Truncated_SVD

August 8, 2020

1 Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

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 Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 [1]. Reading Data

2.1 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is 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 is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

[1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

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

from tqdm import tqdm
import os
```

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly
```

```
Enter your authorization code:
··········
Mounted at /content/drive
```

[39]:
```python
# using SQLite Table to read data.
con = sqlite3.connect('drive/My Drive/FFRDB/database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000␣
↪data points
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3␣
↪LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3␣
↪LIMIT 150000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a␣
↪negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#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
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (150000, 10)
```

[39]:
```
   Id  ...                                               Text
0   1  ...  I have bought several of the Vitality canned d...
1   2  ...  Product arrived labeled as Jumbo Salted Peanut...
2   3  ...  This is a confection that has been around a fe...

[3 rows x 10 columns]
```

[40]:
```python
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
```

```
""", con)
```

[41]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

[41]:
```
                UserId  ... COUNT(*)
0  #oc-R115TNMSPFT9I7  ...        2
1  #oc-R11D9D7SHXIJB9  ...        3
2  #oc-R11DNU2NBKQ23Z  ...        2
3  #oc-R11O5J5ZVQE25C  ...        3
4  #oc-R12KPBODL2B5ZD  ...        2

[5 rows x 7 columns]
```

[42]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

[42]:
```
              UserId  ... COUNT(*)
80638  AZY10LLTJ71NX  ...        5

[1 rows x 7 columns]
```

[43]:
```
display['COUNT(*)'].sum()
```

[43]:
```
393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

[44]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

[44]:
```
       Id  ...                                               Text
0   78445  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  138317  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  138277  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3   73791  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  155049  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

```
[5 rows x 10 columns]
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

[45]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True,␣
↪inplace=False, kind='quicksort', na_position='last')
```

[46]:
```
#Deduplication of entries
final=sorted_data.
↪drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first',␣
↪inplace=False)
final.shape
```

[46]:
```
(126359, 10)
```

[47]:
```
final.sort_values('Time',inplace=True)
print(final.head(5))
```

```
            Id  ...                                              Text
138706  150524  ...  this witty little book makes my son laugh at l...
138683  150501  ...  I can remember seeing the show when it aired o...
70688    76882  ...  I bought a few of these after my apartment was...
1146      1245  ...  This was a really good idea and the final prod...
1145      1244  ...  I just received my shipment and could hardly w...

[5 rows x 10 columns]
```

[48]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

[48]:
```
84.23933333333333
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

[49]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
```

```
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

[49]:
```
      Id  ...                                              Text
0  64422  ...  My son loves spaghetti so I didn't hesitate or...
1  44737  ...  It was almost a 'love at first bite' - the per...

[2 rows x 10 columns]
```

[50]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

[51]:
```
#Before starting the next phase of preprocessing lets see the number of entries␣
 ↪left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(126357, 10)
```

[51]:
```
1    106326
0     20031
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

[52]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
```

```
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
==================================================
These are very tasty especially the blueberries.  A bit pricy but not when
compared to things like this at whole foods and other upscale stores.  I am
ordering more for a road trip in my van when fresh fruit may be limited.
==================================================
The sugarless mix is very satisfactory and it's fewer calories. Go for it.
==================================================
So full of WHOLE wheat that it leaves a few hulls in your teeth after eating.  A
little sweetness in the cracker makes it fine for sweet as well as savory
toppings.  Even good eaten plain as a snack.
==================================================
```

[53]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
```

[54]:
```
# https://stackoverflow.com/questions/16206380/
↪python-beautifulsoup-how-to-remove-all-tags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
==================================================
These are very tasty especially the blueberries.  A bit pricy but not when
compared to things like this at whole foods and other upscale stores.  I am
ordering more for a road trip in my van when fresh fruit may be limited.
==================================================
The sugarless mix is very satisfactory and it's fewer calories. Go for it.
==================================================
So full of WHOLE wheat that it leaves a few hulls in your teeth after eating.  A
little sweetness in the cracker makes it fine for sweet as well as savory
toppings.  Even good eaten plain as a snack.
```

[55]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
```

```
    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

[56]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
The sugarless mix is very satisfactory and it is fewer calories. Go for it.
==================================================
```

[57]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
```

[58]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
The sugarless mix is very satisfactory and it is fewer calories Go for it
```

[59]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st␣
 ↪step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours',␣
 ↪'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he',␣
 ↪'him', 'his', 'himself', \
```

```
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its',␣
↪'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this',␣
↪'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',␣
↪'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',␣
↪'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into',␣
↪'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on',␣
↪'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how',␣
↪'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so',␣
↪'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',␣
↪"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',␣
↪"didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't",␣
↪'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',␣
↪"shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

[60]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in␣
↪stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|| 126357/126357 [00:49<00:00, 2574.30it/s]
```

[61]:
```
preprocessed_reviews[1500]
```

[61]:
```
'sugarless mix satisfactory fewer calories go'
```

[3.2] Preprocessing Review Summary

[62]:
```python
## Similartly you can do preprocessing for review summary also.
```

5 [4] Featurization

5.1 [4.3] TF-IDF

[63]:
```python
preprocessed_reviews=preprocessed_reviews[:100000]
```

[64]:
```python
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=2000)
tfidf = tf_idf_vect.fit_transform(preprocessed_reviews)
```

[65]:
```python
print(tfidf.shape)
```

```
(100000, 2000)
```

6 [5] Assignment 11: Truncated SVD

```
<li><strong>Apply Truncated-SVD on only this feature set:</strong>
    <ul>
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
<br>
<li><strong>Procedure:</strong>
    <ul>
<li>Take top 2000 or 3000 features from tf-idf vectorizers using idf_ score.</li>
<li>You need to calculate the co-occurrence matrix with the selected features (Note: X.X^T
```

doesn't give the co-occurrence matrix, it returns the covariance matrix, check these bolgs blog-1, blog-2 for more information)

```
        <li>You should choose the n_components in truncated svd, with maximum explained
```

variance. Please search on how to choose that and implement them. (hint: plot of cumulative explained variance ratio)

```
        <li>After you are done with the truncated svd, you can apply K-Means clustering and cho
```

the best number of clusters based on elbow method.

```
        <li> Print out wordclouds for each cluster, similar to that in previous assignment. </l
        <li>You need to write a function that takes a word and returns the most similar words u
```

cosine similarity between the vectors(vector: a row in the matrix after truncatedSVD)

```
    </ul>
</li>
<br>
```

6.1 Truncated-SVD

[110]:

```
## using upto 10 cluster centers
NumCenters = range(2,20)
#defining a fucntion to return inertia for every set of cluster center used

def Inertia(NumCenters,data):
  from sklearn.cluster import KMeans
  Inertia=[]
  for i in NumCenters:

      clf = KMeans(n_clusters=i, init='k-means++', verbose=5, n_jobs=-1)
      clf.fit(data)
      kmeans=clf.inertia_
      Inertia.append(kmeans)
  return Inertia


# plotting The Inertia vs K graph

def PlotElbow(NumCenters,Inertia):
  plt.plot(NumCenters, Inertia)
  plt.xlabel('K-values',size=15)
  plt.ylabel('Inertia',size=15)
  plt.title('Inertia VS K-values Plot\n',size=20)
  plt.grid()
  plt.show()

  '''
Algorithm to find elbow of a graph is taken from the following questionare on␣
 ↪Stackoverflow
#######
https://stackoverflow.com/questions/2018178/
 ↪finding-the-best-trade-off-point-on-a-curve
#######
'''

# finding the Elbow of graph

def ElbowFinder(Inertia):
  import numpy as np
  import numpy.matlib
  nPoints = len(Inertia)
  allCoord = np.vstack((range(nPoints), Inertia)).T
  np.array([range(nPoints), Inertia])
  firstPoint = allCoord[0]
  lineVec = allCoord[-1] - allCoord[0]
  lineVecNorm = lineVec / np.sqrt(np.sum(lineVec**2))
  vecFromFirst = allCoord - firstPoint
```

```
  scalarProduct = np.sum(vecFromFirst * np.matlib.repmat(lineVecNorm, nPoints,␣
↪1), axis=1)
  vecFromFirstParallel = np.outer(scalarProduct, lineVecNorm)
  vecToLine = vecFromFirst - vecFromFirstParallel
  distToLine = np.sqrt(np.sum(vecToLine ** 2, axis=1))
  return np.argmax(distToLine)
```

```
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
stopwords = set(STOPWORDS)

# Generating word cloud function for a given dataset of str

def ShowWordcloud(data, title = None):
    wordcloud = WordCloud(
        background_color='white',
        stopwords=stopwords,
        max_words=200,
        max_font_size=40,
        scale=3,
        random_state=1 # chosen at random by flipping a coin; it was heads
    ).generate(str(data))

    fig = plt.figure(1, figsize=(12, 12))
    plt.axis('off')


    if title:
        fig.suptitle(title, fontsize=20)
        fig.subplots_adjust(top=2.3)

    plt.imshow(wordcloud)
    plt.show()



# overall function to generate graph and word cloud

def PrintWordcloud(preprocessed_reviews,vectorizer):

# finding inertia and plotting it against different no of cluster
  inertia=Inertia(NumCenters,vectorizer)
```

```
  print('Plotting elbow graph')
  PlotElbow(NumCenters,inertia)
  print('\n\n')
# defining kmeans with best K
  from sklearn.cluster import KMeans
  clf= KMeans(n_clusters=ElbowFinder(inertia), n_jobs=-1)
  model=clf.fit(vectorizer)
  labels=model.labels_
# printing all cluters
  unq_labels=np.unique(labels)
  print('All clusters are',unq_labels)
  print("\n")

  corpus = preprocessed_reviews
# list of list containing reviews belonging to each cluster
  ListOfReviewsClusters=[[] for i in unq_labels]
# segregating reviews from each cluster
  for index,word in enumerate(corpus):
    real_label = labels[index]
    ListOfReviewsClusters[real_label].append(word)
# printing each review cloud
  for i in range(len(list(unq_labels))):
    print('word cloud for cluster', i+1)
    ShowWordcloud(ListOfReviewsClusters[i])
    print('\n\n')
```

6.1.1 [5.1] Taking top features from TFIDF, SET 2

[70]:
```
tfidf_feat=tf_idf_vect.get_feature_names()
```

[72]:
```
len(tfidf_feat)
```

[72]: 2000

6.1.2 [5.2] Calulation of Co-occurrence matrix

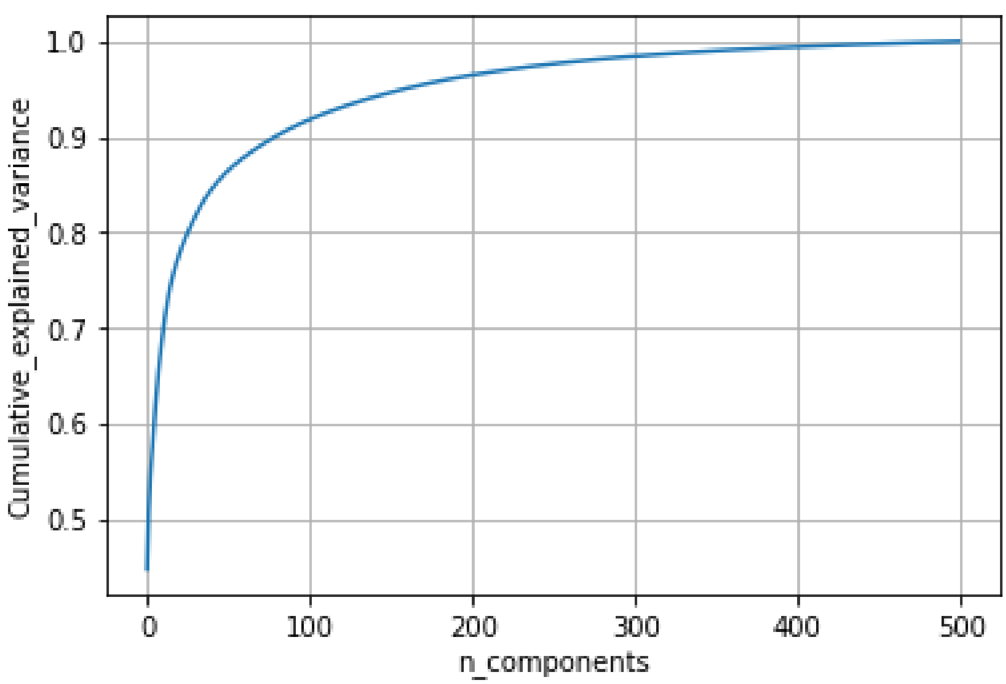
[75]:
```
from tqdm.notebook import tqdm
window = 5
coocc_matrix = np.zeros((2000,2000))
for row in tqdm(preprocessed_reviews):
    words_in_row = row.split()
    for index,word in enumerate(words_in_row):
        if word in tfidf_feat:
            for j in␣
 ↪range(max(index-window,0),min(index+window,len(words_in_row)-1) + 1):
                if words_in_row[j] in tfidf_feat:
```

```
                    coocc_matrix[tfidf_feat.index(word),tfidf_feat.
↪index(words_in_row[j])] += 1
                else:
                    pass
        else:
            pass
```

```
HBox(children=(FloatProgress(value=0.0, max=100000.0), HTML(value='')))
```

6.1.3 [5.3] Finding optimal value for number of components (n) to be retained.

[76]:
```
from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(n_components = 500)
svd_tfidf = svd.fit_transform(coocc_matrix)

percent_var_exp = svd.explained_variance_ / np.sum(svd.explained_variance_);
cum_var = np.cumsum(percent_var_exp)

plt.plot(cum_var)
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
```

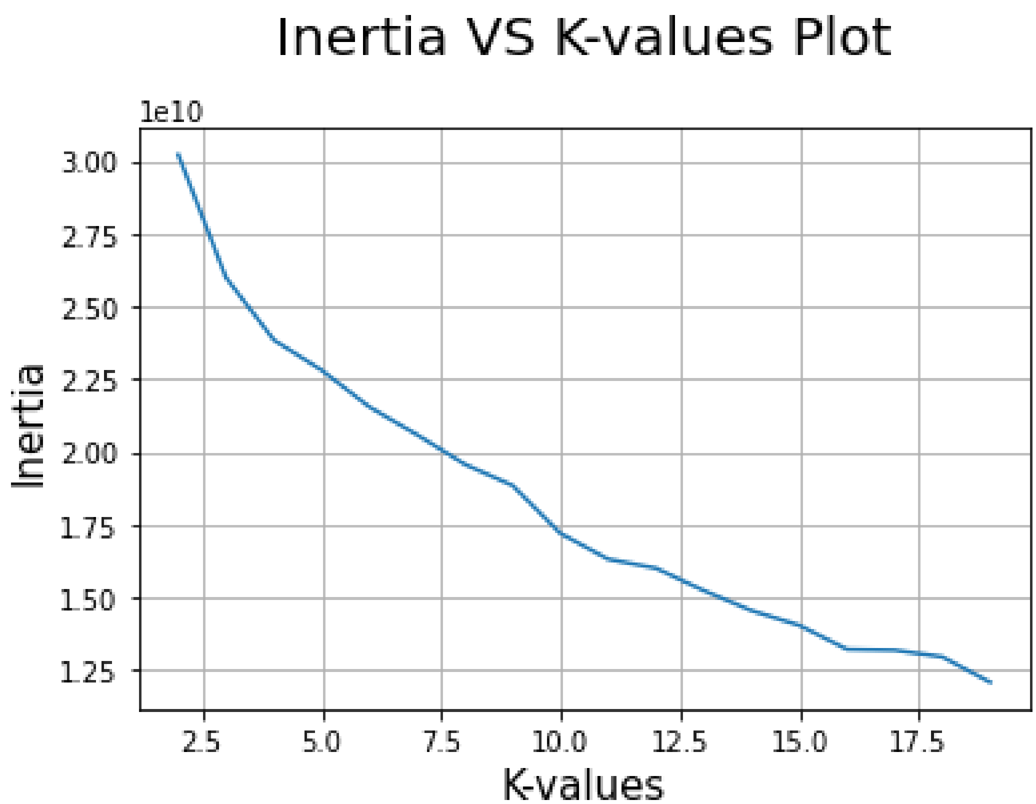


[85]:
```
from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(n_components = 270)
svd_tfidf = svd.fit_transform(coocc_matrix)
```

6.1.4 [5.4] Applying k-means clustering

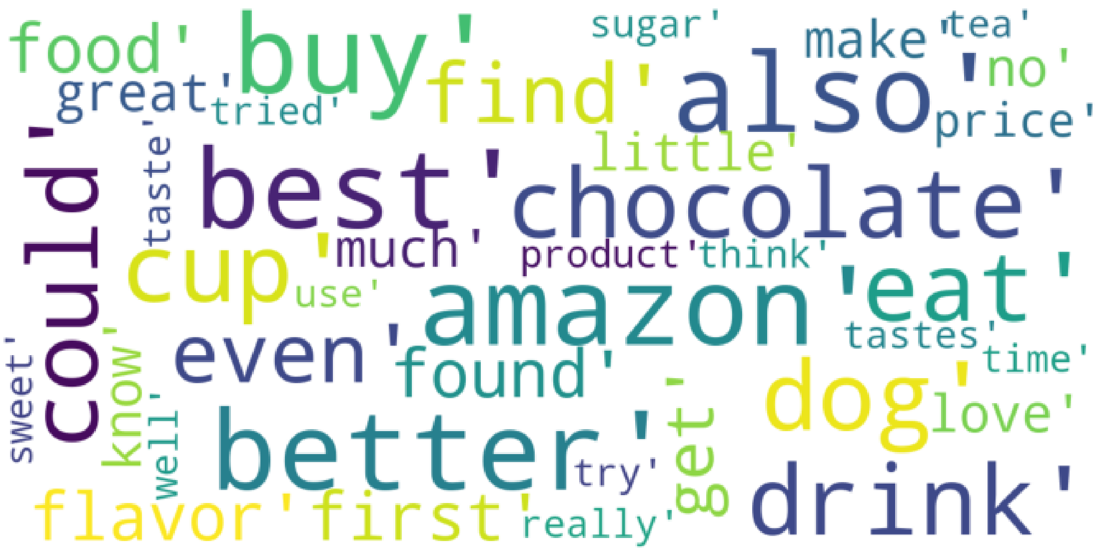
[112]:
```
PrintWordcloud(tfidf_feat,svd_tfidf)
```

```
Plotting elbow graph
```




```
All clusters are [0 1 2 3 4 5 6 7]
```

```
word cloud for cluster 1
```



word cloud for cluster 2

word cloud for cluster 3

word cloud for cluster 4

word cloud for cluster 5

word cloud for cluster 6

word cloud for cluster 7

word cloud for cluster 8

7 Applying DBSCAN

[113]:
```
#defining a fucntion to return inertia for every set of cluster center used
'''
https://towardsdatascience.com/
↪machine-learning-clustering-dbscan-determine-the-optimal-value-for-epsilon-eps-python-examp
↪~:
↪text=In%20layman's%20terms%2C%20we%20find,and%20select%20that%20as%20epsilon.
'''
def NeighborsDist(data,Min_pt=10):
  from sklearn.neighbors import NearestNeighbors
  nbrs = NearestNeighbors(n_neighbors=Min_pt).fit(data)
  distances, indices = nbrs.kneighbors(data)
  distances = np.sort(distances, axis=0)
  distances = distances[:,1][::-1]
  return distances


# plotting The Inertia vs K graph

def PlotElbowdb(data):
  plt.plot(data)
  plt.xlabel('Num_pts',size=15)
  plt.ylabel('Distance',size=15)
  plt.title('distance VS Num_pts Plot\n',size=20)
  plt.grid()
  plt.show()

  '''
Algorithm to find elbow of a graph is taken from the following questionare on␣
↪Stackoverflow
#######
https://stackoverflow.com/questions/2018178/
↪finding-the-best-trade-off-point-on-a-curve
#######
'''

# finding the Elbow of graph

def ElbowFinderdb(Inertia):
  import numpy as np
  import numpy.matlib
  nPoints = len(Inertia)
  allCoord = np.vstack((range(nPoints), Inertia)).T
  np.array([range(nPoints), Inertia])
  firstPoint = allCoord[0]
  lineVec = allCoord[-1] - allCoord[0]
```

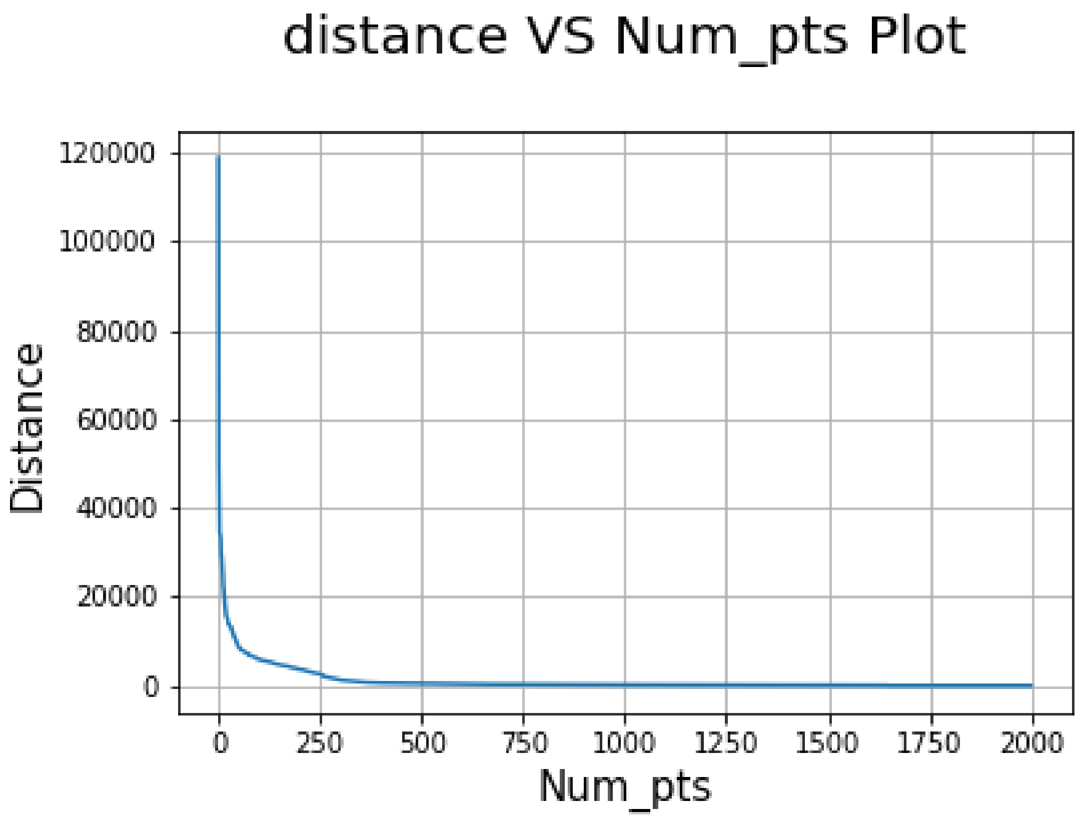
```
    lineVecNorm = lineVec / np.sqrt(np.sum(lineVec**2))
    vecFromFirst = allCoord - firstPoint
    scalarProduct = np.sum(vecFromFirst * np.matlib.repmat(lineVecNorm, nPoints,␣
↪1), axis=1)
    vecFromFirstParallel = np.outer(scalarProduct, lineVecNorm)
    vecToLine = vecFromFirst - vecFromFirstParallel
    distToLine = np.sqrt(np.sum(vecToLine ** 2, axis=1))
    return np.argmax(distToLine)
```

```
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
stopwords = set(STOPWORDS)

# Generating word cloud function for a given dataset of str

def ShowWordcloud(data, title = None):
    wordcloud = WordCloud(
        background_color='white',
        stopwords=stopwords,
        max_words=200,
        max_font_size=40,
        scale=3,
        random_state=1 # chosen at random by flipping a coin; it was heads
    ).generate(str(data))

    fig = plt.figure(1, figsize=(12, 12))
    plt.axis('off')


    if title:
        fig.suptitle(title, fontsize=20)
        fig.subplots_adjust(top=2.3)

    plt.imshow(wordcloud)
    plt.show()



# overall function to generate graph and word cloud

def PrintWordclouddb(preprocessed_reviews,vectorizer,samples=50):
```

```
  nbr=NeighborsDist(vectorizer,Min_pt=samples)
  print('Plotting Epsilon graph')
  PlotElbowdb(nbr)
  print('\n\n')
  print('eps =',ElbowFinderdb(nbr))
  print('\n\n')


  from sklearn.cluster import DBSCAN

  clf = DBSCAN(min_samples=samples,eps=ElbowFinderdb(nbr))
  model=clf.fit(vectorizer)

  labels=model.labels_

  unq_labels=np.unique(labels)
  print('All clusters are',unq_labels)
  print("\n")

  corpus = preprocessed_reviews
  ListOfReviewsClusters=[[] for i in unq_labels]

  for index,word in enumerate(corpus):
    real_label = labels[index]
    ListOfReviewsClusters[real_label].append(word)

  for i in range(len(list(unq_labels))):
    print('word cloud for cluster',i-1)
    ShowWordcloud(ListOfReviewsClusters[i])
    print('\n\n')
```

[114]:
```
PrintWordclouddb(tfidf_feat,svd_tfidf)
```

```
Plotting Epsilon graph
```

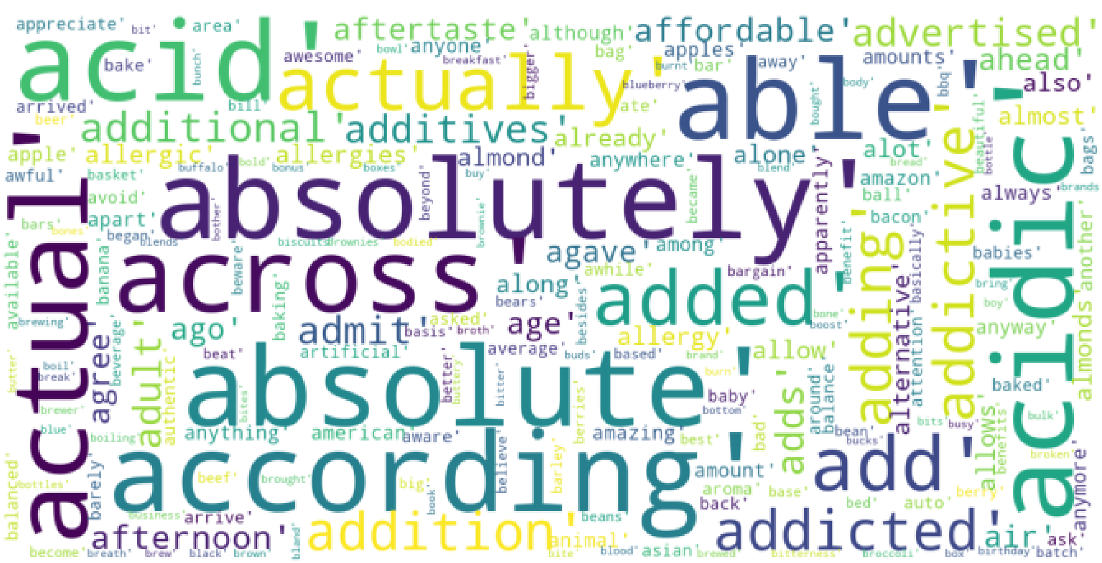



```
eps = 76
```

```
All clusters are [-1  0]
```

```
word cloud for cluster -1
```

word cloud for cluster 0



7.0.1 [5.6] Function that returns most similar words for a given word.

[150]:
```
# Calculate cosine similarity
from sklearn.metrics.pairwise import cosine_similarity
def cos_sim(word, corpus):
  dist=[]
  for wd in corpus:
    dist.append(float(cosine_similarity(word.reshape(1,-1),wd.reshape(1,-1))))

  indices = np.argsort(dist)
  print(' Top 5 similar words are \n')
  for i in range(5):
    print(tfidf_feat[indices[i]])
```

[152]:
```
cos_sim(svd_tfidf[120].reshape(1,-1),svd_tfidf)
```

```
 Top 5 similar words are

best price
anything else
add little
bitter taste
big fan
```

[153]:
```
cos_sim(svd_tfidf[485].reshape(1,-1),svd_tfidf)
```

```
 Top 5 similar words are

absolutely love
also not
amazon price
able find
baby food
```

8 [6] Conclusions

We took the usual Amazon fine food reviews data and 100000 reviews from it. Vectorized it with top 2000 words using IDF count. With this vector we formulate the Co-occurance matrix of words. Each vector is represented here in 2000 dimensions. To reduce this dimension to a resonable size and formulate a good word to vector form we input this data to SVD to reduce the dim with most variance intacted. We find 270 to be a good dimension size for data representation, and with kmeans clusting we found 6 cluters in which the data can be seggregated to while DBSCAN can seggregate the data into 2 clusters only.