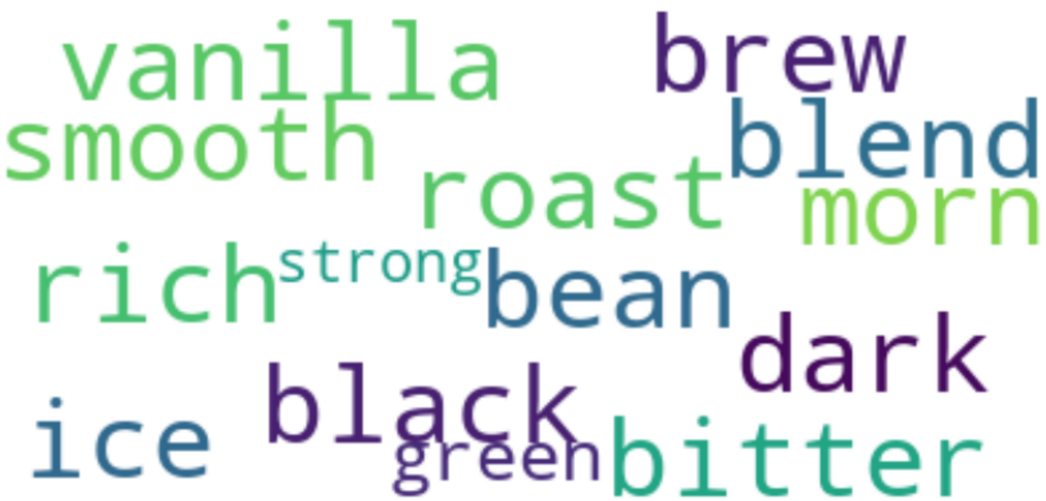
```
In [38]: print("Words in Cluster- 49 :\n",word_cluster[48][27:37])
```

```
Words in Cluster- 49 :
 ['beer', 'benefit', 'berri', 'beverag', 'biscuit', 'bland', 'blue', 'blueberri', 'boil', 'bone
```

SUMMARY :- By observing above cluster we can conclude that words in cluster are related to eatables .

8 Word Clouds :

```
In [37]: # Word Cloud for cluster-1
         wv.generateWordCloud(word_cluster[0])
```




```
In [39]: # Word Cloud for cluster -49
         wv.generateWordCloud(word_cluster[48])
```

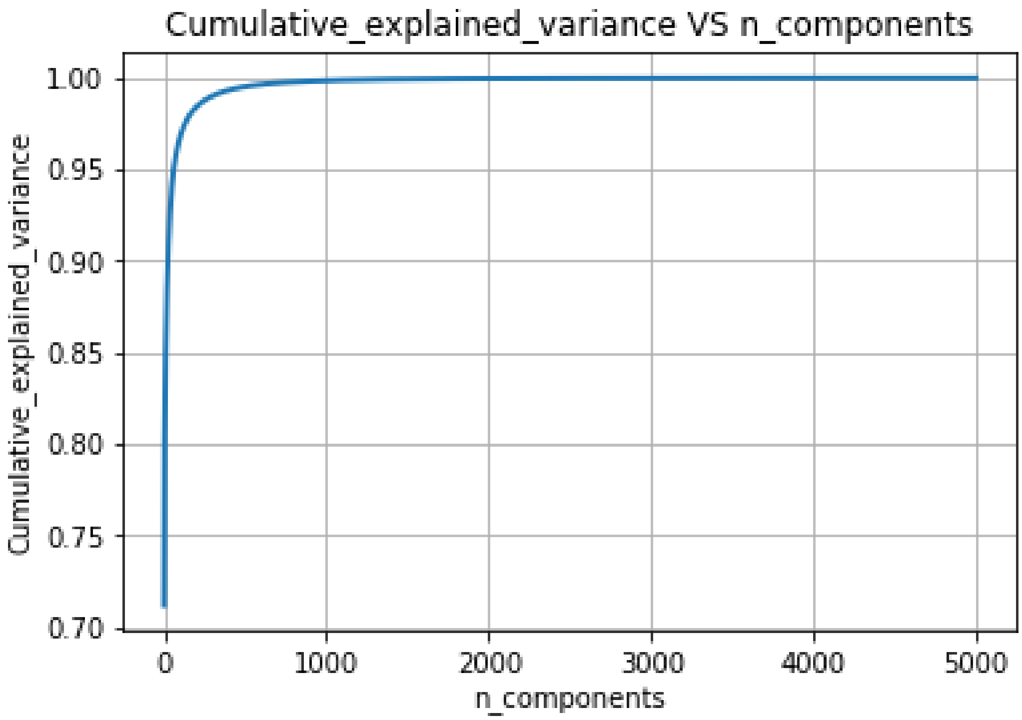
9 (b). Using WordVector class for computing Word Vectors of top 5K words

In [40]:
```
# Creating the object of WordVector class for top 5000 words and using 'sample' datas
wv1 = WordVector(5000,sample)

# Picking top 5000 words
words_top_5000 = wv1.topWords()
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (25000, 5000)
the number of unique words : 5000
```

In [41]:
```
# Computing the co-occurrence matrix for 'words_top_5000' with value of neighbourhood
co_occ_matrix = wv1.cooccurrenceMatrix(5, words_top_5000)
print("Shape of co-occurrence matrix : ",co_occ_matrix.shape )
print('\n')

# drawing Cumulative_explained_variance VS n_components plot to find optimal number o
wv1.plotCumulativeVariance(co_occ_matrix)
```

```
Shape of co-occurrence matrix :  (5000, 5000)
```



OBSERVATION :- From above we can observe that only 500 components can explain almost 99% of variance . So, it will be good to use only 500 components instead of total 5000 components .

```
In [42]: # Computing word vectors with 500 components
         word_vec_matrix = wv1.computeVectors(co_occ_matrix, 500)
         print("Shape of word-vector : ",word_vec_matrix.shape)

         # Applying k-means with no_of_clusters = 50 on 'word_vec_matrix' and get all clusters
         word_cluster = wv1.getClusters(50, word_vec_matrix)
```

```
Shape of word-vector :  (5000, 500)
```

10 Seeing Words In The Clusters :

```
In [45]: print("Words in Cluster- 3 :\n",word_cluster[2])
```

```
Words in Cluster- 3 :
 ['add', 'bit', 'delici', 'differ', 'enjoy', 'favorit', 'fresh', 'hot', 'lot', 'milk', 'nice',
```

SUMMARY :- By observing above cluster we can conclude that words in cluster are related to qualities of different drinkables .

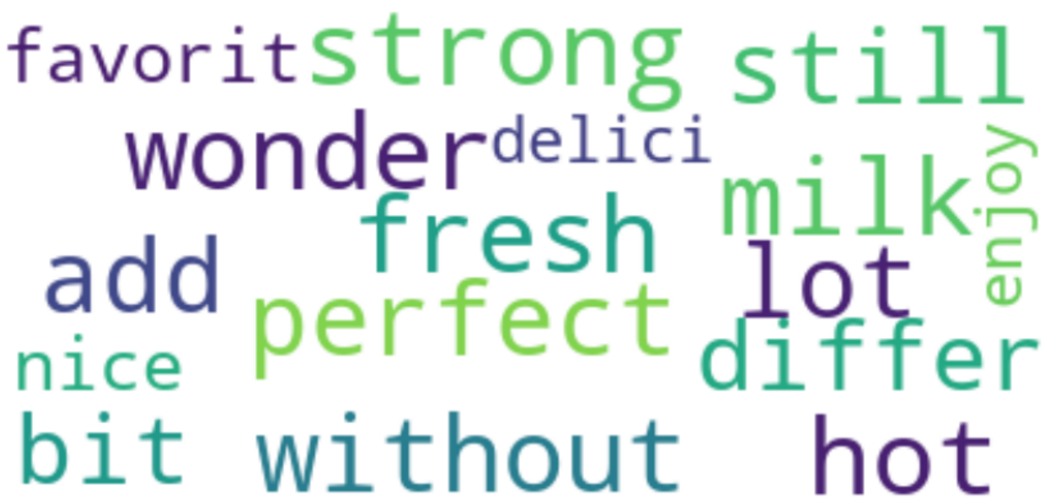
```
In [49]: print("Words in Cluster- 39 :\n",word_cluster[38])
```

```
Words in Cluster- 39 :
 ['actual', 'ad', 'anyth', 'bad', 'bar', 'calori', 'candi', 'cereal', 'chip', 'coconut', 'cook
```

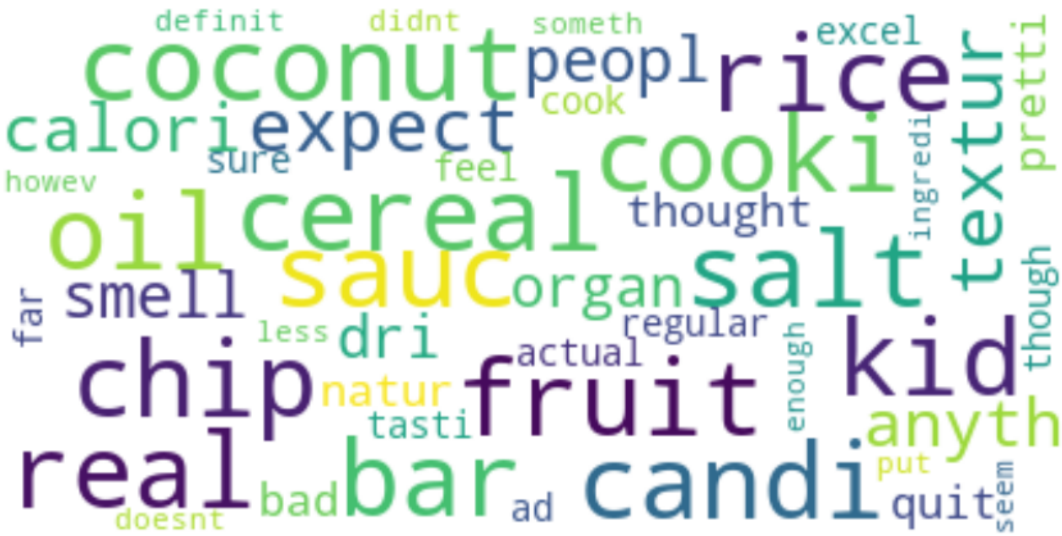
SUMMARY :- By observing above cluster we can conclude that words in cluster are related to eatables and their qualities and quantities .

11 Word Clouds :

```
In [50]: # Word Cloud for cluster-3
         wv1.generateWordCloud(word_cluster[2])
```




```
In [51]: # Word Cloud for cluster-39
         wv1.generateWordCloud(word_cluster[38])
```



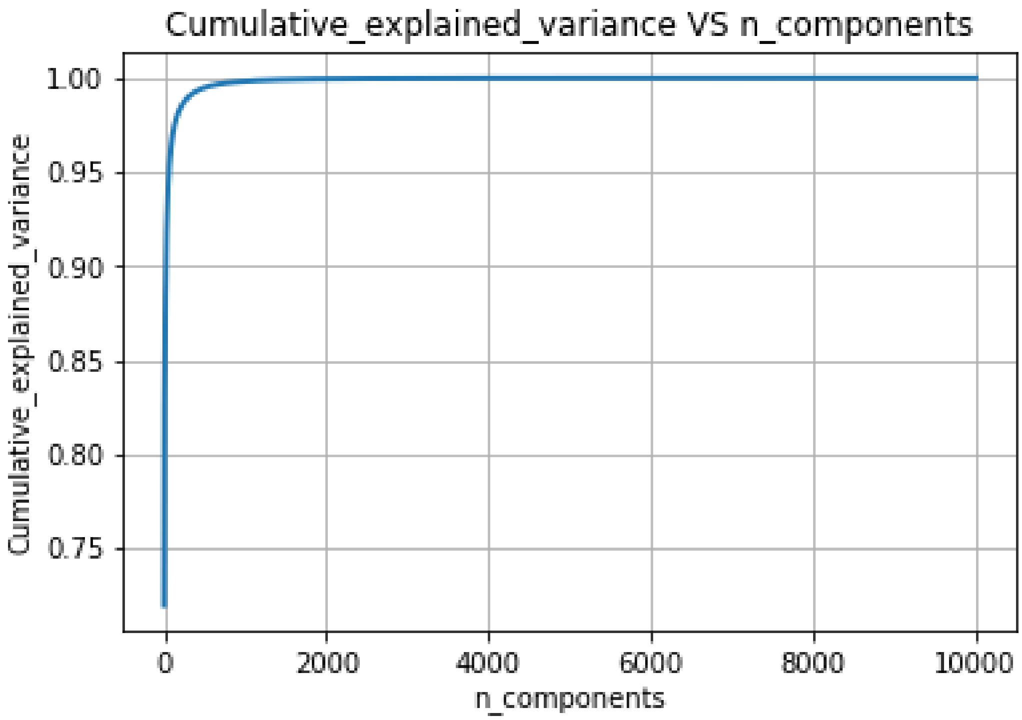
12 (c). Using WordVector class for computing Word Vectors of top 10K words

```
In [52]: # Creating the object of WordVector class for top 10K words and using 'sample' datase
         wv2 = WordVector(10000,sample)

         # Picking top 10K words
         words_top_10k = wv2.topWords()
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (25000, 10000)
the number of unique words : 10000
```

```
In [53]: # Computing the co-occurrence matrix for 'words_top_10k' with value of neighbourhood
         co_occ_matrix = wv2.cooccurrenceMatrix(5, words_top_10k)
         print("Shape of co-occurrence matrix : ",co_occ_matrix.shape )
         print('\n')

         # drawing Cumulative_explained_variance VS n_components plot to find optimal number o
         wv2.plotCumulativeVariance(co_occ_matrix)
```

```
Shape of co-occurrence matrix :  (10000, 10000)
```



OBSERVATION :- From above we can observe that only 700 components can explain almost 99% of variance . So, it will be good to use only 700 components instead of total 10000 components .

```
In [54]: # Computing word vectors with 700 components
         word_vec_matrix = wv2.computeVectors(co_occ_matrix, 700)
         print("Shape of word-vector : ",word_vec_matrix.shape)

         # Applying k-means with no_of_clusters = 50 on 'word_vec_matrix' and get all clusters
         word_cluster = wv2.getClusters(50, word_vec_matrix)

Shape of word-vector :  (10000, 700)
```

13 Seeing Words In The Clusters :

```
In [58]: print("Words in Cluster- 10 :\n",word_cluster[9][4:14])

Words in Cluster- 10 :
 ['bad', 'bar', 'butter', 'calori', 'candi', 'cereal', 'chip', 'coconut', 'contain', 'cooki']
```

SUMMARY :- By observing above cluster we can conclude that words in cluster are related to eatables .

```
In [62]: print("Words in Cluster- 15 :\n",word_cluster[14])
```

```
Words in Cluster- 15 :
 ['buy', 'get', 'order']
```

SUMMARY :- By observing above cluster we can conclude that words in cluster are related to online shopping actions .

```
In [63]: print("Words in Cluster- 40 :\n",word_cluster[39])
```

```
Words in Cluster- 40 :
 ['bag', 'box', 'packag']
```

SUMMARY :- By observing above cluster we can conclude that words in cluster are related to containers semantically .

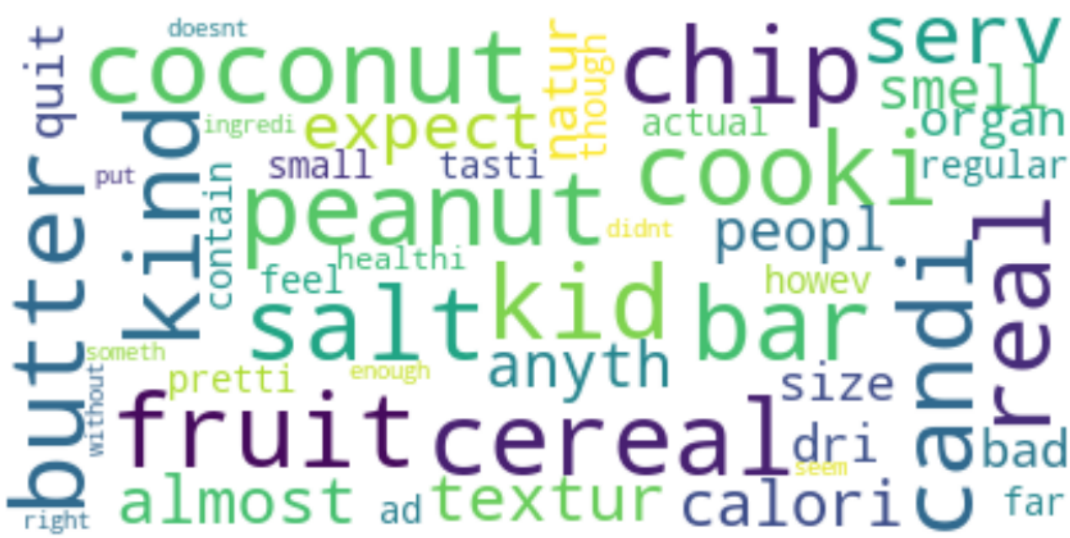
```
In [64]: print("Words in Cluster- 50 :\n",word_cluster[49])
```

```
Words in Cluster- 50 :
 ['anoth', 'arriv', 'back', 'big', 'bottl', 'came', 'case', 'compani', 'definit', 'disappoint'
```

SUMMARY :- By observing above cluster we can conclude that words in cluster have some verbs and adjectives and are semantically related to each other .

14 Word Clouds :

```
In [65]: # Word Cloud for cluster-10
         wv2.generateWordCloud(word_cluster[9])
```



```
In [66]: # Word Cloud for cluster-50
         wv2.generateWordCloud(word_cluster[49])
```


```
In [72]: # Word Cloud for cluster-18
         wv2.generateWordCloud(word_cluster[17])
```

15 CONCLUSION

16 Procedure Followed :

STEP 1 :- Text Preprocessing

STEP 2 :- Taking all text data and ignoring class variable .

STEP 3:- Definig WordVector class for computing word vectors using TruncatedSVD

STEP 4:- Finding top ′n′ words using TFIDF vectorizer

STEP 5:- Computing co-occurrence matrix using these top ′n′ words

STEP 6:- Finding right number of components using cumulative_explained_variance VS n_components plot .

STEP 7 :- Applying TruncatedSVD on this co-occurrence matrix with right number of components in order to find matrix of word-vectors .

STEP 8:- Apply k-means clustering on this matrix of word-vectors and manually seeing the words in the clusters to check whether they are semantically related or not .

STEP 9:- Also creating WordClouds for few clusters for better presentation

Repeat from STEP 4 to STEP 9 using value of n = 2K , 5K and 10K