39.15.Amazon_food_review_truncated_SVD

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1 Amazon food review dataset apply truncated SVD

Data set from https://www.kaggle.com/snap/amazon-fine-food-reviews

2 Objective

1. Take 2000 words by TFIDF importance
2. Calculate cooccurance matrix with neighbourhood of size 5 and count how many times wi occur in context of wj
3. Then do truncated SVD
4. try multiple value of k(find optimal k by amount of variance explained)[use singular value]
5. cluster(kmeans k=50) word vector for top 2000
6. word cluster together should be related

3 Import data and libraries

In [1]:
```
from sklearn.manifold import TSNE
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 TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
from sklearn.cross_validation import train_test_split,KFold
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
```

```
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression

con = sqlite3.connect('database.sqlite')

#get only +ve and -ve review
raw_data = pd.read_sql_query("""SELECT * FROM Reviews WHERE Score != 3""", con)
```

```
C:\Users\suman\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning:
  "This module will be removed in 0.20.", DeprecationWarning)
C:\Users\suman\Anaconda3\lib\site-packages\sklearn\grid_search.py:42: DeprecationWarning: This
  DeprecationWarning)
```

4 Data preprocessing

In [2]:
```
filtered_data=raw_data
# Score>3 a positive rating, and score<3 a negative rating.
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative

filtered_data.sample(5)
filtered_data['Score'].value_counts()

#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals

#Deduplication of entries for same profilename,userid, time, text and take first eleme
sorted_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
```

In [43]:
```
#take only 50000 data
print('total data \n',sorted_data['Score'].value_counts())
#clean_data=sorted_data.sample(frac=1).groupby('Score').head(10000)
#take stratified sampling i.e. positive and negative reviews are proportionate to raw
#testing
_ , clean_data = train_test_split(sorted_data, test_size = 50000, random_state=0,stra
clean_data['Score'].value_counts()
```

```
total data
 positive    307063
```

```
negative     57110
Name: Score, dtype: int64
```

```
Out[43]: positive    42159
         negative     7841
         Name: Score, dtype: int64
```

```
In [68]: # Clean html tag and punctuation
         import re
         import string
         from nltk.corpus import stopwords
         from nltk.stem import PorterStemmer
         from nltk.stem.wordnet import WordNetLemmatizer

         stop = set(stopwords.words('english')) #set of stopwords
         sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

         #substitute html tag and punctuation
         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
         #print(sno.stem('tasty'))

         i=0
         str1=' '
         mystop={'of','four','one','would'}
         final_string=[]
         all_positive_words=[] # store words from +ve reviews here
         all_negative_words=[] # store words from -ve reviews here.
         s=''
         #Create new catagory as Cleanedtext after removing htmltag and punctuation and upperc
         for sent in clean_data['Text'].values:
             #change later
             #testing
             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) & (cleaned_words.lower() not i
                             s=(sno.stem(cleaned_words.lower())).encode('utf8')
```

```
                    filtered_sentence.append(s)
                    if (clean_data['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to descr
                    if(clean_data['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to descr
                else:
                    continue
            else:
                continue
        str1 = b" ".join(filtered_sentence) #final string of cleaned words

        final_string.append(str1)
        i+=1

clean_data['CleanedText']=final_string
print(clean_data.shape)
#Sort data on timestamp
clean_data=clean_data.sort_values(by=['Time'],ascending=False)
#clean_data
clean_data['CleanedText'].sample(2)
clean_data['CleanedText'].iloc[0]
```

```
(50000, 11)
```

Out[68]: b'plum sweet juici aroma like perfum doesnt hurt good'

5 Get top 2000 words by TFIDF score and create co-occurence matrix by window 5

In [69]:
```
x=clean_data['CleanedText'].values
y = clean_data['Score']
#n=x.shape[0]
#n1=int(n*.3)
#X_test_raw = x[0:n1]
#X_train_raw= x[n1:n+1]
#y_test=y[0:n1]
#y_train=y[n1:n+1]
# Create BOW and try grid search for logistic regreession with penalty l1 and l2
tf_idf_vect = TfidfVectorizer()
final_counts = tf_idf_vect.fit_transform(x)
#use the same vectors to convert test data
#X_test=count_vect.transform(X_test_raw)
indices = np.argsort(tf_idf_vect.idf_)[::-1]
features = tf_idf_vect.get_feature_names()
#testing
top_n = 2000
```

```
top_features = [features[i] for i in indices[:top_n]]
print (top_features[0:20])
print('len of top feature',len(top_features))

#remove other words from review
final_string=[]
all_string=[]

i=0
for sent in clean_data['CleanedText'].values:
    i=i+1
    filtered_sentence=[]
    for w in sent.decode('utf8').split():
                #print(w)
                if(w in top_features):
                    filtered_sentence.append(w.encode('utf8'))
                    #if (i==1):
                    #print('print')
                else:
                    continue
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    if (str1.decode('utf8') !=''):
      final_string.append(str1)
    all_string.append(str1)

clean_data['CleanedText']=all_string
#Now final_string is ready to work with
#print(clean_data['CleanedText'].shape)
final_string[0]
```

```
['île', 'foetida', 'filo', 'plait', 'filteer', 'filterbag', 'filtr', 'plactic', 'finagl', 'pla
len of top feature 2000
```

Out[69]: b'disform'

In [80]:
```
#Convert to cooccurance mat
#type(final_string)
#print(final_string)
window=5
len1=len(top_features)
#print(len)
m=np.zeros([len1,len1])
columns=top_features
rows=top_features
df=pd.DataFrame(m,columns=columns,index=rows)
#print(df)
```

```
def cal_occ(sentence,df):
    sen=sentence.split()
    l=len(sen)-1
    for i,word in enumerate(sen):
        for j in range(max(i-window,0),min(i+window+1,l+1)):
            if word!=sen[j]:
                #print('printing',word,sen[j])
                df[word][sen[j]]+=1

for sentence in final_string:
    #print('call',sentence)
    cal_occ(sentence.decode('utf8'),df)

print(df.shape)
```

```
(2000, 2000)
```

```
In [81]: #top_features
         #final_string[0]
         print(len)
         len(top_features)
         #df
         from sklearn.preprocessing import StandardScaler
         #scaler = StandardScaler(with_mean=False).fit(df)
         #df = scaler.transform(df)
```

```
<built-in function len>
```

```
In [90]: #df
```

```
In [74]: type(U)
```

```
Out[74]: numpy.ndarray
```

6 Create countvectorizer using cooccurence matrix

```
In [85]: #count_vect = CountVectorizer(vocabulary=top_features) #in scikit-learn
         #X = count_vect.fit_transform(final_string)

         #print(X.shape)

         #Cooccurance matrix
         #X = (X.T * X) # this is co-occurrence matrix in sparse csr format
         #X.setdiag(0) # sometimes you want to fill same word cooccurence to 0
         #print(X.todense())
```

```
#print(count_vect.vocabulary_)

#Create truncated SVD
from sklearn.decomposition import TruncatedSVD

#Try different component
l=[20,50,100,150,200,250]
for i in l:
  svd = TruncatedSVD(n_components=i, n_iter=7, random_state=0)
  svd.fit(df.values)
  #print(svd.explained_variance_ratio_)
  l1=svd.explained_variance_ratio_
  print('% variance explained with component ',i,svd.explained_variance_ratio_.sum())
  #print('singular values',svd.singular_values_)

#So looks like with 25 component 96% variance is explained
#print(svd)
```

```
% variance explained with component  20 0.596657737216
% variance explained with component  50 0.716447280124
% variance explained with component  100 0.825836500755
% variance explained with component  150 0.869494648993
% variance explained with component  200 0.913161825629
% variance explained with component  250 0.956826688872
```

SO by 250 component 96% variance is explained # Use SVD

In [86]:
```
#VT = svd.components_
#TruncatedSVD is basically a wrapper around sklearn.utils.extmath.randomized_svd; you

from sklearn.utils.extmath import randomized_svd

U, Sigma, VT = randomized_svd(df.values,
                              n_components=250,
                              n_iter=50,
                              random_state=0)

print('U value\n')
#print(U)
print('sigma value\n')
#print(Sigma)
print('VT value\n')
#print(VT)
print(U.shape,Sigma.shape,VT.shape)
```

```
U value

sigma value
```

```
VT value

(2000, 250) (250,) (250, 2000)
```

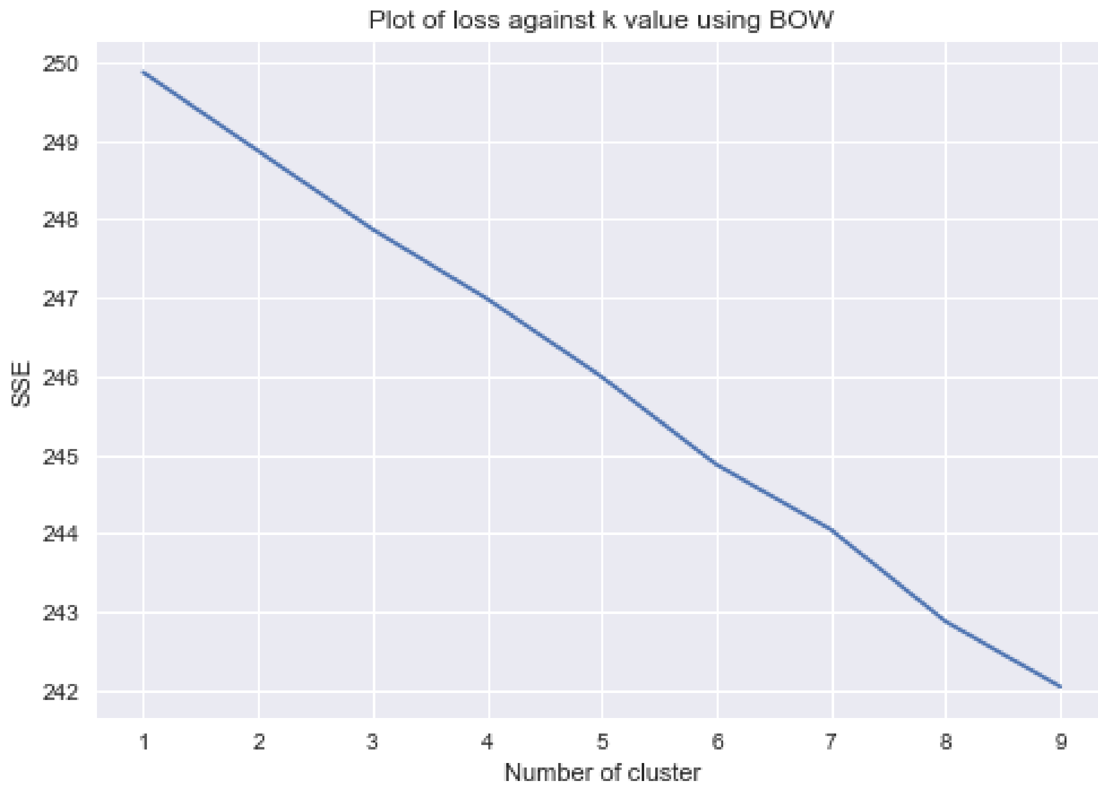
7 Form cluster of 10 using those important words SVD value

```
In [89]: from sklearn.cluster import KMeans
         # Now U is vec presentation of words
         n_clusters=10
         kmeans=KMeans(n_clusters=10, random_state=0).fit(U)
         kmeans.cluster_centers_

         sse = {}
         for k in range(1, 10):
             kmeans = KMeans(init='k-means++',n_clusters=k, max_iter=100).fit(U)
             sse[k] = kmeans.inertia_ # Inertia: Sum of distances of samples to their closest
         plt.figure()
         plt.plot(list(sse.keys()), list(sse.values()))
         plt.title("Plot of loss against k value using BOW")
         plt.xlabel("Number of cluster")
         plt.ylabel("SSE")
         plt.show()

         #a=np.where(kmeans.labels_ == 1)[0]
         #b=np.where(kmeans.labels_ == 0)[0]
         #check 5 text for cluster 1

         kmeans = KMeans(init='k-means++',n_clusters=50, max_iter=100).fit(U)
         n_clusters=50
         print(a.shape)
         for i in range(n_clusters):
           a=np.where(kmeans.labels_ == i)[0]
           print('in cluster \n',i)
           print(a[0:])
           for j in a:
             print(top_features[j])
```




```
(1,)
in cluster
 0
[   0    1    2 ..., 1997 1998 1999]
île
foetida
filo
plait
filteer
filterbag
filtr
plactic
finagl
placei
finali
financ
findabl
pkt
findaspr
finefar
pkging
finess
```

fing
fingerfood
pizzell
finiski
finki
pizzaria
pizzaiola
filmsi
filltrat
plani
figh
plavor
plave
fica
platypus
ficus
fidd
fiddlestick
fieldss
fifficult
figgi
figish
planifolia
fike
plaqueoff
planti
planthard
plantfus
fila
filful
filibert
filippo
fillo
finlandia
pizett
finley
pipa
piroulin
piripiri
firepot
firest
firewood
firmiliar
firsat
piperin
firshand
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fishermen
fishnet
fishstick
fissur
pinhol
fiter
pingshui
pirtl
pistacho
finncrisp
pitr
finnecki
piut
piulp
pitur
finnicki
pittmix
finniki
finnish
pittbul
pitiabl
pith
pite
fiocchetti
firecrack
firefight
pitango
firend
pistol
pistil
pistchio
playabl
fiberi
playdoh
fentimin
podner
podmerch
podg
podd
feng
pocuch
pocono
fennugreek
fenstermach
fentiman

pobabl
podunk
feodorovich
poa
pnw
pnfs
fer
pnb
pnam
ferdi
plzd
poduct
poe
fermi
feistier
polarpack
feeel
feell
feh
poivr
feild
poisin
feint
feisti
pointsplus
fel
femor
feldcamp
feldman
poictur
poi
poha
pogo
felix
felll
poetic
feloni
ferel
fern
playdooh
pleasnt
pli
feul
plesent
plese
feverish
fevertre
pleni

few
fexex
ffamili
ffor
pliant
ffortless
fhe
pleaas
plazma
playmat
playground
fiat
fiberglass
fettucin
plier
ferquent
fescu
ferrera
plumros
plumpynut
ferrerro
ferric
plummit
fert
plummer
plumber
ferul
plugra
plight
fesh
fess
fetaccini
ploughman
plot
fetish
plocki
fettuccini
pllllleas
plink
piney
pinewood
pinenut
flouresc
phallic
phal
phad
pgtip
pgpr

pgh
pfrespak
pfpc
flounder
pfffft
peychaud
floorsweep
pewter
pew
pevent
petzlif
petunia
petticoat
flourid
petso
flourless
floz
phantom
pharmacut
petsaf
pheramon
flexse
philistin
philanthropi
philanthrop
philadelphian
flimsey
flimsier
phew
pheronet
phenylalin
floati
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phenylalani
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phenomon
flipper
phenomenen
flippin
phenobarbit
phelan
phd
petshop
petruska
flexatarian
focd
pestil
flybuy

flypap
pestal
foamer
fob
pessim
pesci
pescetarian
pescatarian
pervious
flux
pervert
pervers
foco
fodmap
perugia
foertun
perturb
pertin
pertfect
foetid
fluxuat
flutter
flub
fluey
fluditi
petrol
petrodex
petrifi
petri
petrefi
petra
petperk
fluentli
petm
petguy
peta
fluffer
petey
fluffiest
petersburg
fluor
flur
flushabl
petcar
petbot
petag
phillipp
fitst

piecrust
pilao
flamenco
pik
pignoli
flandr
flann
pigg
flapjack
flashcard
flathead
flatish
pilat
flatt
picutr
pictu
flattop
pickypicki
flavanol
pickmeup
flavarcol
flavir
pilau
flavocol
fizzer
fitsugar
fitt
fitter
fitz
fivehundr
fiver
fixat
fixi
fizzel
pimb
flambeau
fji
pillpocket
flacker
flagil
flagstaff
pilliow
pilgrimag
pilfer
pileup
flakier
flavius
pickest

phillippin
phospat
flavourt
flavr
photoshoot
flaxmilk
photograh
flaxusa
phosporus
flee
fleec
phos
phyllo
fleishmann
phonetag
flem
fleshi
phoeb
flex
phlem
flexabl
philosoph
philmont
phylli
flavourless
flavorcol
flavori
pickemup
pickel
pickard
flavord
flavordo
picdog
flavorfil
picaridin
flavorfukl
flavorgan
pib
physican
piano
flavoric
piac
phytonutri
flavorsw
phytocyt
phytochem
physiqu
flavorul

febreez
featurett
featherweight
experci
exorcis
premak
expat
expatri
prelud
prelin
expediti
expen
prehistori
experiec
exlaim
pregneson
expierenc
expl
preggo
prefrenc
prefix
explainatori
explaiun
explanatori
exploit
premi
preminum
expound
prepara
excut
prescott
prescient
prescib
execept
prerequisit
preprint
preposter
preponder
exerienc
exersic
existenti
preorder
preoocupi
preoccupi
preoccup
prenat
premuim
premonit

premius
premiun
exil
preferenti
expr
preselect
prayish
precio
extclus
precancer
exterm
preasant
extinguish
extort
extractd
extractish
prduce
extractor
ext
extraordinair
extravaganzo
prato
pratfal
prasi
pranw
extravergin
extreem
pramesan
extri
extant
exstract
prefab
predicat
expreesso
expreso
predominatey
expressio
expressivo
prednisolon
predisposit
expung
predilect
exract
exrem
exstat
prediabet
exsist
predawn

exspeci
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exspect
exspeic
precondit
exspens
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exctract
excpet
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eveyth
evinc
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primula
evn
evoc
primia
primer
evolutionali
evri
evrywher
evvvveeerr
everythign
everyflavor
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problema
everal
problabl
probioticsmart
probiotc
everclear
probioit
probelem
probar
evergrow
probal
priviledg

everida
everon
probabali
everorgan
everremind
everri
prmote
everycup
everydayhealth
everyewher
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prik
presentaion
excellet
pretz
pretyt
prettti
excelencia
excelent
pretoria
pretezel
preterm
excellect
excellentdeliveri
excelnt
pretzelli
excema
exceptthat
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preview
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excalibur
prevar
excat
extrins
featheri
fastfood
popcornwhatels
farmingtonhil
faro
popcicl
farrrr
fasatchi
pooti
poorest
fashin
fasta
pooper
fark
fastpitch
fatcat
fatcream
poofi
fatdog
fatdogmustard
fatertast
fathi
fatkitten
ponytail
poper
popocorn
poni
popup
familiy
familyit
fanatast
porchini
porchin

fanboi
porcelin
porc
porag
fancyfeast
fanfar
popp
fanfreakintast
fantastc
fantastica
fantastico
fantasticveri
popppi
fantstic
farder
farewel
poppabl
pont
fatoush
familey
polpo
favort
favorti
favortit
favotit
polynesian
polym
polyethylen
polydextros
polycycl
polycarbon
polo
favorito
fax
fay
fazer
fbd
fbi
polka
politician
fearsom
polino
fearur
polyscia
favoritesth
pomtast
fatto
pomston

pompous
fattest
pomodoro
pommeri
pomm
fattiest
pomgran
pomganit
pometta
pomerainian
favoritebreakfast
pomengrant
pomengran
pomelo
fatwallet
fauchon
pomegranet
fauna
pomad
faverit
favoit
familiari
porphyra
extrovert
poulsbo
faaaaaantast
faaaar
faboo
poundcak
poundbag
poundag
faborit
pounch
fabulos
poultic
pouf
pourgouri
poudr
pouchkin
fabulousthey
pottl
fabuluo
facecream
facin
pottasium
potstick
potroast
faa

pourin
facp
exxtrem
extrud
practico
practicament
exuber
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ppm
exxcel
exxit
powerlift
exxxtra
pourov
powerf
powercaf
powerberri
eyerol
powederi
ezcema
ezek
pow
poverti
ezin
facori
facter
porport
fallot
falafil
faleev
posion
posh
falili
fallaci
fallback
fallon
portrait
fallout
possiabl
falsest
falsifi
porter
portal
fam
famer
porselain
porrig
familar

posol
possibilitiesavail
faction
faeriesfinest
potencey
faculti
potatoey
facundo
potat
faddl
potassim
potasium
faecium
postur
postprandi
fairchild
fago
postpartum
postmeal
postiv
postassium
faillac
failsaf
fairacr
fairbank
possit
pert
fogchas
problemno
fogger
pachag
galic
pacakg
pacaket
gallari
pacak
gallat
pablum
paack
ozzi
galleri
ozarka
gallet
gallolea
gallston
galvan
galveston
galz

oxford
gam
gamier
gamze
gan
pacifica
galaxey
packa
gaia
padfilt
paddywack
paddlefish
gaget
paddington
gagia
padano
gah
paco
packsg
packmat
galanga
gaiser
gait
gala
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genardi
gaur
gastriti
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overhwhelm
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gaylord
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gerard
outlaw
genus
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geraldin
outgrew
outgo
geranium
outerwear
outermost
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fray
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dolli
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redvelvetless
reenlist

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8 Observation

Most of the cluster contains 1-2 words and most of the words in one cluster

```
In [ ]:
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Ignore the above 2 plots those plots are plotted below again