[1] Problem Statement :

Word Vectors Using Truncated SVD:

- **Finding the top n words using Tfidf**
- **Computing the co-occurence matrix of n * n for those top n words**
- **Matrix Decomposition of co-occurence matrix using Truncated SVD**
- **Applying Kmeans Clustering with the wordvectors**
- **Visualization of wordvectors using wordcloud**

[2] Overview of Dataset :

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

Objective: Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2).

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

[Ans] We could use 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.

[3] Loading the Data :

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 [30]:

```
#Importing the necessary Packages
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import time
import random
from tqdm import tqdm
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
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 sklearn.preprocessing import StandardScaler
from sklearn.decomposition import TruncatedSVD
from sklearn.cluster import KMeans
from PIL import Image
from IPython.display import Image
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
import pickle
```

Using SQLite Table to load preprocessed data already saved in disk:

In [131]:

```
# using the SQLite Table to read data.
conn = sqlite3.connect('final.sqlite')

final = pd.read_sql_query(""" SELECT * FROM Reviews """,conn)
```

In [132]:

```
#Listing out the number of positive and negative reviews
final = final.reset_index(drop=True)
final['Score'].value_counts()
```

Out[132]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

In [133]:

```
final.shape
```

Out[133]:

```
(363599, 12)
```

In [134]:

```
(final['Score'].value_counts()/len(final['Score']))*100
```

Out[134]:

```
positive    84.314313
negative    15.685687
Name: Score, dtype: float64
```

In [136]:

```
sampled_data = final.sample(n = 100000)
sampled_data.head()
```

Out[136]:

	index	Id	ProductId	UserId	ProfileName	Helpfulne
245335	455172	492120	B002LVACUE	A1W2HEN9QS9W5Z	Elementsk892	0
342430	494760	534890	B005PXZ6JM	AMAJZF06BXVTA	londons first	0
136414	128530	139493	B00112EUPM	A2YCLNTYHY22KR	Jessica Long	1
125530	298065	322868	B000VBSL3Q	A2079CA8KJ1YJ1	TeariNiTuP	2
343104	125373	136012	B005SPQENY	AFDJGY68CQL2X	Snail Dealer "Snail"	0

In [264]:

```
X = sampled_data["CleanedText"].values
print("Shape of Input Data: ",X.shape)
```

```
Shape of Input Data:  (100000,)
```

[4] Word Vectors Using Truncated SVD :

Tf-idf Vectorization :

In [33]:

```
%%time
tfidf_vect = TfidfVectorizer(ngram_range=(1, 1),stop_words='english', strip_accents='un
icode')
X_tfidf = tfidf_vect.fit_transform(X)
print("Type of count vectorizer ",type(X_tfidf))
print("Shape of out text TFIDF vectorizer ",X_tfidf.get_shape())
print("Number of unique words including both unigrams and bigrams ", X_tfidf.get_shape
()[1])
```

```
Type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
Shape of out text TFIDF vectorizer  (100000, 38067)
Number of unique words including both unigrams and bigrams  38067
CPU times: user 5 s, sys: 16 ms, total: 5.02 s
Wall time: 5.02 s
```

In [34]:

```
tfidf_scores =  zip(tfidf_vect.get_feature_names(),np.asarray(X_tfidf.sum(axis = 0)).ra
vel())
sorted_scores = sorted(tfidf_scores, key=lambda x: x[1], reverse = True)
```

Finding top n words :

In [35]:

```
def top_n_features(n):

    word = []
    tfidf = []
    for i in sorted_scores[0:n]:
        word.append(i[0])
        tfidf.append(i[1])
    top_features = pd.DataFrame(np.column_stack([word,tfidf]),columns=["Word","Tfidf"])
    print(top_features["Word"].head(10))
    print(top_features.shape)
    return top_features
```

Computing Co-occurence Matrix :

In [36]:

```
Image(filename = "co-occurence.JPG")
```

Out[36]:

Co-occurrence – For a given corpus, the co-occurrence of a pair of words say w1 and w2 is the number of times they have appeared together in a Context Window.

Context Window – Context window is specified by a number and the direction. So what does a context window of 2 (around) means? Let us see an example below,

Quick Brown Fox Jump Over The Lazy Dog

The green words are a 2 (around) context window for the word 'Fox' and for calculating the co-occurrence only these words will be counted. Let us see context window for the word 'Over'.

Quick Brown Fox Jump Over The Lazy Dog

Let take an example corpus to calculate a co-occurrence matrix with context window 2

Red box - It is the number of times 'He' and 'is' have appeared in the context window 2 and it can be seen that the count turns out to be 4.
Blue box - word 'lazy' has never appeared with 'intelligent' in the context window and therefore has been assigned 0.

In [37]:

```
Image(filename = "demo.JPG")
```

Out[37]:

Corpus = He is not lazy. He is intelligent. He is smart.

	He	is	not	lazy	intelligent	smart
He	0	4	2	1	2	1
is	4	0	1	2	2	1
not	2	1	0	1	0	0
lazy	1	2	1	0	0	0
intelligent	2	2	0	0	0	0
smart	1	1	0	0	0	0

In [38]:

```
corpus = ["he is not lazy he is intelligent he is smart"]
print(corpus)

vect = TfidfVectorizer(ngram_range=(1, 1))
corpus_vect = vect.fit_transform(corpus)
words = vect.get_feature_names()

C = np.zeros((len(words),len(words)))
C = pd.DataFrame(C, index = words, columns = words)
context_window = 2

for i in corpus:
    text = i.split(" ")
    for i in range(len(text)):
        for j in range(max(i - context_window,0),min(i + context_window+1,len(text))):
            if text[i] != text[j]:
                try:
                    C.loc[text[i], text[j]] += 1
                except:
                    pass

print(C)
```

```
['he is not lazy he is intelligent he is smart']
              he  intelligent   is  lazy  not  smart
he           0.0          2.0  4.0   1.0  2.0    1.0
intelligent  2.0          0.0  2.0   0.0  0.0    0.0
is           4.0          2.0  0.0   2.0  1.0    1.0
lazy         1.0          0.0  2.0   0.0  1.0    0.0
not          2.0          0.0  1.0   1.0  0.0    0.0
smart        1.0          0.0  1.0   0.0  0.0    0.0
```

In [39]:

```
def compute_cooccurencematrix(X,top_features,context_window):

    Xc = np.zeros((top_features.shape[0],top_features.shape[0]))
    Xc = pd.DataFrame(Xc, index = top_features['Word'].tolist(), columns = top_features
['Word'].tolist())

    for review in tqdm(X):
        text = review.split(" ")
        for i in range(len(text)):
            for j in range(max(i - context_window,0),min(i + context_window+1,len(text
))):
                if text[i] != text[j]:
                    try:
                        Xc.loc[text[i], text[j]] += 1
                    except:
                        pass
    print("Dimesions of Cooccuranece matrix:" , Xc.shape)
    return Xc
```

Selecting The Best Number Of Components For TSVD :

In [40]:

```
def best_ncomponents(x):

    tsvd = TruncatedSVD(n_components = x.shape[1] - 1)
    U = tsvd.fit_transform(x)

    percentage_var_explained = tsvd.explained_variance_ /np.sum(tsvd.explained_variance
_)
    cum_var_explained = np.cumsum(percentage_var_explained)

    plt.figure(figsize= (10,6))
    plt.clf()
    plt.plot(cum_var_explained)
    plt.xlabel("No of components",fontsize=12,fontweight="bold")
    plt.ylabel("Cummulative explained variance",fontsize=12,fontweight="bold")
    plt.grid("on")
    plt.show()
```

Matrix Factorization and Kmeans Clustering :

In the definition of SVD, an original matrix A is decomposed as a product A ≈ U Σ V* where U and V have orthonormal columns, and Σ is non-negative singular values.
Here A, is the co-occurence matrix of top n words.
Then we apply kmeans and visualize the word vectors(U) that we get.

In [41]:

```
def matrix_factorization(x,n_components):

    tsvd = TruncatedSVD(n_components = n_components,random_state = 3)
    U = tsvd.fit_transform(x)
    sigma = tsvd.singular_values_
    VT = tsvd.components_
    print("Dimensions of U: ", U.shape)
    print("Dimensions of sigma: ", sigma.shape)
    print("Dimensions of U: ", VT.shape)
    print(tsvd.explained_variance_ratio_.sum())
    return U,sigma,VT



def best_k(x):
    n_clusters = list(np.arange(10,101,10))
    loss = []

    for k in n_clusters:
        km = KMeans(n_clusters = k)
        km.fit(x)
        loss.append(km.inertia_)

    #print("-------Best k using Elbow Method---------")
    plt.figure(figsize = (10,8))
    plt.plot(n_clusters,loss,'r-*')
    plt.title("Elbow Method",fontsize = 20,fontweight = "bold")
    plt.xlabel("Clusters(k)")
    plt.ylabel("Loss")
    plt.grid('on')
    plt.show()
```

In [42]:

```
def kmeans(U,n_clusters):
    kmeans = KMeans(n_clusters=n_clusters)
    kmeans.fit(U)
    labels = kmeans.labels_

    return labels
```

Visualisation of WordVectors:

In [43]:

```
stopwords = set(STOPWORDS)

def words_visualisation(U,top_features,labels):

    wordvector = pd.DataFrame(U)
    wordvector['Label'] = labels
    wordvector['Feature'] = top_features['Word']

    clusters = wordvector['Label'].value_counts()
    clusters = clusters.index.tolist()
    top_clusters = clusters[:10]
    fig = plt.figure(figsize=(20,20))
    for index,val in enumerate(top_clusters):
        df = wordvector.loc[wordvector['Label'] == val]
        text = " ".join(x for x in df.Feature)

        wordcloud = WordCloud(stopwords=stopwords, background_color="black").generate(t
ext)
        ax = fig.add_subplot(5,2,index+1)

        ax.imshow(wordcloud, interpolation='bilinear')
        ax.set_title("Cluster {},size = {}".format(val,df.shape[0]),fontsize=15,fontwei
ght="bold")
        ax.axis("off")
    plt.subplots_adjust(bottom=0.01, wspace=0.01)
```

[4.1] For Top 2000 words :

In [15]:

```
top_features_2000  = top_n_features(n = 2000)
```

```
0       tast
1       like
2       love
3       good
4      great
5     flavor
6      coffe
7    product
8        tea
9        use
Name: Word, dtype: object
(2000, 2)
```

In [152]:

```
Xc_2000 = compute_cooccurencematrix(X,top_features_2000,context_window = 4)
```

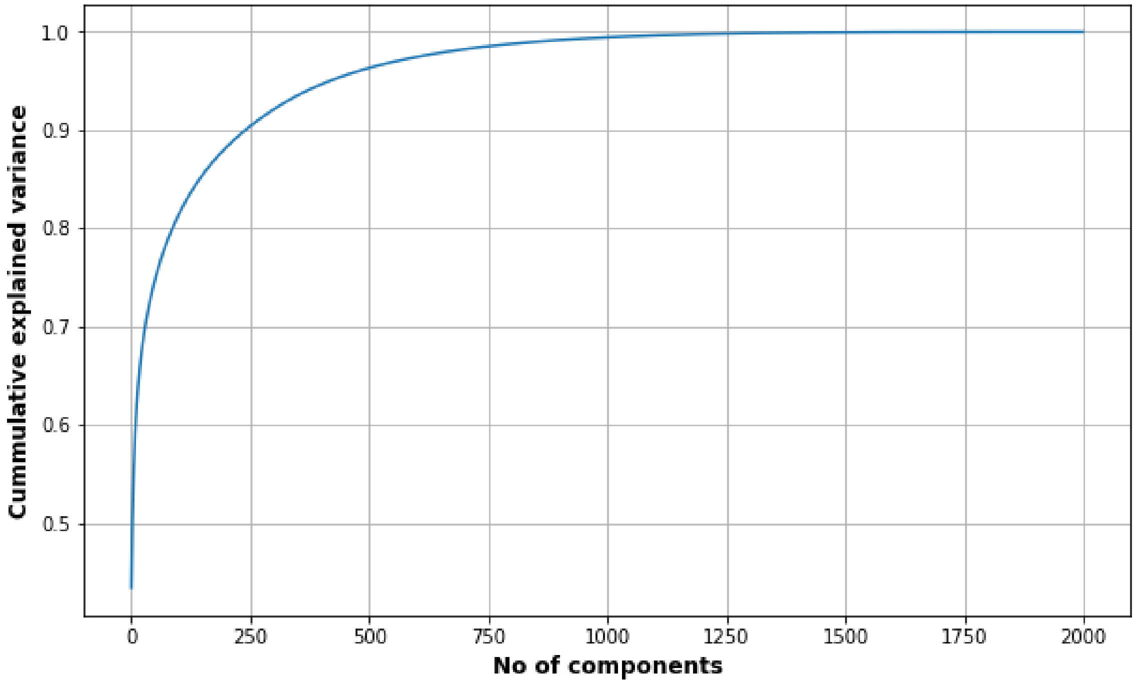
```
100%|██████████| 100000/100000 [1:30:51<00:00, 18.34it/s]

Dimesions of Cooccuranece matrix: (2000, 2000)
```

In [17]:

```
#standarization of data
sc = StandardScaler(with_mean=False)
Xc_2000std = sc.fit_transform(Xc_2000)
```

In [15]:

```
best_ncomponents(Xc_2000std)
```



OBSERVATION :
It is observed from the above plot, with n_components = 750 around 98% of variance is explained. So, selecting n_components = 750.

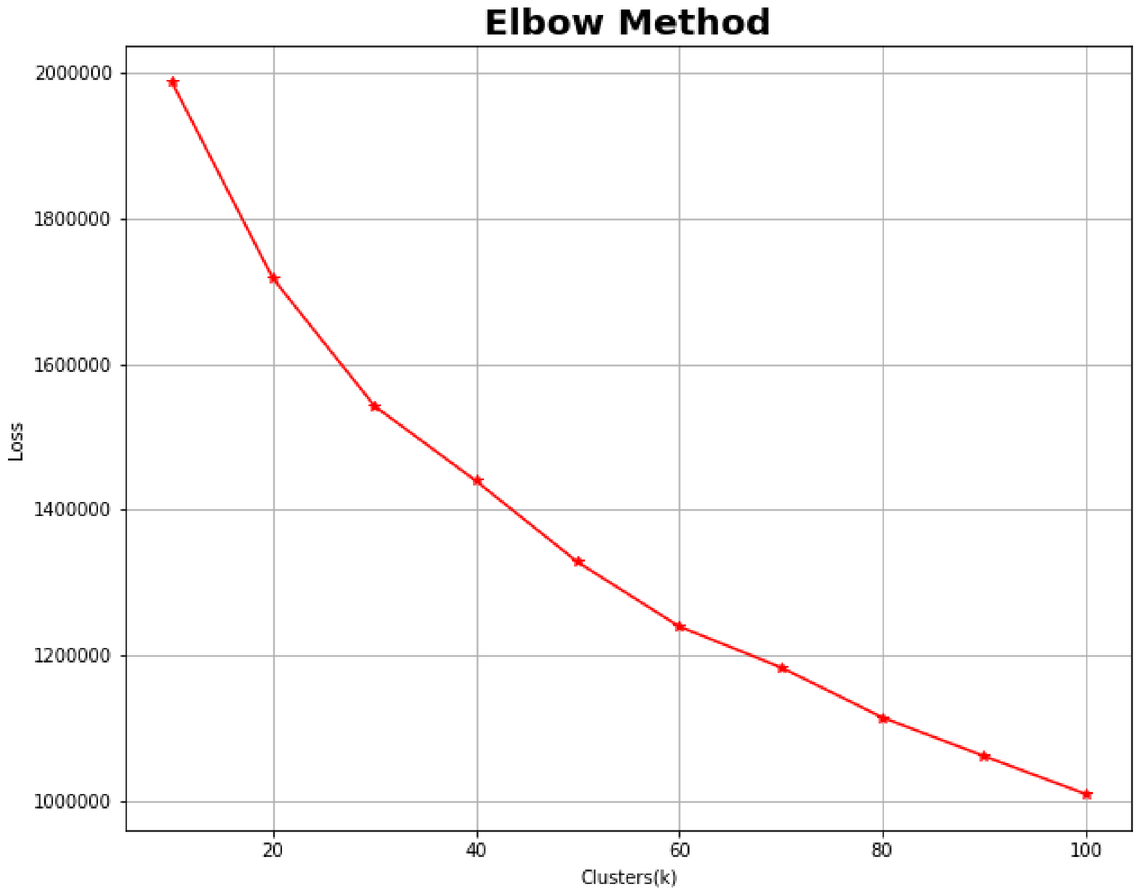
In [18]:

```
%%time
U1, sigma1, VT1 = matrix_factorization(Xc_2000std,n_components=750)
```

```
Dimensions of U:  (2000, 750)
Dimensions of sigma:  (750,)
Dimensions of U:  (750, 2000)
0.9868338368067965
CPU times: user 28.8 s, sys: 216 ms, total: 29.1 s
Wall time: 2.2 s
```

In [19]:

```
best_k(U1)
```



OBSERVATION :
It is observed that around 60-70 clusters, loss reduction is very small.
So,chosing number of clusters = 60(inflexion point).

In [20]:

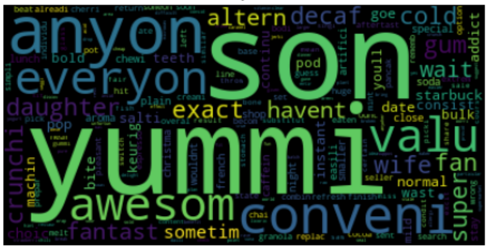
```
labels1 = kmeans(U1,n_clusters = 60)
```

In [21]:

```
words_visualisation(U1,top_features_2000,labels1)
```

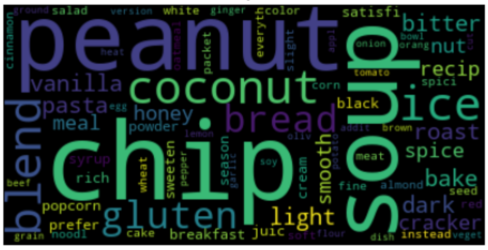
Cluster 32,size = 1239

Cluster 13,size = 396

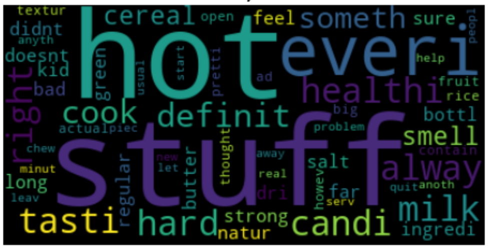


Cluster 51,size = 112

Cluster 31,size = 78



Cluster 33,size = 60



Cluster 23,size = 14

Cluster 48,size = 12

Cluster 50,size = 9

Cluster 0,size = 8

Cluster 5,size = 7

OBSERVATION :

- **Cluster 50 is about nutritional and diet related foods as it contains terms like fiber,protien,sodium,calorie,fat,carb,vitamin etc.**
- **Cluster 31 is about sweet and snacks as it contains terms like honey,vanilla,juice,cake,popcorn,cream,peanuts etc.**
- **Cluster 31 is about spicy and salty realted food items as it contains terms like chicken,meal,beef,noodle,pepper,egg,soup,roast,spice,pasta,salt.**
- **It is also observed that terms like husband,son,wife,daughter are grouped to cluster 13 as they have semantic meaning of a person's gender.**
- **Some clusters do not show any pattern as it contains only one or two words.**

[4.2] For Top 5000 words :

In [48]:

```
top_features_5000  = top_n_features(n = 5000)
```

```
0       tast
1       like
2       love
3       good
4      great
5     flavor
6      coffe
7    product
8        tea
9        use
Name: Word, dtype: object
(5000, 2)
```

In [ ]:

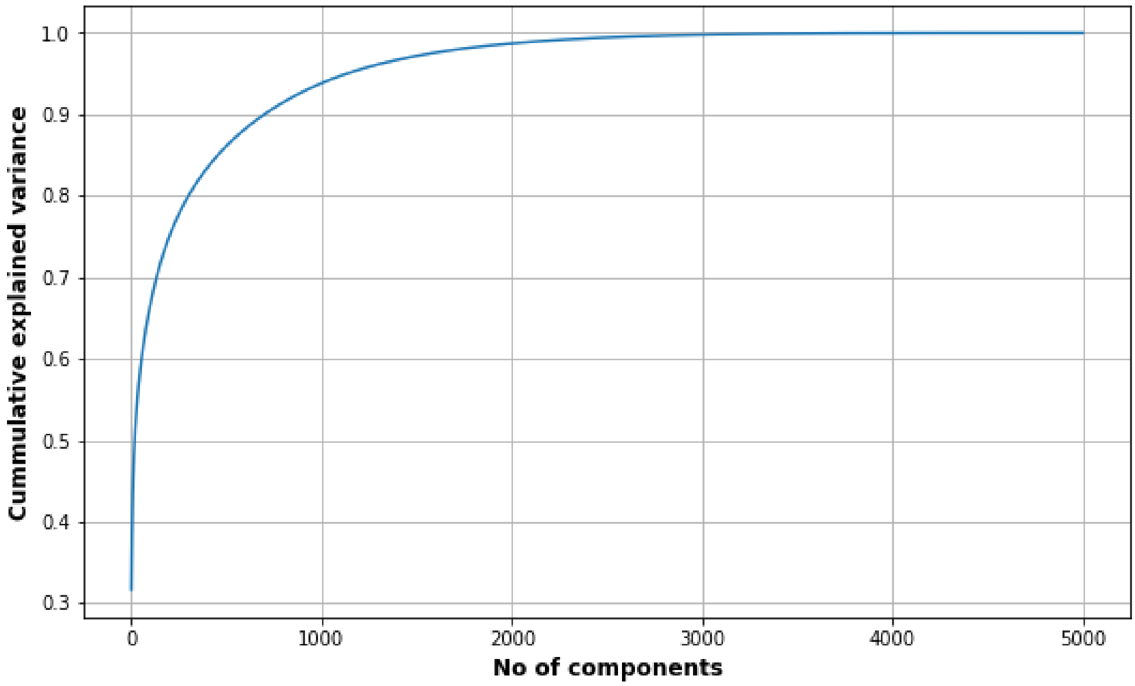
```
Xc_5000 = compute_cooccurencematrix(X,top_features_5000,context_window = 4)
```

In [50]:

```
#standardization of data
sc = StandardScaler(with_mean=False)
Xc_5000std = sc.fit_transform(Xc_5000)
```

In [23]:

```
best_ncomponents(Xc_5000std)
```



OBSERVATION :
It is observed from the above plot, with n_components = 1700 around 98% of variance is explained.
So, selecting n_components = 1700.

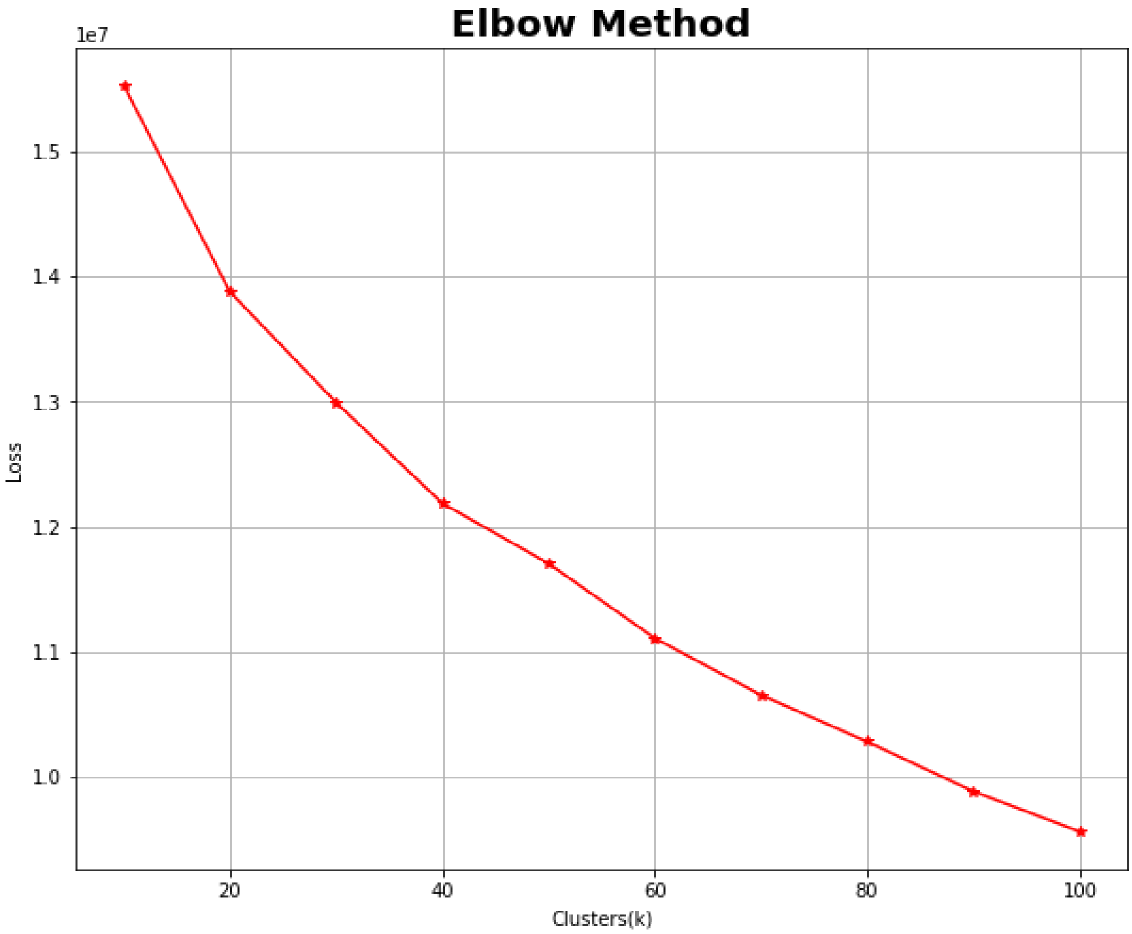
In [51]:

```
U2, sigma2, VT2 = matrix_factorization(Xc_5000std,n_components=1700)
```

```
Dimensions of U:  (5000, 1700)
Dimensions of sigma:  (1700,)
Dimensions of U:  (1700, 5000)
0.9789813466732388
```

In [55]:

```
best_k(U2)
```



OBSERVATION :
It is observed that around 60-70 clusters, loss reduction is very small.
So,chosing number of clusters = 60(inflexion point).

In [56]:

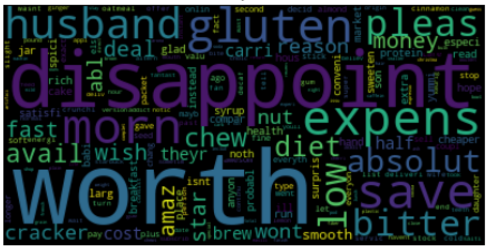
```
labels2 = kmeans(U2,n_clusters = 60)
```

In [57]:

```
words_visualisation(U2,top_features_5000,labels2)
```

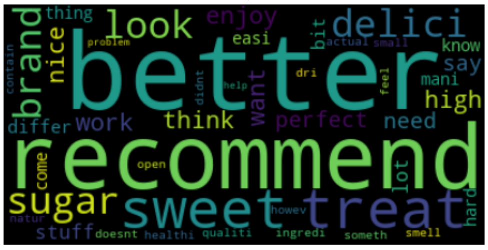
Cluster 7,size = 4330

Cluster 40,size = 454



Cluster 14,size = 64

Cluster 20,size = 44



Cluster 9,size = 42

Cluster 2,size = 13

Cluster 16,size = 4

Cluster 29,size = 3

Cluster 0,size = 3

Cluster 41,size = 2

OBSERVATION :

- **Cluster 14 is about spicy food items as it contains terms like chicken,rice,meat,soup,oil,spice,noodle,hot,pasta etc.**
- **Cluster 2 is about vegaetables and grocery items as it contains terms like potato,tomato,onion,corn,olive,garlic,wheat,flour etc.**
- **It is also observed that terms like big,long,small,minut,weak are grouped to cluster 9 as they have semantic meaning of a size.**

[4.3] For Top 10000 words :

In [62]:

```
top_features_10000  = top_n_features(n = 10000)
```

```
0       tast
1       like
2       love
3       good
4      great
5     flavor
6      coffe
7    product
8        tea
9        use
Name: Word, dtype: object
(10000, 2)
```

In [ ]:

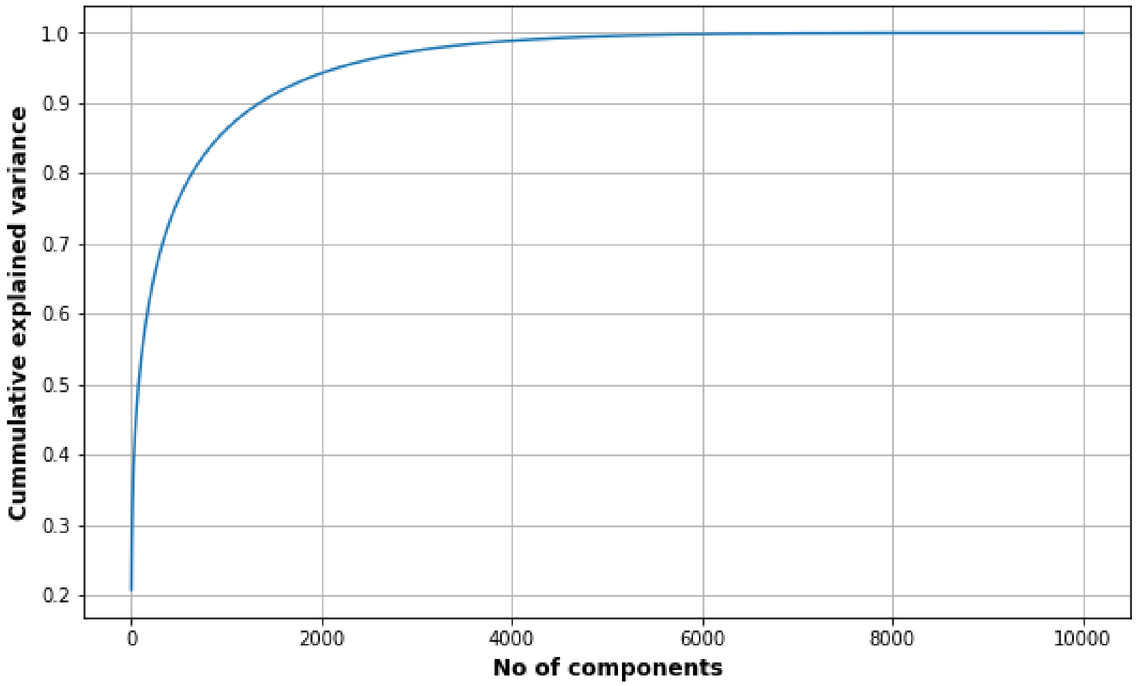
```
Xc_10000 = compute_cooccurencematrix(X,top_features_10000,context_window = 4)
```

In [64]:

```
#standardization of data
sc = StandardScaler(with_mean=False)
Xc_10000std = sc.fit_transform(Xc_10000)
```

In [19]:

```
best_ncomponents(Xc_10000std)
```



OBSERVATION :
It is observed from the above plot, with n_components = 3500 around 98% of variance is explained. So, selecting n_components = 3500.

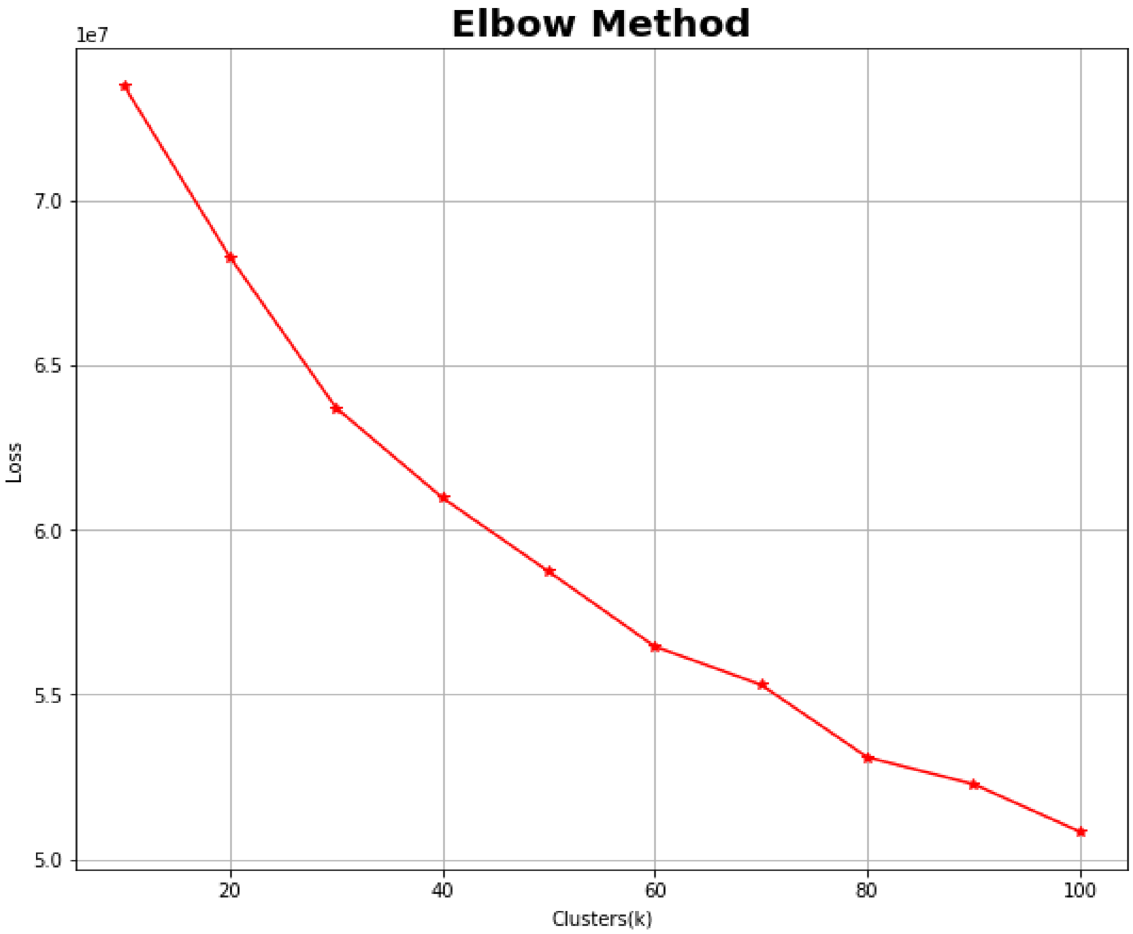
In [65]:

```
U3, sigma3, VT3 = matrix_factorization(Xc_10000std,n_components=3500)
```

```
Dimensions of U:  (10000, 3500)
Dimensions of sigma:  (3500,)
Dimensions of U:  (3500, 10000)
0.9826501681277517
```

In [66]:

```
best_k(U3)
```



OBSERVATION :
It is observed that around 60-70 clusters, loss reduction is very small.
So,chosing number of clusters = 60(inflexion point).

In [67]:

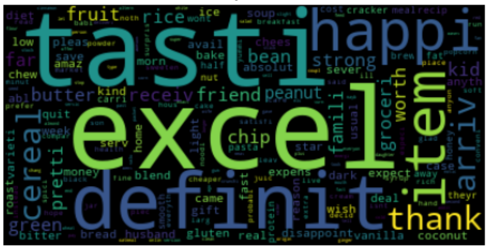
```
labels3 = kmeans(U3,n_clusters = 60)
```

In [68]:

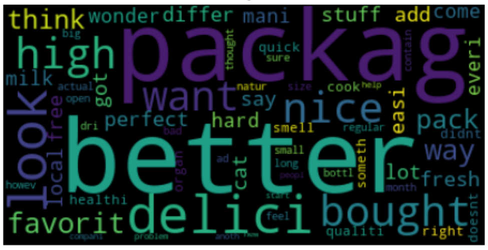
```
words_visualisation(U3,top_features_10000,labels3)
```

Cluster 38,size = 9410

Cluster 1,size = 458



Cluster 24,size = 65



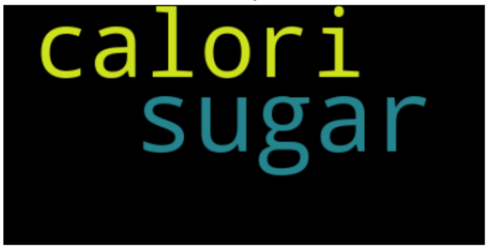
Cluster 11,size = 3

Cluster 0,size = 2

Cluster 56,size = 2

Cluster 36,size = 2

Cluster 45,size = 2



Cluster 30,size = 2

Cluster 58,size = 2

[5] Conclusion :

(1) Co-occurence matrix for top 2k,5k and 10k words(Tfidf vectorization) is computed.
(2) Co-occurence matrix is decomposed to obtain word vector matrix by using Truncated SVD.
(3) Kmeans Clustering is applied with 50 clusters for wordvectors obtained.
(4) Some pattern of clusters like nutrition,grains,grocery,sweets,snacks,spicy products are obtained.
(5) It is also observed that words that have semantic meaning are grouped to one cluster.
(6) As the number of top words increases from 2k to 10k, it is observed that we start losing pattern of clusters. It can be seen when we take 10k top words, lot of clusters have only one word which dont give any information.