K Means Clustering

June 4, 2018

0.0.1 K-Means Clustering for Amazon food reviews:

In [1]:
```
#importing required Modules
%matplotlib inline
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import pickle
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 nltk.stem.porter import PorterStemmer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#getting cleaned data from db
conn = sqlite3.connect('final_clean_LR.sqlite')
final_review = pd.read_sql_query("""
SELECT *
FROM Reviews_final
""", conn)
```

In [3]:
```
#SORT by time for TBS
final_review = final_review.sort_values(by='Time')
```

In [ ]:
```
final_review.drop('Score',axis=1,inplace=True)
```

In [4]:
```
#info of data
final_review.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364171 entries, 23 to 345187
Data columns (total 15 columns):
level_0                   364171 non-null int64
index                     364171 non-null int64
Id                        364171 non-null int64
ProductId                 364171 non-null object
UserId                    364171 non-null object
ProfileName               364171 non-null object
HelpfulnessNumerator      364171 non-null int64
HelpfulnessDenominator    364171 non-null int64
Score                     364171 non-null object
Time                      364171 non-null int64
Summary                   364171 non-null object
Text                      364171 non-null object
CleanedTextBow            364171 non-null object
final_text                364171 non-null object
final_stem_text           364171 non-null object
dtypes: int64(6), object(9)
memory usage: 44.5+ MB
```

```
In [5]: #Converting to int8
        final_review.HelpfulnessNumerator = final_review.\
                                HelpfulnessNumerator.astype(np.int8)
        final_review.HelpfulnessDenominator = final_review.\
                                HelpfulnessDenominator.astype(np.int8)
```

```
In [6]: train_df = final_review.iloc[:round(final_review.shape[0]*0.70),:]
        test_df = final_review.iloc[round(final_review.shape[0]*0.70):,:]
```

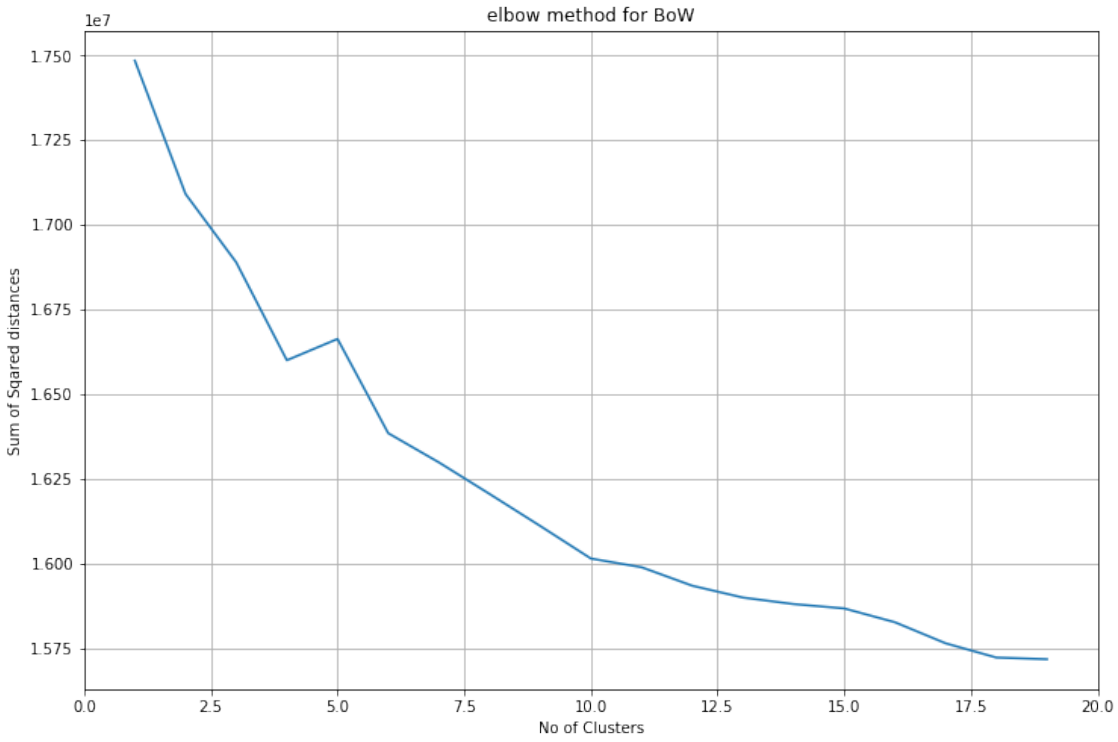
Bag of Words

```
In [7]: #BoW with cleaned data and without stopwords
        #simple cv for train data
        scores_train = []
        from nltk.corpus import stopwords
        stop = set(stopwords.words('english'))
        stop.remove('not')
        stop.remove('very')
        #CountVectorizer for BoW
        count_vect = CountVectorizer(stop_words=list(stop),dtype=np.int8)
        #X_test_cv = train_df.iloc[round(train_df.shape[0]*0.70):,:]
        final_counts_train = count_vect.fit_transform(
                train_df['final_text'].values)
        final_counts_test = count_vect.transform(
                test_df['final_text'].values)
```

```
In [11]: ssd = {}
         centers = {}
         for k in range(1,31):
             model = KMeans(n_clusters=k,n_init=10,max_iter=800,random_state=25,n_jobs=-1)
             model.fit(final_counts_train)
             ssd[k] = model.inertia_
             centers[k] = model.cluster_centers_
             print('No of clusters',k,'Sum of Squared dist',model.inertia_)
```

```
No of clusters 2 Sum of Squared dist 17090972.935039584
No of clusters 3 Sum of Squared dist 16889129.80389441
No of clusters 4 Sum of Squared dist 16599901.618375564
No of clusters 5 Sum of Squared dist 16662864.771436755
No of clusters 6 Sum of Squared dist 16384658.648390105
No of clusters 7 Sum of Squared dist 16298392.490236422
No of clusters 8 Sum of Squared dist 16205244.435071379
No of clusters 9 Sum of Squared dist 16110676.756141247
No of clusters 10 Sum of Squared dist 16014505.905228948
No of clusters 11 Sum of Squared dist 15988800.120337114
No of clusters 12 Sum of Squared dist 15934268.485165115
No of clusters 13 Sum of Squared dist 15899301.555551339
No of clusters 14 Sum of Squared dist 15880090.2596671
No of clusters 15 Sum of Squared dist 15867199.892136786
No of clusters 16 Sum of Squared dist 15826427.815612264
No of clusters 17 Sum of Squared dist 15764300.773115376
No of clusters 18 Sum of Squared dist 15722229.345665809
No of clusters 19 Sum of Squared dist 15717216.974098468
No of clusters 20 Sum of Squared dist 15722633.094975237
No of clusters 21 Sum of Squared dist 15681793.791078253
No of clusters 22 Sum of Squared dist 15655262.02774996
No of clusters 23 Sum of Squared dist 15622175.54597837
No of clusters 24 Sum of Squared dist 15573855.17671994
No of clusters 25 Sum of Squared dist 15564228.805704951
No of clusters 26 Sum of Squared dist 15552663.195803063
No of clusters 27 Sum of Squared dist 15544752.867035514
No of clusters 28 Sum of Squared dist 15471454.512619289
No of clusters 29 Sum of Squared dist 15464379.974905053
No of clusters 30 Sum of Squared dist 15455837.630540872
```

```
In [229]: plt.figure(figsize=(12,8))
          plt.plot(list(ssd.keys()),list(ssd.values()))
          plt.xlim(0,20)
          plt.xlabel('No of Clusters')
          plt.ylabel('Sum of Sqared distances')
          plt.title('elbow method for BoW')
          plt.grid()
```



from above we can observe that 10 cluster are good

```
In [9]: model_bow = KMeans(n_clusters=10,n_init=10,random_state=25)
        model_bow.fit(final_counts_train)

In [233]: #labes for all the data in train_df
          model_bow.labels_

Out[233]: array([0, 0, 0, ..., 0, 0, 2], dtype=int32)

In [234]: train_df['bow_pred_label'] = model_bow.labels_

In [235]: #no of points in each group
          train_df.groupby('bow_pred_label')['final_text','ProductId'].count()

Out[235]:                  final_text  ProductId
          bow_pred_label
          0                    142764     142764
          1                      9029       9029
          2                     14666      14666
          3                      2027       2027
          4                     22661      22661
          5                      5917       5917
          6                      3289       3289
          7                     10456      10456
          8                      1222       1222
          9                     42889      42889
```

```
In [236]: grp = train_df.groupby('bow_pred_label')[['final_text','ProductId']]
```

```
In [131]: print('group 0')
          for i in grp.get_group(0).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 0
great product bad price but why would pay amazon twice what they charge brick and mortar store
B000NN5GU8

this awesome this better than peanut butter hand down it only got one ingredient and thats orga
B002OK2FCA

little guy these are perfect for little guy they are the perfect size for him and love that the
B003GBHX5K

awesome popcorn have been ordering this popcorn from bob red mill for several year and great al
B004VLV6ES

too good there huge problem with these cracker cant limit myself cant describe the taste except
B002ZJMSKO
```

```
In [132]: print('group 1')
          for i in grp.get_group(1).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 1
great dog food great price and very good food for our dog her coat shiny bad breath and she lov
B0009X63VS

great price great ingredient searched the dog food rating page and found this one the best for
B0018CE6DQ

great treat dog loved this treat wouldnt recommend for large dog mine lb and she finished about
B000RI40UQ

aggressive chewer semi satisfied saying month lab puppy aggressive chewer understatement she tr
B0061PPLYI

garlic juice spray recently ordered this product because wa told would help control flea dog re
B002G8EJSI
```

```
In [134]: print('group 2')
          for i in grp.get_group(2).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 2
alkaline tea for all who have acid reflux Gerd great tasting alkaline decaf tea which should us
B000CMIZ0I

garbage purchased the december and returned back bus wholesale club the have very little coffe
B003WAX3H2

awesome flavor love this coffee the morning noon night doe not have too much coconut flavor but
B003G52BN0

disappointing you may wondering what disappointing about four star coffee this better than aver
B006N3HYYS

coffee Folgers instant coffee come jar which very convenient because coffee not loos it freshne
B001EQ4F14
```

```
In [138]: print('group 3')
          for i in grp.get_group(3).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 3
great coffee decided try this coffee whim since the town college town that ha very limited cof
B003OP558A

Dumm bought this local grocery store use new coffee espresso machine big coffee nut even roast
B001E5DYTE

kick Starbucks butt ive never been huge fan the overpriced coffee Starbucks even the minority
B0024KGQJI

timothy world coffee pack first all favorite cup the timothy colombian decaffeinated you are lo
B002AQ0OW6

great coffee and price have been purchasing this brand coffee for approximately year now first
B001E95KLK
```

```
In [144]: print('group 4')
          for i in grp.get_group(4).sample(5).values:
```

```
            print(i[0])
            print(i[1])
            print()
```

```
group 4
work expected after month chasing two dog out the garden and ruining few plant ordered the fro
B000HHO9EE

soft and yummy wa hesitant give these try because they are expensive but after reading the ingr
B004GYFK9M

magic indeed the aroma upon opening the lentil wa intense and appealing wa expecting one spice
B0043OU7LG

rare treat from the black sesame porridge first discovered black sesame porridge when wa taiwa
B000LQPLOI

big hit senior doxie wa extremely picky about treat begin with then she wa diagnosed with rena
B002R8J7YS
```

```
In [148]: print('group 5')
          for i in grp.get_group(5).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 5
were these review written dale corporate short and girlfriend sent bottle for christmas she li
B001EO5YR0

nice treat but substitute moderate drinker both soda and juice wa intrigued the promise the sw
B001LG940E

wonderful fresh herb received aerogarden two and half week ago and thrilled with the only reas
B000FI4O90

from blog picked package accelerate hydro today accelerate the direct competitor favorite drin
B003CN5NPE

flavor not for hesitate give bad review especially when it some type food and there the whole
B005A1LINC
```

```
In [150]: print('group 6')
          for i in grp.get_group(6).sample(5).values:
              print(i[0])
```

```
            print(i[1])
            print()
```

```
group 6
 not normally one for writing review since normally other people cover own concern praise thei
B001BOVE54

the worst part cat day now the best have struggled for over year and half giving cat daily pil
B000JOE224

impressive aroma taste very impressive aroma fresh bit wild impressive taste impressive ingred
B001EGZKH2

BPA lid bought this line baby food because wa organic and came glass jar prefer make own baby
B001BM8SS2

made kitty into addict have three cat the two older one are huge dish male litter mate who hav
B001BCVY4W
```

```
In [151]: print('group 7')
          for i in grp.get_group(7).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 7
deliciously cool this second purchase this tea this year and love ha such crisp clean cool tas
B001ELLB20

great tea this wonderful smooth and flavorful tea love this stuff and when serve guest they ra
B000SATIKK

real cup tea this the only decaf tea the dozen have tried that make real cup tea strong with t
B002M3QZKM

good price for loose leaf tea used get mine from english tea store that ha recloseable ziplock
B000SAPXF4

great tea great price fast shipping love this tea cost much le than most other brand ive seen
B001F10XUU
```

```
In [153]: print('group 8')
          for i in grp.get_group(8).sample(5).values:
              print(i[0])
```

```
            print(i[1])
            print()
```

```
group 8
fine camomile tea lazos calm herbal infusion nice chamomile tea taste the chamomile and some fl
B004EDFLPS

rather splendid keen blend this blend tea from few different regional plantation overall the ta
B000F4DK9Y

this tea yummy ive been drinking the republic tea strawberry chocolate tea for almost whole yea
B00478L5T6

really nice blend smooth tasty satisfying recommended our local supermarket phasing out their (
B0000DBN1Q

make great iced tea ive been using this tea for for about month and drink iced tea daily microw
B001EHDMY4
```

```
In [241]: print('group 9')
          for i in grp.get_group(9).sample(5).values:
              print(i[0])
              print(i[1])
              print()
```

```
group 9
great buy husband diabetic and this ha carbs which are sugar not too bad for snack have many pr
B001M08XS8

not recommended the manufacturer but work anyway although sugar floss not recommended for use t
B000UYICMO

quality product thats surpassed expectation chose this product because it shipped quickly wonde
B00029F5E0

didnt find all that jazzy have admit that when first tried this one wasnt crazy about seemed la
B001D0GVAO

sriracha discovered this tasty condiment the asian food section the grocery store maybe wa the
B001EO5ZHO
```

0 - Some Miscellaneous food products and reviews size are small
1 - Dog food related produtc
2 - coffee related products with small reviws
3- Coffe related produts with high reviews

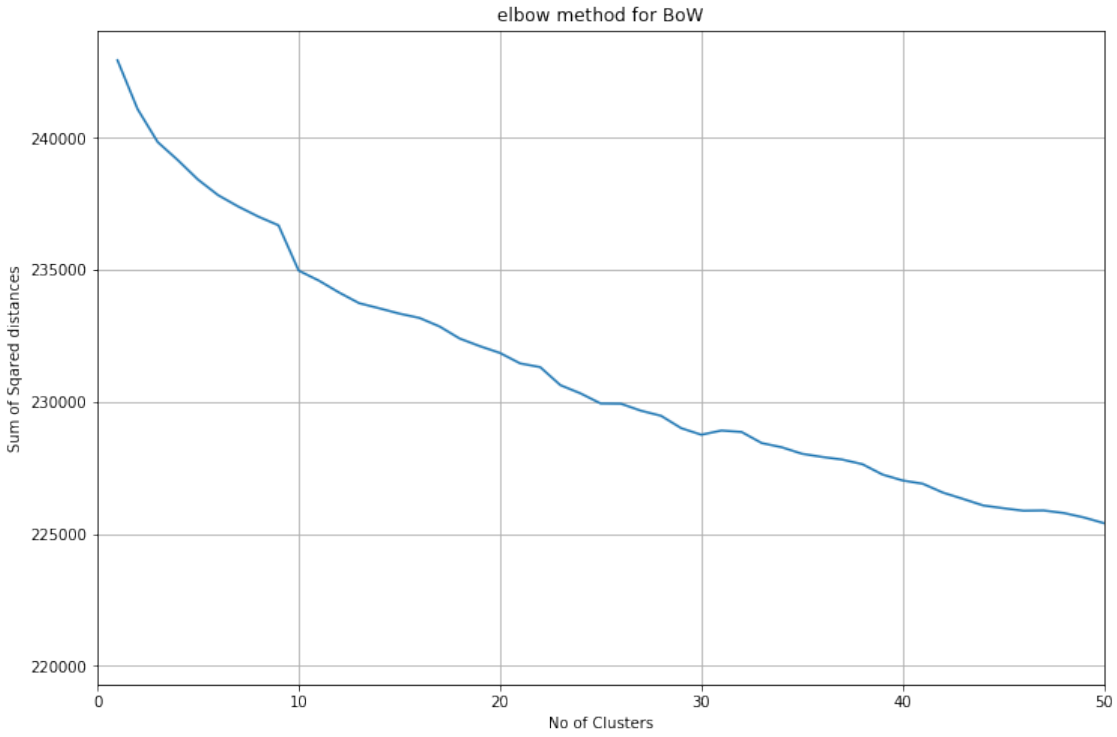
4 - Some coffe related products with differnt flovers
5 - related to drinks and soups
6 - some animal foods
7 - about tea
8 - about tea with large reviews
9 - Miscellaneous food products with some good reviews

0.0.2 Tf-Idf

```
In [12]: #TFIDF with (1,2) gram with cleaned data
         #tfidf vec
         tf_idf_vect = TfidfVectorizer(ngram_range=(1,1))
         final_counts_train = tf_idf_vect.fit_transform(
                 train_df['final_text'].values)
```

```
In [13]: for i in range(1,100):
             model = KMeans(n_clusters=i,n_init=50,max_iter=300,random_state=25,n_jobs=-1)
             model.fit(final_counts_train)
             ssd[i] = model.inertia_
             centers[i] = model.cluster_centers_
             labels = model.labels_
             print('No of clusters',i,'Sum of Squared dist',model.inertia_)
```

```
In [16]: plt.figure(figsize=(12,8))
         plt.plot(list(ssd.keys()),list(ssd.values()))
         plt.xlim(0,50)
         plt.xlabel('No of Clusters')
         plt.ylabel('Sum of Sqared distances')
         plt.title('elbow method for BoW')
         plt.grid()
```



after 10 clusters squared distances is decreasing by very less rate than before 10. so 10 may be better choice of clusters.

```
In [27]: model = KMeans(n_clusters=10,n_init=10,max_iter=300,random_state=25,n_jobs=-1)
         model.fit(final_counts_train)

In [28]: model.labels_

Out[28]: array([2, 2, 2, ..., 9, 9, 0], dtype=int32)

In [30]: train_df['tfidf_pred_label'] = model.labels_

In [32]: #no of points in each group
         train_df.groupby('tfidf_pred_label')['final_text','ProductId'].count()

Out[32]:                    final_text  ProductId
         tfidf_pred_label
         0                        18315      18315
         1                        16372      16372
         2                        85268      85268
         3                         3611       3611
         4                         7254       7254
         5                        18734      18734
         6                         4713       4713
         7                        59518      59518
         8                         2300       2300
         9                        38835      38835
```

```
In [34]: grp = train_df.groupby('tfidf_pred_label')[['final_text','ProductId']]

In [65]: for i in range(10):
             print('group ',i)
             for i in grp.get_group(i).sample(5).values:
                 print(i[0])
                 print(i[1])
                 print()

group  0
great cup coffee this coffee really good have been drinking for our morning for the last year
B0001ES9FI

perfect for aeropress this coffee the best ive found far and love that it organic wa using majo
B000KSTY86

yum crave this coffee didnt expect never order chocolate glazed donut but for tastebud this hit
B0033HPPIO

bam this great coffee this coffee ha spoiled for all the other flavor need good strong coffee a
B001D0IZBM

definite favorite delicious like chocolate covered cherry especially like added coffee will giv
B000KFVAF4

group  1
must for chai lover picked this tea with another chai white tea and mix the too together the te
B0026GBTQA

better than tip but the bag are poorly made variety must with tea best tea ive had always look
B000GINU0S

great intro loose tea reasonable price and good quality got this sampler because came after sea
B0009TMZIM

best tea vendor service wa exceptionally quick and the tea ha been the best tea for after dinne
B004EDFLPS

great quality great price really great quality for little price the tea bit strong first but af
B001UO52TY

group  2
yummy this chocolate yummy delicious and will make you fat enjoy and then get the treadmill
B000MM4SC2

very good seed bought these seed not spice for food but for hair ive read that fenugreek seed a
B000JMAVZS
```

great source when turned vegan worried about finding reliable source ground Salba ultra conveni
B0017I9P3W

soy oil undermines taste and health benefit decent large sardine for cheap moroccan production
B002T5TLYA

house vermont curry curry fan like the savory aroma delivered the finished product unless your
B001ATZQ68

group 3
doe not taste like pumpkin sadly this pumpkin soup tasted nothing like pumpkin the pumpkin used
B005DHXVVK

lousy after getting this make believe product wrote the distributor bookbinder soup and bookbi
B000H27MQG

one option when you cant find locally cannot always find this locally happy see here even the p
B00286BJ90

great for gluten free cooking since being diagnosed with celiac disease nearly two year ago hav
B001BM3POY

delicious soup kind expensive the taste this soup really great taste just good those japanese i
B001IZ9NDQ

group 4
best eaten right away youre going baking this your bread machine then sharing with friend famil
B001EPQ9JG

absolutely delicious this mix delicious not much cook but easy make amazing healthy waffle with
B000V1O3ZQ

great product love this mix taste great and easy use family ha celiac disease and cant have glu
B001D0676C

terrific bran muffin mix recently purchased this mix after twice ordering the vitalicious deep
B002MAX026

great product for baking already tried the poppy seed filling and got this too for more special
B000GZSB6E

group 5
very convenient thrilled can get friskiest subscribe and save disabled and have two old cranky
B002CJAOR6

perfect for aggressive chewer have american Staffordshire terrier aka pitbull and she just over
B0041LHND6

mint bone dog love them and they give her minty pleasing breath for short period time
B000G6T2UW

frustrating for dog got the this morning and have used twice dispense dog breakfast and dinner
B000KV61FC

cat love this stuff cat were never very enthusiastic about dry food premium otherwise until the
B001PMCFL4

group 6
best cereal ever ive been looking for cereal like this for many year taste great stay crunchy m
B001E5E0AG

worst tasting cereal ever have complains about the nutritional benefit kashi lean cereal it got
B001E5E05G

great for breakfast bought these bar because never eat breakfast hate egg dont like most cereal
B000P09RJA

great taste absolutely love this cereal the raisin are plump and there are plenty them and lot
B000QSR2X4

sweet and crunchy life it name taste sweeter than calorie and gram fat zero saturated fat the c
B0044CPA28

group 7
Olivier olive oil from france very hard find store usa used sold occitan store all over that fi
B001GR3VUM

lavazza daily standard really like lavazza coffee general recently tried the super cream since
B000SDKDM4

steak strip good brand they must pay their sale people lot tho saw these store for least more a
B000GW46D4

perfection this very good quality candy with elongated shape that come assortment fruit flavor
B004TLVVUE

excellent popcorn okay didnt buy this product from amazon actually but will consider ordering i
B000SU1LUU

group 8
wonderful leave the italian make great pasta sure have colander with tiny hole before cooking l
B000R9Q40E

great pasta amazon price lousy live this pasta gluten free house however amazon bulk price more
B000FK7PQW

```
great angel hair pasta debones gluten free angel hair pasta great for people with gluten intole
B002DZRZ80

best brown rice elbow ive tried many different brand and shape rice pasta over the year even yo
B000FK7PQW

love give you the taste and texture fresh pasta also like the fact cook quick and doesnt keep i
B001IZBT0Q

group  9
great meat substitute have been eating these child usually bread and fry these but they can als
B000DLB2E4

you want white plastic piece all over your floor get after week having them really dont care fo
B000084E6V

baking bargain bonanza love bake and probably bake time per week hate running out ingredient bu
B000IMSSF4

love these little bunny absolutely love sannies snack mix ha great flavor and love the unique s
B002QU2ILQ

absolutely wonderful first saw these cousin house and wa just amazed they are the best for roas
B003WKO150
```

0 - coffe
1- tea
2 - some seed like produts but overlap is there
3- soups 4- bread cakes
5 -dog related
6 - some cereal produts
7 - misc produts
8 - pasta and noodle based
9 -candys and some junk food

Word2Vec

```
In [10]: #importing
         from gensim.models import Word2Vec
         from gensim.models import KeyedVectors
         import pickle
         import gensim
```

```
In [11]: import gensim
         list_of_sent=[]
         for sent in final_review.final_text.values:
             list_of_sent.append(sent.split())
```

In [89]:
```
#word2vec model with 50 dim vector
w2v_model_50=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, workers=8)
#word2vec model with 100 dim vector
w2v_model_100=gensim.models.Word2Vec(list_of_sent,min_count=5,size=100, workers=8)
#word2vec model with 300 dim vector
w2v_model_300=gensim.models.Word2Vec(list_of_sent,min_count=5,size=300, workers=8)
```

In [12]:
```
#loading from disk
w2v_model_100 = pickle.load(open('w2v_model_dt_100.p','rb'))
w2v_model_50 = pickle.load(open('w2v_model_dt_50.p','rb'))
w2v_model_300 = pickle.load(open('w2v_model_dt_300.p','rb'))
```

Avg Word2Vec

In [13]:
```
# the avg-w2v for each sentence/review is stored in this list
def avg_w2v(list_of_sent,model,d):
    '''
    Returns average of word vectors for
    each sentance with dimension of model given
    '''
    sent_vectors = []
    for sent in list_of_sent: # for each review/sentence
        doc = [word for word in sent if word in model.wv.vocab]
        if doc:
            sent_vec = np.mean(model.wv[doc],axis=0)
        else:
            sent_vec = np.zeros(d)
        sent_vectors.append(sent_vec)
    return sent_vectors
```

In [14]:
```
list_of_sent_train=[]
for sent in train_df.final_text.values:
    list_of_sent_train.append(sent.split())
```

In [15]:
```
#avg word2vec for
sent_vector_avgw2v_300 = avg_w2v(list_of_sent_train,w2v_model_300,300)
#stacking columns
train_avgw2v_300 = np.hstack((sent_vector_avgw2v_300,
            train_df[['HelpfulnessNumerator','HelpfulnessDenominator']]))
column = list(range(0,300))
column.extend(['HelpfulnessNumerator','HelpfulnessDenominator'])
train_df_avgw2v_300 = pd.DataFrame(train_avgw2v_300,columns=column)
```

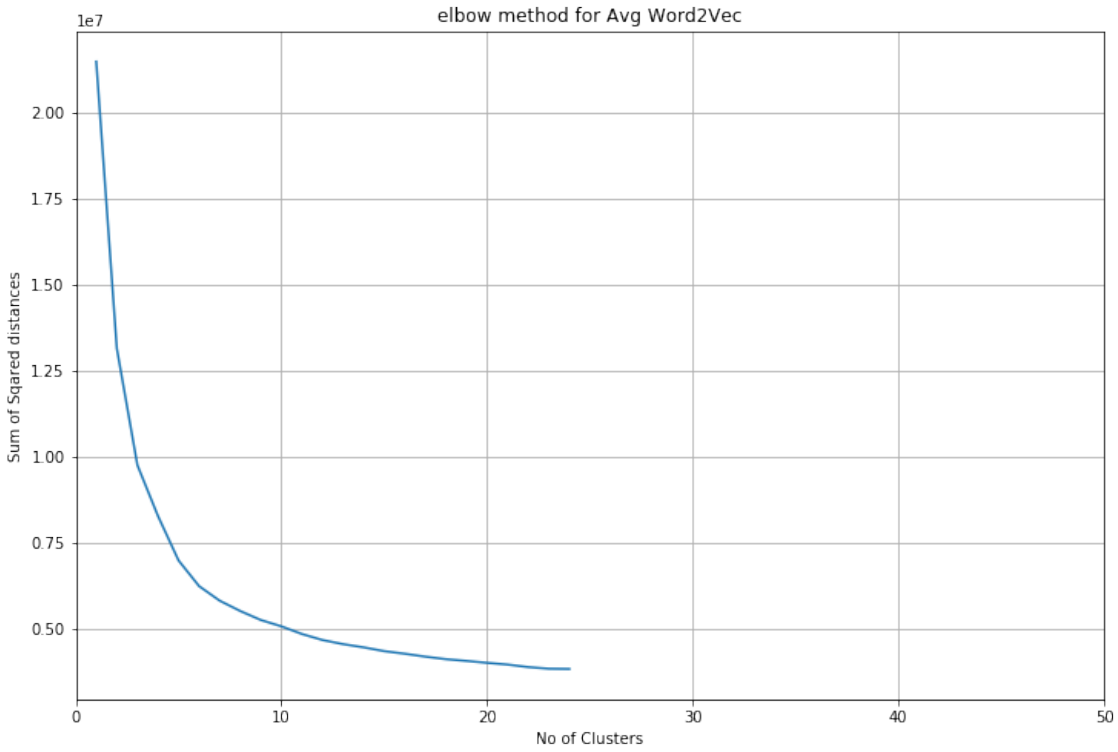
In [125]:
```
train_df_avgw2v_300.to_csv('train_df_avgw2v_300_km.csv')
```

In [18]:
```
ssd = {}
centers = {}
s = []
for i in range(1,25):
```

```
            model = KMeans(n_clusters=i,n_init=10,max_iter=300)
            model.fit(train_df_avgw2v_300)
            ssd[i] = model.inertia_
            centers[i] = model.cluster_centers_
            print('No of clusters',i,'Sum of Squared dist',model.inertia_)
```

```
No of clusters 1 Sum of Squared dist 21478458.5677
No of clusters 2 Sum of Squared dist 13151425.9848
No of clusters 3 Sum of Squared dist 9763301.69767
No of clusters 4 Sum of Squared dist 8287436.51602
No of clusters 5 Sum of Squared dist 6996673.5982
No of clusters 6 Sum of Squared dist 6249683.64389
No of clusters 7 Sum of Squared dist 5827920.66685
No of clusters 8 Sum of Squared dist 5528591.41371
No of clusters 9 Sum of Squared dist 5267355.5692
No of clusters 10 Sum of Squared dist 5083635.81328
No of clusters 11 Sum of Squared dist 4860846.33753
No of clusters 12 Sum of Squared dist 4685988.30479
No of clusters 13 Sum of Squared dist 4566925.31898
No of clusters 14 Sum of Squared dist 4473099.36642
No of clusters 15 Sum of Squared dist 4363387.89202
No of clusters 16 Sum of Squared dist 4288240.38983
No of clusters 17 Sum of Squared dist 4203399.91147
No of clusters 18 Sum of Squared dist 4130410.6869
No of clusters 19 Sum of Squared dist 4079661.38805
No of clusters 20 Sum of Squared dist 4024256.8153
No of clusters 21 Sum of Squared dist 3973378.92582
No of clusters 22 Sum of Squared dist 3900402.97946
No of clusters 23 Sum of Squared dist 3853867.75265
No of clusters 24 Sum of Squared dist 3846995.83497
```

In [19]:
```
plt.figure(figsize=(12,8))
plt.plot(list(ssd.keys()),list(ssd.values()))
plt.xlim(0,50)
plt.xlabel('No of Clusters')
plt.ylabel('Sum of Sqared distances')
plt.title('elbow method for Avg Word2Vec')
plt.grid()
```




```
In [103]: model = KMeans(n_clusters=8,n_init=10,max_iter=300)
          model.fit(train_df_avgw2v_300)
```

```
Out[103]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
              n_clusters=8, n_init=10, n_jobs=1, precompute_distances='auto',
              random_state=None, tol=0.0001, verbose=0)
```

```
In [109]: model.labels_
```

```
Out[109]: array([6, 0, 6, ..., 6, 6, 6], dtype=int32)
```

```
In [110]: train_df['avgw2v_label'] = model.labels_
```

```
In [111]: #no of points in each group
          train_df.groupby('avgw2v_label')['final_text','ProductId'].count()
```

Out[111]:

avgw2v_label	final_text	ProductId
0	66829	66829
1	2043	2043
2	25081	25081
3	75	75
4	227	227
5	6721	6721
6	153289	153289
7	655	655

```
In [112]: grp = train_df.groupby('avgw2v_label')[['final_text','ProductId']]

In [132]: for i in range(8):
              print('group ',i)
              for i in grp.get_group(i).sample(5).values:
                  print(i[0])
                  print(i[1])
                  print()

group  0
this too expensive this cost the super market why going pay almost for one can this product
B00510NMKO

atomic fire ball not sure why but order came and most the fireball are soft and few are harder
B003U4QOE8

super ordered the pop tart and they came within week really nice have this option available tha
B000M2UNIO

good for the money must admit after realized this wa foreign honey did feel bit guilty for orde
B001652KD8

comparable Kellogg nutrigrain bar very similar Kellogg nutrigrain cereal bar but little more ta
B000PIX38S

group  1
keurig cause keurig coffee maker problem are our third keurig coffee maker the original model k
B002AQOOS0

minty sweet herbal sedation between third and fourth year medical school did four week elective
B00020HHEA

great for diabetic wow wa surprised the negative review because think miracle noodle are great
B004WZ4HC6

musty wa very excited find this product bulk healthy and organic what wasnt happy about wa the
B001IZM92S

best coffee ive ever had bought the coffee originally because liked the idea organic coffee tha
B002ESSASK

group  2
organic and great price since not being able get Kirkland organic ground coffee Costco searched
B002ESSASK

great honey that packaged not great bottle ambrosia pure honey delicious and unlike most honey
B001EO616S
```

way too salty see this product got lot excellent review but disagree with the other reviewer wi
B000F2RIQC

contaminated bought this product from Costco this past weekend student teacher and gave jar mer
B002SHYCQQ

very fine quality have tried lot different coffee brand this year and this one far the best alt
B00015ECGC

group 3
fettuccini shape inedible texture and taste cant believe this wa made and packaged for human co
B000AQFQC6

wine get the venturi skip the stand first all you are wine drinker get this work else ive been
B002OL2MWM

gastrointestinal armageddon when got these couldnt contain excitement and ate about quarter bag
B000EVQWKC

yum wa the fence about buying these for month read the review and were impressed them but the p
B001RVFDOO

good price for popular gift bought this for parent christmas gift wa big hit and immediately bi
B005NYXE8S

group 4
very pleased far studied the keurig machine and others for over month before deciding this one
B004GWSWCQ

not what appears sent this item close relative for christmas having read the review this produc
B0010OF8UW

full medium roast espresso bean espresso bean can roasted different way lavazza and illy repres
B0002E2GQU

great tasting coffee many other review have mentioned these are not the normal but they work mu
B005ZBZLT4

betty crocker frosting fancy package they charged for shipping and handling figured okay temper
B0008IT4OM

group 5
great inexpensive little item have been using these cap constantly for the past week and havent
B00764BRS2

overpriced amazon like all the larabars that have tried they taste good and are able satisfy ap
B000ENUC3S

```
wonderfully smooth and great flavor better than almond alternative have been drinking this sinc
B002BG38I2

classy and romantic this wa gift wife for valentine day and she really liked wa worried the lav
B0001WAMN2

fry chicken this oil great high smoking point great for deep frying doesnt actually add any fla
B001EO5RBS

group  6
great comfort food the noodle are big and have firm texture dont follow the cheese sauce recipe
B000CQ01NS

great flour add waffle make waffle with about the mix being this flour and they taste great are
B001EO682A

the best these are favorite tomato the world put them everything everything and sometimes just
B000LKVH8S

some the best for pasta sauce the thing that make these great for pasta sauce aside from the ta
B000N17T4G

favorite tea have found this flavor Gazo tea hard find and wa very happy have found amazon this
B0017WO2H2

group  7
great mainstream option people please dont review product before youve tried give the impressio
B002AQP5FW

easter bunny make great alternative chocolate egg five year old daughter loved this easter pres
B00012182G

really work well ill this silly little thing actually work how can you get the effect decanted
B002OL2MWM

triclopyr the good stuff kill poison ivy dead this contains triclopyr which more aggressive tha
B000A0OG5K

way too expensive much cheaper through espresso these pod cost way more than ordering through e
B0099HD3YA
```

There is so much overlap in many groups and not able to divide by product types. because of Word similarity avg vectors some reviews are overlapping. some of them i find
0 - Misc products but maximum contains good ratings
1- Candies chocolates
2 - oil/seed related

3- Misc products so much overlap but maximum contains bad ratings
4- Coffe/tea related
5 - max dog related

Tf-Idf Weighted Word2Vec

```
In [14]: from sklearn.base import BaseEstimator, TransformerMixin

         class TfidfWeightedWord2Vec(BaseEstimator, TransformerMixin):
             '''
             Class for Tfidf Weighted Word2Vec Calculations
             '''
             def __init__(self, word2vec):
                 self.word2vec = word2vec
                 self.word2weight = None
                 self.dim = word2vec.vector_size
                 self.tfidf = None

             def fit(self, X, y=None):
                 tfidf = TfidfVectorizer()
                 tfidf.fit(X[:,0])
                 self.tfidf = tfidf
                 #print(self.word2vec.wv.vocab.keys())
                 return self

             def tf_idf_W2V(self,feature_names,tf_idf_trans_arr,list_of_sent):
                 '''
                 tfidf weighted word2vec calculation
                 '''
                 import operator
                 dict_tfidf = {k: v for v, k in enumerate(feature_names)}
                 sent_vectors = []
                 i = 0
                 for sent in list_of_sent: # for each review/sentence
                     doc = [word for word in sent if word in self.word2vec.wv.vocab.keys()]
                     if doc:
                         #itemgetter
                         f = operator.itemgetter(*doc)
                         try:
                             #itemgetter from dict
                             final = f(dict_tfidf)
                             final = tf_idf_trans_arr[i,final]
                             #converting to dense
                             final = final.toarray()
                             #converting to diagnol matrix for multiplication
                             final= np.diag(final[0])
                             sent_vec = np.dot(final,np.array(self.word2vec.wv[doc]))
                             #tfidf weighted word to vec
```

```
                            sent_vec = np.sum(sent_vec,axis=0) / np.sum(final)
                        except:
                            sent_vec = np.zeros(self.dim)
                    else:
                        sent_vec = np.zeros(self.dim)
                    sent_vectors.append(sent_vec)
                    i = i+1
                return sent_vectors

            def transform(self, X):
                #transform data
                tf_idf_trans_arr = self.tfidf.transform(X[:,0])
                feature_names = self.tfidf.get_feature_names()
                list_of_sent = []
                for sent in X[:,0]:
                    list_of_sent.append(sent.split())
                temp_vec = self.tf_idf_W2V(feature_names,tf_idf_trans_arr,list_of_sent)
                temp_vec= np.hstack((temp_vec,X[:,[1,2]]))
                return temp_vec
```

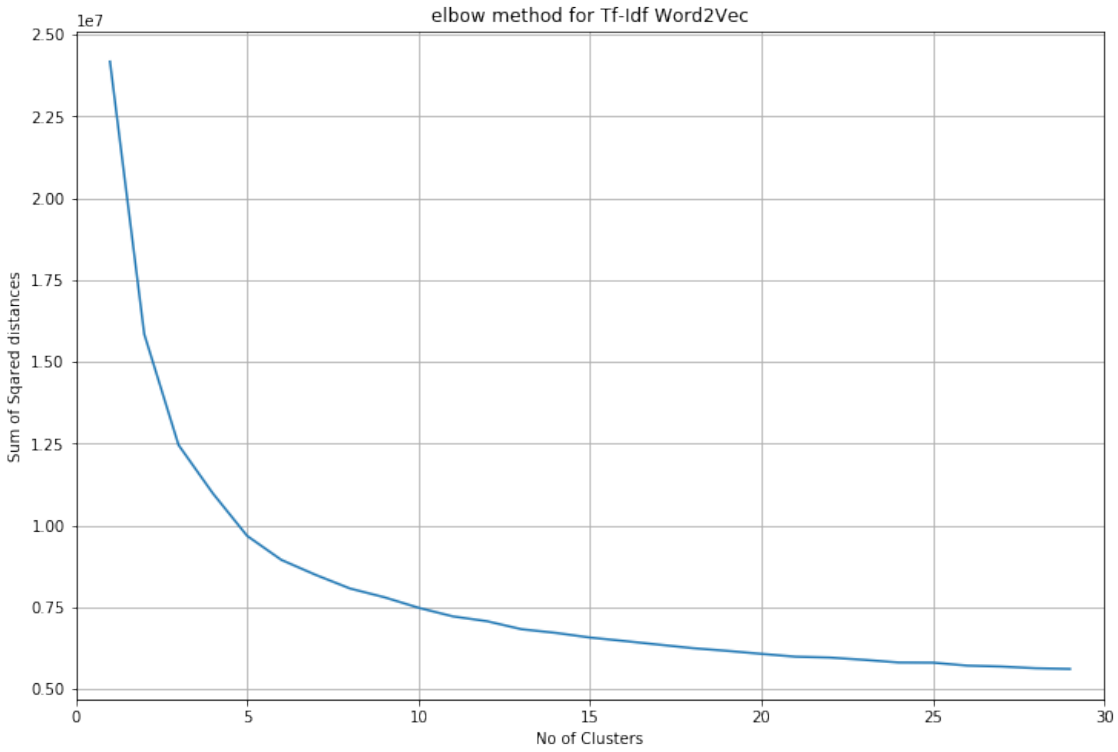
```
In [15]: # For simple cv
         tfidfvect_w2v = TfidfWeightedWord2Vec(w2v_model_300)
         tfidfvect_w2v.fit(train_df[['final_text','HelpfulnessNumerator',
                                     'HelpfulnessDenominator']].values)
         X_train = tfidfvect_w2v.transform(train_df[['final_text',
                         'HelpfulnessNumerator','HelpfulnessDenominator']].values)
```

```
In [140]: ssd = {}
          centers = {}
          s = []
          for i in range(1,30):
              model = KMeans(n_clusters=i,n_init=10,max_iter=300)
              model.fit(X_train)
              ssd[i] = model.inertia_
              centers[i] = model.cluster_centers_
              print('No of clusters',i,'Sum of Squared dist',model.inertia_)
```

```
No of clusters 1 Sum of Squared dist 24171833.5224
No of clusters 2 Sum of Squared dist 15844570.7006
No of clusters 3 Sum of Squared dist 12456011.6976
No of clusters 4 Sum of Squared dist 10979501.604
No of clusters 5 Sum of Squared dist 9679840.63928
No of clusters 6 Sum of Squared dist 8944502.93965
No of clusters 7 Sum of Squared dist 8487686.19372
No of clusters 8 Sum of Squared dist 8071787.08606
No of clusters 9 Sum of Squared dist 7804478.04089
No of clusters 10 Sum of Squared dist 7482311.49733
No of clusters 11 Sum of Squared dist 7219493.00424
```

```
No of clusters 12 Sum of Squared dist 7071082.9754
No of clusters 13 Sum of Squared dist 6827409.11229
No of clusters 14 Sum of Squared dist 6715620.45991
No of clusters 15 Sum of Squared dist 6573033.69893
No of clusters 16 Sum of Squared dist 6466839.46489
No of clusters 17 Sum of Squared dist 6356654.12795
No of clusters 18 Sum of Squared dist 6247787.95109
No of clusters 19 Sum of Squared dist 6166076.20957
No of clusters 20 Sum of Squared dist 6073954.80593
No of clusters 21 Sum of Squared dist 5987239.57045
No of clusters 22 Sum of Squared dist 5960550.71549
No of clusters 23 Sum of Squared dist 5891144.76002
No of clusters 24 Sum of Squared dist 5810811.42773
No of clusters 25 Sum of Squared dist 5805908.30299
No of clusters 26 Sum of Squared dist 5714962.28228
No of clusters 27 Sum of Squared dist 5686507.08913
No of clusters 28 Sum of Squared dist 5634394.73677
No of clusters 29 Sum of Squared dist 5613232.60975
```

In [142]:
```
plt.figure(figsize=(12,8))
plt.plot(list(ssd.keys()),list(ssd.values()))
plt.xlim(0,30)
plt.xlabel('No of Clusters')
plt.ylabel('Sum of Sqared distances')
plt.title('elbow method for Tf-Idf Word2Vec')
plt.grid()
```



from elbow metod we can find after 10 decrease is less so optimal may be 10.

```
In [109]: model = KMeans(n_clusters=10,n_init=10,max_iter=300)
          model.fit(X_train)
```

```
Out[109]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
              n_clusters=10, n_init=10, n_jobs=1, precompute_distances='auto',
              random_state=None, tol=0.0001, verbose=0)
```

```
In [110]: train_df['tfidfw2v_pred_label'] = model.labels_
```

```
In [111]:  #no of points in each group
          train_df.groupby('tfidfw2v_pred_label')['final_text','ProductId'].count()
```

```
Out[111]:                       final_text  ProductId
          tfidfw2v_pred_label
          0                          24524      24524
          1                          74134      74134
          2                           2142       2142
          3                           6315       6315
          4                            742        742
          5                          42445      42445
          6                          17689      17689
          7                             76         76
          8                          86578      86578
          9                            275        275
```

```
In [112]: grp = train_df.groupby('tfidfw2v_pred_label')[['final_text','ProductId']]

In [113]: for i in range(10):
              print('group ',i)
              for i in grp.get_group(i).sample(5).values:
                  print(i[0])
                  print(i[1])
                  print()
```

```
group  0
delightful tea think this the best jasmine tea ever full jasmine flower and fragrance and not l
B000NIHZMU

instant coffee hope you are reading these review did not this instant coffee inside container t
B006N3I69A

kahlua mocha coffee review wonderful tasting and wonderful smell the kahlua mocha coffee also r
B002TIR3BU

tea good addictive dont single day without drinking least one cup revolution sweet ginger peach
B000OWEOHY

very good husband just love this green tea buy allot get the diet with berry and the diet with
B003NL4TSM

group  1
wow this stuff awesome this time better than cheerio love this cereal eat for breakfast and eve
B001E5E060

great pistachio these pistachio arrived very quickly and tasted great other pistachio have trie
B001KW8UIG

chaka mm sauce marinade this hand down the best marinade weve ever tasted used year grilling it
B000E4AMUA

versatile received the seasoning gift and loved especially with olive oil for dipping warm crus
B001E5DR5K

sugar free cooky enjoyed the cooky they are great snack love the chocolate chip the best the br
B0008JF9FY

group  2
awesome these tablet are the best brand have tried far and they work very well the tablet itsel
B002INDU22

longer good used love them most recent purchase through amazon wa not good wa wild planet susta
B002EY5TTW
```

label changed but hurrah found favorite quirky ingredient what pomegranate molasses some probal
B001TZMCD8

vanilla bean the product excellent and fragrant have already used half what purchased making ic
B000ET4SM8

great nut almost dud love pistachio nut tried these since the price wa good and always looking
B001IZIEGS

group 3
read and read well one read this product ingredient they will find that the first ingredient co
B0026RHUP8

restricted diet beware for those restricted diet concerned about what you are ingesting aware t
B000QSS2C4

acquired taste but good grew big frank admit they are acquired taste they dont taste like regul
B000BEZVW2

get what you pay for the price wa cheap wa the product these rawhide bone literally disintegrat
B001CMMJFY

never received goat milk wa given track number and told wa delivered POBox never happened recei
B001E5DZTS

group 4
not the plant ordered dont buy this plant ordered this plant and cant even believe youre allowe
B0000DGF5S

puff pastry frozen dough ordered this product and arrived thawed and soured very disappointing
B000NY4SYW

not happy with this product have great amount experience with water have been producing home fo
B003JO71D8

cross contamination possible safe for diet just got order not here comment how the product beha
B0006ZN538

not too weak not too strong it just right found these first local supermarket ive been looking
B001EYUE5M

group 5
had better decided try and find horchata that tasted like the kind drink when growing san diego
B002GPNT32

exquisite balsamic vinegar this exquisite thick sweet aged balsamic vinegar when traveled rome
B000306AUG

both dog love these treat have australian shepherd and border collie both love these treat due
B0029NIF44

hot but not since amazon doesnt carry the hot and spicy sardine love thought would try these fo
B001225KXM

good for insulin spike why earth did start taking cinnamon powder you ask diet le than perfect
B001EQ5ABI

group 6
great but not this price Nornis are great they are all natural and even fit into weight loss pr
B003FY82YE

grreeaatt got first package the chili mix from did not know what wa for but gave try made accor
B000H2405M

not soy milk tasty like coffee mate which actually like but afraid it far le nutritious than so
B001E5E1PA

egg protein review found this good alternative whey based protein powder have only used this pr
B00166D8TW

really good ive been eating low carb for while now and every once while make some type low carb
B004LCCGZK

group 7
energy this green powder good just had get the word out others ive tried whole food brand orlea
B00112ILZM

neat and cheap alternative espresso capsule although wa bit skeptical first got say these are p
B005UP1M4I

having just eaten this for dinner have advice and raf first all dont put off the price youve ke
B000KEPBBY

prepare them yummy way following the south beach diet and saw these who wouldnt want have pasta
B004CLCEDE

our favorite rich jet fuel our favorite the coffee people fuel wake call and black tiger it dar
B0029XLH4Y

group 8
worst ever worst cinnamon tooth pick ive ever had dont know the were old what they are terrible
B0007OPW5C

wheres the bulk discount why would pay for can buy one pack for love udon noodle and difficult
B000LKX6RS

```
old ate the entire box didnt like this product all that well wa really tangy and hurt stomach w
B000Q5X876

shell purchased two package the stand stuff shell out twenty shell only five were intact very p
B000EFBMCQ

smart buy fit need perfectly more sticky finger lick off use only what you need and plenty ther
B0025UCA3I

group  9
inexpensive nylon grocery bag bag are very fashionable and useful they are also least bigger th
B00384ABOA

new out box and blender doe not work solved with DIY fix many other one star reviewer have post
B004Q3LBTG

little rainforest kitchen well have five these garden now obviously this product ive been very
B000FI4O90

great little sushi making kit this kit great gift idea and really good way start making yer ver
B000H241DS

bait switch fraud where come from bait switch called fraud thought that surely now amazon com w
B001HTJ2BQ
```

Not find any tyoe of groups by product type and upto 3 clusters the sum of sqared distance drop is very high so tried with 3 and got some results as below

```
In [56]: model = KMeans(n_clusters=3,n_init=10,max_iter=300)
         model.fit(X_train)

Out[56]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=3, n_init=10, n_jobs=1, precompute_distances='auto',
             random_state=None, tol=0.0001, verbose=0)

In [57]: model.labels_

Out[57]: array([1, 1, 1, ..., 1, 1, 1], dtype=int32)

In [58]: train_df['tfidfw2v_pred_label'] = model.labels_

In [59]: train_df.tfidfw2v_pred_label.value_counts()

Out[59]: 1    231946
         0     21462
         2      1512
         Name: tfidfw2v_pred_label, dtype: int64
```

```
In [50]: train_df['Score'] = train_df['Score'].apply(lambda x : 0 if x == 'positive' else 1)

In [60]: train_df.Score.value_counts()

Out[60]: 0    216889
         1     38031
         Name: Score, dtype: int64

In [61]: #no of points in each group
         train_df.groupby('tfidfw2v_pred_label')['final_text','ProductId'].count()

Out[61]:                       final_text  ProductId
         tfidfw2v_pred_label
         0                           21462      21462
         1                          231946     231946
         2                            1512       1512

In [88]: acc = 0
         pos = 0
         for idx,row in train_df.iterrows():
             c = row['tfidfw2v_pred_label']
             if c == 1:
                 c = 0
             elif c == 0:
                 c = 1
             if row['Score'] == c:
                 acc = acc + 1
                 if c == 0:
                     pos = pos + 1

In [89]: accuracy = acc/len(train_df)
         accuracy

Out[89]: 0.8151851561274125

In [90]: tpr = pos/sum(train_df.Score==0)
         tpr

Out[90]: 0.92610044769444277
```

Bag of Word representation:

there is overlap but i can find maximum of them as below categories. 0 - Some Miscellaneous food products and reviews size are small
1 - Dog food related produtc 2 - coffee related products with small reviws
3- Coffe related produts with high reviews
4 - Some coffe related products with differnt flovers
5 - related to drinks and soups
6 - some animal foods
7 - about tea

8 - about tea with large reviews
9 - Miscellaneous food products with some good reviews
Tf-Idf representation: 0 - coffe related
1- tea related
2 - some seed like produts but overlap is there
3- soups 4- bread cakes
5 -dog related
6 - some cereal produts
7 - misc produts
8 - pasta and noodle based
9 -candys and some junk food
avg Word2Vec: There is so much overlap in many groups and not able to divide by product types. because of Word similarity avg vectors some reviews are overlapping. some of them i find
0 - Misc products but maximum contains good ratings
1- Candies chocolates
2 - oil/seed related
3- Misc products so much overlap but maximum contains bad ratings
4- Coffe/tea related
5 - max dog related
Tf-Idf Weighted Word2vec: i find there is so much overlap in the clusters and tried with 3 clusters, and checked for positive and negative samples in those clusters and got accuracy of 82% and true positive rate of 92%.