Compute Word Vectors using TruncatedSVD in Amazon Food Reviews.

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. index
2. Id
3. ProductId - unique identifier for the product
4. UserId - unqiue identifier for the user
5. ProfileName
6. HelpfulnessNumerator - number of users who found the review helpful
7. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
8. Score - rating between 1 and 5
9. Time - timestamp for the review
10. Summary - brief summary of the review
11. Text - text of the review
12. ProcessedText - Cleaned & Preprocessed Text of the review

Objective: Perform following tasks on Amazon Food reviews:

Task 1. Sample 25000 reviews then find top 10000 words corresponding to top 10000 Inverse Document Frequency(IDF) values.
Task 2. Compute co-occurrence matrix on those 10000 words.
Task 3. Find optimal value of number of components(reduced dimensions) using maximum variance.
Task 4. Apply TruncatedSVD using optimal value of number of components.
Task 5. Cluster words using K-Means.

[Q] How to determine if a review is positive or negative?

[Ans] We could use the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

Loading the data

SQLite Database

In order to load the data, We have used the SQLITE dataset as it easier to query the data and visualise the data efficiently. Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [173]:
```
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

import re
import string
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from sklearn.preprocessing import StandardScaler

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.cluster import KMeans
from sklearn.utils.extmath import randomized_svd
```

In [174]:
```
connection = sqlite3.connect('FinalAmazonFoodReviewsDataset.sqlite')

data = pd.read_sql_query("SELECT * FROM Reviews", connection)
data.head()
```

Out[174]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Positive	1303862400	Good Quality Dog Food	se
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Negative	1346976000	Not as Advertised	lal
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Positive	1219017600	"Delight" says it all	F . cc a
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Positive	1350777600	Great taffy	t
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	Positive	1342051200	Nice Taffy	.

In [175]:
```
print(data.shape)
print(data["Score"].value_counts())
```

```
(364171, 12)
Positive    307061
Negative     57110
Name: Score, dtype: int64
```

In [176]:
```
stop = set(stopwords.words("english")) #set of stopwords
sno = nltk.stem.SnowballStemmer("english")
print(stop)
```

```
{'against', 'couldn', 're', 't', "won't", 'i', "that'll", 'ain', 'its', 'up', 'isn', 'from', 'yours', 'doesn', 'or', 'w
hy', 'haven', 'between', 'me', 'that', 'weren', 'what', 'not', 'other', 'm', "you'd", 'we', 'been', 'theirs', 'she', 't
hey', 'out', "should've", 've', "doesn't", 'mightn', 'on', "it's", 'such', 'about', "hadn't", 'hasn', 'herself', 'has',
'all', "she's", "you'll", "weren't", 'myself', 'above', 'him', 'below', 'does', 'his', 'very', "hasn't", 's', 'just',
'this', 'of', 'o', 'it', 'do', "mightn't", 'the', 'through', 'own', 'no', 'only', "didn't", 'down', 'any', 'your', 'did
n', 'y', 'mustn', 'himself', 'should', 'needn', 'our', 'under', 'there', 'some', 'as', 'my', 'because', 'until', 'whe
n', "you've", "aren't", 'was', 'then', 'itself', 'shouldn', "mustn't", 'few', 'her', 'over', 'd', 'll', 'by', 'having',
'he', "haven't", 'don', 'than', 'once', 'each', 'for', 'will', 'won', "shan't", 'shan', "wasn't", 'can', 'at', 'these',
'and', 'wouldn', 'themselves', 'being', 'same', 'am', 'had', 'while', "isn't", 'be', "don't", 'now', 'ma', 'so', 'hav
e', 'where', 'ourselves', 'you', 'in', 'whom', "needn't", 'more', 'ours', 'too', 'hadn', 'but', 'who', 'hers', 'into',
"couldn't", 'further', 'off', 'their', "you're", 'did', 'during', 'is', 'here', "shouldn't", 'after', 'a', 'aren', 'you
rselves', 'them', 'an', 'how', 'wasn', 'before', 'those', "wouldn't", 'if', 'again', 'nor', 'with', 'were', 'to', 'mos
t', 'both', 'which', 'are', 'yourself', 'doing'}
```

In [177]:
```
def cleanhtml(sentence): #function to clean htmltags
    cleanr = re.compile("<.*?>")
    cleantext = re.sub(cleanr, " ", sentence)
    return cleantext

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

In [178]:
```
#Code for removing stop-words from 'Text' column

i = 0
final_string = []
s = ""
for sentence in data["Text"].values:
    filteredSentence = []
    EachReviewText = ""
    sentenceHTMLCleaned = cleanhtml(sentence)
    for eachWord in sentenceHTMLCleaned.split():
        for sentencePunctCleaned in cleanpunc(eachWord).split():
            if (sentencePunctCleaned.isalpha()) & (len(sentencePunctCleaned)>2):
                if sentencePunctCleaned.lower() not in stop:
                    sentenceLower = sentencePunctCleaned.lower()
                    s = (sno.stem(sentenceLower))
                    filteredSentence.append(s)

    EachReviewText = ' '.join(filteredSentence)
    final_string.append(EachReviewText)
```

In [179]:
```
data["CleanedText"] = final_string
```

In [180]:
```
data.head()
```

Out[180]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Positive	1303862400	Good Quality Dog Food
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Negative	1346976000	Not as Advertised
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Positive	1219017600	"Delight" says it all
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Positive	1350777600	Great taffy
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	Positive	1342051200	Nice Taffy

Task 1. Sample 25000 reviews then find top 10000 words corresponding to top 10000 Inverse Document Frequency(IDF) values.

In [181]:
```
#taking 25000 random samples
Data = data.sample(n = 25000)
Data.head()
```

Out[181]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Sum
316493	455533	492508	B0000YUTUW	A2QNPL3DCV5ITK	L. Such	0	0	Negative	1244332800	Not \ th f
73322	104508	113463	B000FL08B0	A109L3WXD1SJFU	Cookbook Gal "Cookbook Gal"	0	0	Positive	1212019200	prc p pack
323959	466801	504764	B000H241DS	A1SQZTQCLKWTED	Ella B.	2	5	Negative	1323993600	Q C
176289	249921	270984	B000EQSAIY	A3M91P9K64YADW	carol998	0	0	Positive	1320019200	W won
330298	476046	514800	B000CSEFQ0	A2B1I205ZNBVLY	Rudy Bonn	2	3	Negative	1347062400	Wha

In [182]:
```
print(Data.shape)
print(Data["Score"].value_counts())
```

```
(25000, 13)
Positive    21060
Negative     3940
Name: Score, dtype: int64
```

In [183]:
```
TFIDF_Vec= TfidfVectorizer(ngram_range=(1,1), stop_words = "english")
TFIDF_Count = TFIDF_Vec.fit_transform(Data["CleanedText"].values)
```

In [184]:
```
TFIDF_Count.shape
```

Out[184]:
```
(25000, 19690)
```

In [185]:
```
features = TFIDF_Vec.get_feature_names()
```

In [186]:
```
idfValues = TFIDF_Vec.idf_
```

In [189]:
```
d = dict(zip(features, 11 - idfValues))
```

In [190]:
```
sortedDict = sorted(d.items(), key = lambda d: d[1], reverse = True)
#here we are sorting a dictionary where first value(keys) are words and second value(values) are IDF values. There is a '
#argument in sorted function takes a function which will be used to determine according to what values to sort by. Here,
#given an anonymous function which takes the data followed by colon then d[1] means in our data second value is idf value
#are telling the sorted function to sort the dictionary according to idf values.
```

In [191]:
```
sortedDict = sortedDict[0:10000]
#taking top 10000 words corresponding to top 10000 Inverse Document Frequency(IDF) values.
```

In [192]:
```
len(sortedDict)
```

Out[192]:
```
10000
```

In [194]:
```
for i in range(10):
    print(sortedDict[i])
```

```
('like', 8.864144163134325)
('tast', 8.83904668593449)
('good', 8.69756551429628)
('love', 8.628436018583539)
('great', 8.60288776650821)
('flavor', 8.58575987042638)
('product', 8.55654487219033)
('use', 8.49829968053931)
('tri', 8.478532965688592)
('make', 8.317306026034618)
```

In [195]:
```
for i in range(10):
    print(sortedDict[i][0])
```

```
like
tast
good
love
great
flavor
product
use
tri
make
```

In [196]:
```
wordList_idf = []
for i in range(len(sortedDict)):
    wordList_idf.append(sortedDict[i][0])
```

In [197]:
```
len(wordList_idf)
```

Out[197]:
```
10000
```

Task 2. Compute co-occurrence matrix on those 5000 words.

In [198]:
```
Data["CleanedText"].head()
```

Out[198]:
```
316493    disappoint sucker stick plastic thought least ...
73322     read previous review excit find compani solv p...
323959    gave product poor review allow return yet prod...
176289    finish salt never tast salt subtl almost sweet...
330298    kellogg cereal contain genet modifi organ crop...
Name: CleanedText, dtype: object
```

In [199]:
```
sent = Data["CleanedText"].iloc[3]
sent
```

Out[199]:
```
'finish salt never tast salt subtl almost sweet flavor put spare finish toss salad fish edaman winter squash potato swe
et white truli gem first tri year ago ran couldnt find anywher bought give gift thank'
```

In [200]:
```
len(sent.split())
```

Out[200]:
```
35
```

In [201]:
```
#checking for any empty text
cnt = 0
for i in Data["CleanedText"]:
    cnt += 1
    if len(i.split()) == 0:
        print(cnt)
```

In [202]:
```
def co_occurrence(sentence_array, window_size, word_list):

    co_occ = np.zeros((len(word_list), len(word_list)), dtype = int)

    for i in sentence_array:
        for word in i.split():
            if word in word_list:
                row = word_list.index(word)   #this will give index of a word in word_list array
                wordIndexInSentence = i.split().index(word)  #this will give index of a word in sentence 'i'

                window_left = wordIndexInSentence - window_size
                if window_left < 0:
                    window_left = 0

                window_right = wordIndexInSentence + window_size
                if window_right > len(i.split()):
                    window_right = len(i.split())

                for context_word in i.split()[window_left:window_right]:
                    if context_word in word_list:
                        column = word_list.index(context_word)
                        co_occ[row][column] += 1
    return co_occ

#this is a function to create co-occurrence matrix of all the words which will be passed into "word_list" argument.
#basically this function takes three arguments:

#First: "sentence_series"(numpy ndarray) which is an array which should contain all the reviews/sentences.

#Second: "window_size"(integer) this determines the context size upto which you may want to find the co-occurring words.

#Third: "word_list"(list) this should contain list of words which you may want to find as co-occurring.

#it returns co-occurrence matrix which is a square matrix and each row and column corresponds to a word as defined in
#"word_list"
```

In [204]:
```
sent_series = Data["CleanedText"].values
print(type(sent_series))
print(sent_series.shape)
```

```
<class 'numpy.ndarray'>
(25000,)
```

In [205]:
```
print(len(wordList_idf))
```

```
10000
```

In [206]:
```
co_occur_matrix = co_occurrence(sent_series, 5, wordList_idf)
```

In [207]:
```
print(co_occur_matrix)
print(co_occur_matrix.shape)
```

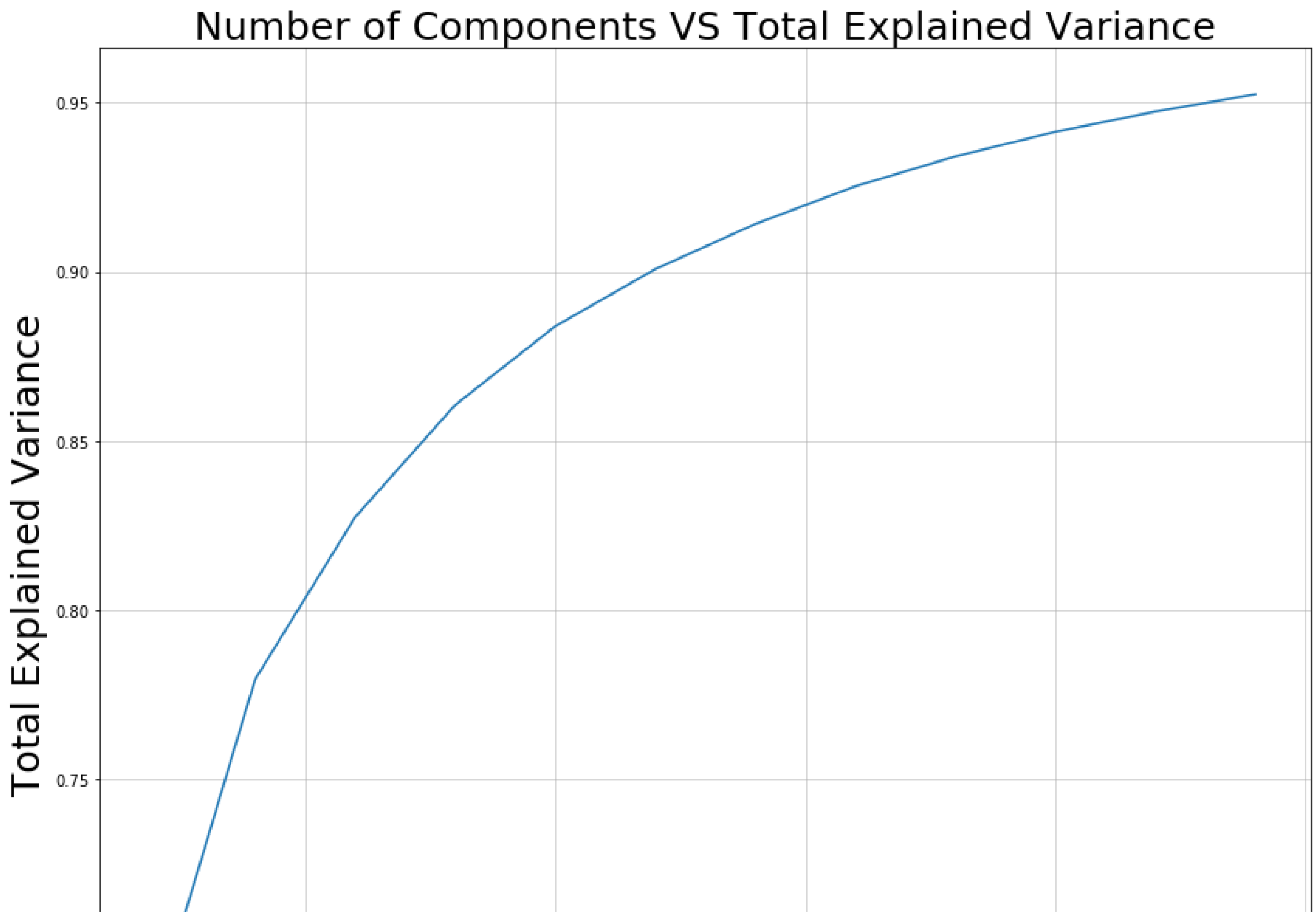
```
[[13064  3063   890 ...     0     0     0]
 [ 2905 12236  1889 ...     0     3     0]
 [  956  1898  9816 ...     0     0     0]
 ...
 [    0     0     0 ...     2     0     0]
 [    0     1     0 ...     0     2     0]
 [    0     0     0 ...     0     0     2]]
(10000, 10000)
```

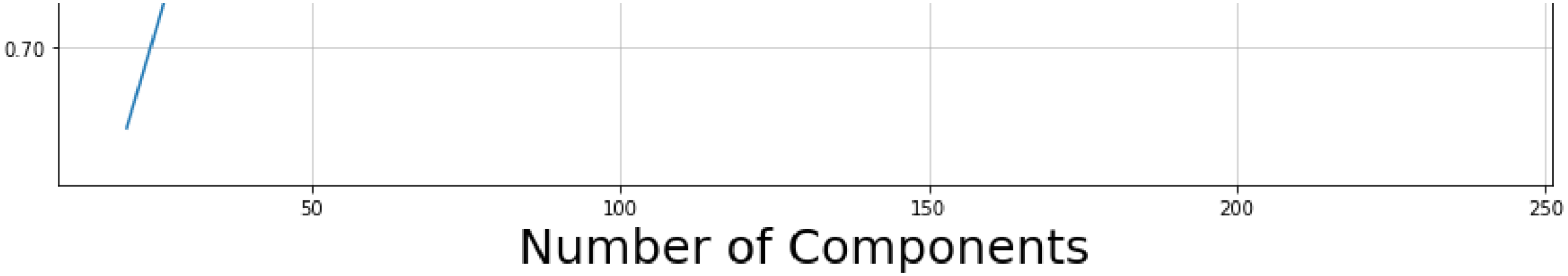
Task 3. Find optimal value of number of components(reduced dimensions) using maximum variance.

In [210]:
```
k = [i for i in range(20,241,20)]
components = []
total_var = []

for j in k:
    svd = TruncatedSVD(n_components=j, n_iter=10)
    svd.fit(co_occur_matrix)
    var_perc = sum(svd.explained_variance_ratio_)
    components.append(j)
    total_var.append(var_perc)

xy = list(zip(components, total_var))
xy
```

Out[210]:
```
[(20, 0.680916805693981),
 (40, 0.7795932630180603),
 (60, 0.8274989266485523),
 (80, 0.8606353176834907),
 (100, 0.8838791551841226),
 (120, 0.9007604176008285),
 (140, 0.9140905587270168),
 (160, 0.9252313729437507),
 (180, 0.9340579389749889),
 (200, 0.9413266320118187),
 (220, 0.9473163368196609),
 (240, 0.952410173701445)]
```

In [211]:
```
plt.figure(figsize = (14, 12))
plt.plot(components, total_var)
plt.title("Number of Components VS Total Explained Variance", fontsize=25)
plt.xlabel("Number of Components", fontsize=25)
plt.ylabel("Total Explained Variance", fontsize=25)
plt.grid(linestyle='-', linewidth=0.5)
```





We can see from the graph that we are getting approximately 91% variance at number of components equal to 140. It further means that we are preserving 91% of data even by reducing our dimension from 5000 to 140. Therefore, we are considering our number of components to be 140

Task 4. Apply TruncatedSVD using optimal value of number of components.

In [218]:
```
svd = TruncatedSVD(n_components = 140, n_iter = 10)
svd.fit(co_occur_matrix)
var_perc = sum(svd.explained_variance_ratio_)
print("Percentage of variance explained = "+str(var_perc * 100)+"%")
```

```
Percentage of variance explained = 91.40980500709482%
```

In [219]:
```
U, Sigma, VT = randomized_svd(co_occur_matrix, n_components = 140, n_iter = 10)
U.shape
```

Out[219]:
```
(10000, 140)
```

Task 5. Cluster words using K-Means.

In [222]:
```
Data_Std = StandardScaler(with_mean = False).fit_transform(U)
print(Data_Std.shape)
print(type(Data_Std))
```

```
(10000, 140)
<class 'numpy.ndarray'>
```

In [223]:
```
#taking number of cluster = 1000
KMeans_Apply = KMeans(n_clusters=1000, init = "k-means++", max_iter = 100, n_jobs = -1).fit(Data_Std)
```

In [240]:
```
Cluster_indices = {i: np.where(KMeans_Apply.labels_ == i) for i in range(KMeans_Apply.n_clusters)}
```

Checking for similarity of words in clusters manually

In [234]:
```
#checking for review 981
for i in Cluster_indices[981][0]:
    print(wordList_idf[i])
```

```
understand
sorri
hesit
warn
despit
talk
trust
rare
post
skeptic
regard
trap
earlier
vine
titl
wrote
sampler
mislead
refer
deserv
advic
convinc
ignor
accur
listen
written
error
edit
critic
slim
subject
disagre
fda
video
copi
jim
glow
```

```
influenst
rebecca
lingonberri
```

Now in cluster number 981, the above words are related like: understand, sorri, hesit, disagre, error, edit, written, convinc etc

In [237]:
```
#checking for review 954
for i in Cluster_indices[954][0]:
    print(wordList_idf[i])
```

```
sort
grew
favor
popular
sister
peppermint
assort
everywher
parent
reach
cute
hadnt
memori
purs
childhood
section
theyll
tub
dad
dispens
wrapper
watermelon
germani
lollipop
haribo
law
henc
halloween
display
cowork
dye
oversea
valentin
vend
crate
jolli
nausea
```

```
cigarett
wilton
butterscotch
rancher
surf
buffet
belt
judi
```

Now in cluster number 954, the above words are related like: parent, childhood, cute, sister, memori, cigarett, nausea, butterscotch,peppermint etc

In [238]:
```
#checking for review 925
for i in Cluster_indices[925][0]:
    print(wordList_idf[i])
```

```
plenti
job
appreci
supplement
upset
besid
period
prevent
medicin
relax
excess
sooth
loss
rid
diseas
settl
hurt
timothi
tummi
maintain
suspect
appetit
soften
dental
decis
fight
leg
track
properti
stress
symptom
med
watcher
phone
reflux
hunger
immun
```

```
arthriti
regul
antibiot
curb
heal
vote
plaqu
listmania
thyroid
mastic
```

Now in cluster number 925, the above words are related like: upset, relax, stress, diseas, symptom, antibiot, heal, thyroid, immun etc

In [239]:

```
#checking for review 904
for i in Cluster_indices[904][0]:
    print(wordList_idf[i])
```

```
admit
power
strang
initi
disgust
gross
distinct
spoil
funni
kinda
butteri
attract
spray
compliment
familiar
detect
yuck
crap
dead
fragranc
welcom
stink
harsh
earthi
gag
appet
linger
divin
faint
sweat
potent
rabbit
bergamot
stinki
lavend
margarita
pungent
```

```
sniff
offens
pellet
deodor
overweight
whiff
pee
waft
potti
salami
soapi
deterg
```

Now in cluster number 904, the above words are related like: disgust, gross, spoil, yuck, crap, pungent, harsh, stink, fragranc, lavend etc