10affrc

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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".

In [35]:
```
%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

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn import preprocessing
from sklearn.model_selection import GridSearchCV
from prettytable import PrettyTable
from sklearn.cluster import KMeans
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import DBSCAN
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect('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 point
# 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 5
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 400

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negativ
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 (4000, 10)
```

Out[2]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      1  1303862400
1                     0                       0      0  1346976000
2                     1                       1      1  1219017600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
```

In [3]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
```

```
        HAVING COUNT(*)>1
        """, con)
```

```
In [4]: print(display.shape)
        display.head()
```

```
(80668, 7)
```

```
Out[4]:                   UserId   ProductId             ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
        3  #oc-R11O5J5ZVQE25C  B005HG9ET0           Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B007OSBE1U   Christopher P. Presta  1348617600      1

                                                        Text  COUNT(*)
        0  Overall its just OK when considering the price...         2
        1  My wife has recurring extreme muscle spasms, u...         3
        2  This coffee is horrible and unfortunately not ...         2
        3  This will be the bottle that you grab from the...         3
        4  I didnt like this coffee. Instead of telling y...         2
```

```
In [5]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[5]:               UserId   ProductId                       ProfileName        Time  \
        80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

               Score                                               Text  COUNT(*)
        80638      5  I was recommended to try green tea extract to ...         5
```

```
In [6]: display['COUNT(*)'].sum()
```

```
Out[6]: 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:

```
In [7]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
```

```
Out[7]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
        1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
        2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
        3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
        4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2

           HelpfulnessDenominator  Score        Time  \
        0                       2      5  1199577600
        1                       2      5  1199577600
        2                       2      5  1199577600
        3                       2      5  1199577600
        4                       2      5  1199577600

                                     Summary  \
        0  LOACKER QUADRATINI VANILLA WAFERS
        1  LOACKER QUADRATINI VANILLA WAFERS
        2  LOACKER QUADRATINI VANILLA WAFERS
        3  LOACKER QUADRATINI VANILLA WAFERS
        4  LOACKER QUADRATINI VANILLA WAFERS

                                                        Text
        0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

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.

```
In [8]: #Sorting data according to ProductId in ascending order
        sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

```
In [9]: #Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
        final.shape
```

Out[9]: (3989, 10)

In [10]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[10]: 99.725

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

In [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[11]:
```
      Id   ProductId          UserId              ProfileName  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     3                       1      5  1224892800
1                     3                       2      4  1212883200

                                    Summary  \
0            Bought This for My Son at College
1  Pure cocoa taste with crunchy almonds inside

                                                Text
0  My son loves spaghetti so I didn't hesitate or...
1  It was almost a 'love at first bite' - the per...
```

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#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()
```

```
(3989, 10)
```

Out[13]:
```
1    3328
0     661
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

```
In [14]: # 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)
```

```
We have used the Victor fly bait for 3 seasons.  Can't beat it.  Great product!
==================================================
Fast, professional transaction.  I needed this one ingredient for a new recipe and it turned ou
==================================================
Please ignore the one-star comments, if you check the bag the main ingredient IS in fact whole
==================================================
```

```
In [15]: # 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)
```

```
We have used the Victor fly bait for 3 seasons.  Can't beat it.  Great product!
```

```
In [16]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
         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)
```

```
We have used the Victor fly bait for 3 seasons.  Can't beat it.  Great product!
==================================================
Fast, professional transaction.  I needed this one ingredient for a new recipe and it turned ou
==================================================
Please ignore the one-star comments, if you check the bag the main ingredient IS in fact whole
==================================================
```

```
In [17]: # 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
```

```
In [18]: sent_1500 = decontracted(sent_1500)
         print(sent_1500)
         print("="*50)
```

```
Please ignore the one-star comments, if you check the bag the main ingredient IS in fact whole
==================================================
```

```
In [19]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
         sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
         print(sent_0)
```

```
We have used the Victor fly bait for  seasons.  Can't beat it.  Great product!
```

```
In [20]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
         sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
         print(sent_1500)
```

```
Please ignore the one star comments if you check the bag the main ingredient IS in fact whole
```

```
In [21]: # 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', 'ourselve
                     "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
                     'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
                     'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
                     'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', '
                     'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
                     's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
                     've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
                     "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                     "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                     'won', "won't", 'wouldn', "wouldn't"])
```

```
In [22]: # Combining all the above stundents
         from tqdm import tqdm
         preprocessed_reviews_a = []
         # 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 stopwo
            preprocessed_reviews_a.append(sentance.strip())
```

```
100%|| 3989/3989 [00:01<00:00, 3191.95it/s]
```

```
In [23]: preprocessed_reviews_a[1500]
```

```
Out[23]: 'please ignore one star comments check bag main ingredient fact whole grain brown rice
```

```
In [24]: X = preprocessed_reviews_a
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [205]: #BoW
          vectorizer = CountVectorizer(min_df = 10)
          vectorizer.fit(X) # fit has to happen only on train data
          print(vectorizer.get_feature_names()[:20])# printing some feature names
          print("="*50)

          # we use the fitted CountVectorizer to convert the text to vector
          X_bow = vectorizer.transform(X)

          print("After vectorizations")
          print(X_bow.shape)
```

```
['able', 'absolute', 'absolutely', 'according', 'acid', 'across', 'actual', 'actually', 'add',
==================================================
After vectorizations
(3989, 1885)
```

5.2 [4.3] TF-IDF

```
In [206]: tfidf_vect = TfidfVectorizer(min_df=10)
          tfidf_vect.fit(X)
          print("some sample features ",tfidf_vect.get_feature_names()[0:10])
          print('='*50)

          # we use the fitted CountVectorizer to convert the text to vector
          X_tfidf = tfidf_vect.transform(X)

          print("After vectorizations")
          print(X_tfidf.shape)
```

```
some sample features  ['able', 'absolute', 'absolutely', 'according', 'acid', 'across', 'actual
==================================================
After vectorizations
(3989, 1885)
```

5.3 [4.4] Word2Vec

```
In [25]: # Train your own Word2Vec model using your own text corpus
         list_of_sentance=[]
         for sentance in X:
             list_of_sentance.append(sentance.split())
```

```
In [26]: # this line of code trains your w2v model on the give list of sentances, fitting the 
         w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=-1)
```

```
In [27]: w2v_words = list(w2v_model.wv.vocab)
         print("number of words that occured minimum 5 times ",len(w2v_words))
         print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  3295
sample words  ['used', 'ca', 'not', 'beat', 'great', 'product', 'available', 'course', 'total'
```

5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

```
In [28]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(list_of_sentance): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             cnt_words =0; # num of words with a valid vector in the sentence/review
             for word in sent: # for each word in a review/sentence
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
                 sent_vec /= cnt_words
             sent_vectors.append(sent_vec)
         sent_vectors = np.array(sent_vectors)
         print(sent_vectors.shape)
         print(sent_vectors[0])
```

```
100%|| 3989/3989 [00:02<00:00, 1547.61it/s]
```

```
(3989, 50)
[-2.08258765e-04 -8.50573182e-04  2.57958284e-03  2.20642064e-03
 -1.71055952e-03 -3.63902928e-03 -6.52334265e-04 -5.79028856e-05
 -7.47786544e-04  3.84051945e-03  6.23511267e-04 -1.74325439e-03
 -1.89252077e-03 -3.41529450e-03 -2.72196962e-03  6.18074198e-03
 -1.91327788e-03 -1.91387531e-03  1.19264730e-03  3.76884969e-03
 -3.26800897e-04 -4.88491396e-03 -5.03189743e-03  5.63717913e-04
  3.16440483e-03 -1.71693283e-03  2.64091755e-03  1.90477484e-03
 -1.91613872e-05  6.20621620e-04  9.31884861e-04 -2.53918026e-03
 -1.32379202e-03 -3.06696869e-03  3.17091262e-03  1.44844991e-04
 -3.40751510e-03 -7.03583501e-05  2.41178134e-03 -4.22656394e-03
 -5.21609705e-04 -2.34397727e-03  1.75464394e-03  6.09099118e-04
 -6.44757223e-04  1.30831664e-03 -6.67121669e-04  2.37091296e-03
  2.22094264e-03  7.60357982e-04]
```

In [211]:
```
type(sent_vectors)
```

Out[211]: numpy.ndarray

[4.4.1.2] TFIDF weighted W2v

In [29]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(X)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [30]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
row=0;
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
```

```
                sent_vec /= weight_sum
            tfidf_sent_vectors.append(sent_vec)
            row += 1
```

```
100%|| 3989/3989 [00:13<00:00, 289.11it/s]
```

6 [5] Assignment 10: K-Means, Agglomerative & DBSCAN Clustering

```
<li><strong>Apply K-means Clustering on these feature sets:</strong>
    <ul>
<li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors using
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
<li>Find the best k using the elbow-knee method (plot k vs inertia_)</li>
<li>Once after you find the k clusters, plot the word cloud per each cluster so that at a singl
```

go we can analyze the words in a cluster.

```
    </ul>
</li>
<br>
<li><strong>Apply Agglomerative Clustering on these feature sets:</strong>
    <ul>
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
<li>Apply agglomerative algorithm and try a different number of clusters like 2,5 etc.</li>
<li>Same as that of K-means, plot word clouds for each cluster and summarize in your own words
        <li>You can take around 5000 reviews or so(as this is very computationally expensive or
    </ul>
</li>
<br>
<br>
<li><strong>Apply DBSCAN Clustering on these feature sets:</strong>
    <ul>
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
<li>Find the best Eps using the <a href='https://stackoverflow.com/questions/12893492/choosing-
<li>Same as before, plot word clouds for each cluster and summarize in your own words what that
        <li>You can take around 5000 reviews for this as well.</li>
    </ul>
</li>
```

6.1 [5.1] K-Means Clustering

6.1.1 [5.1.1] Applying K-Means Clustering on BOW, SET 1

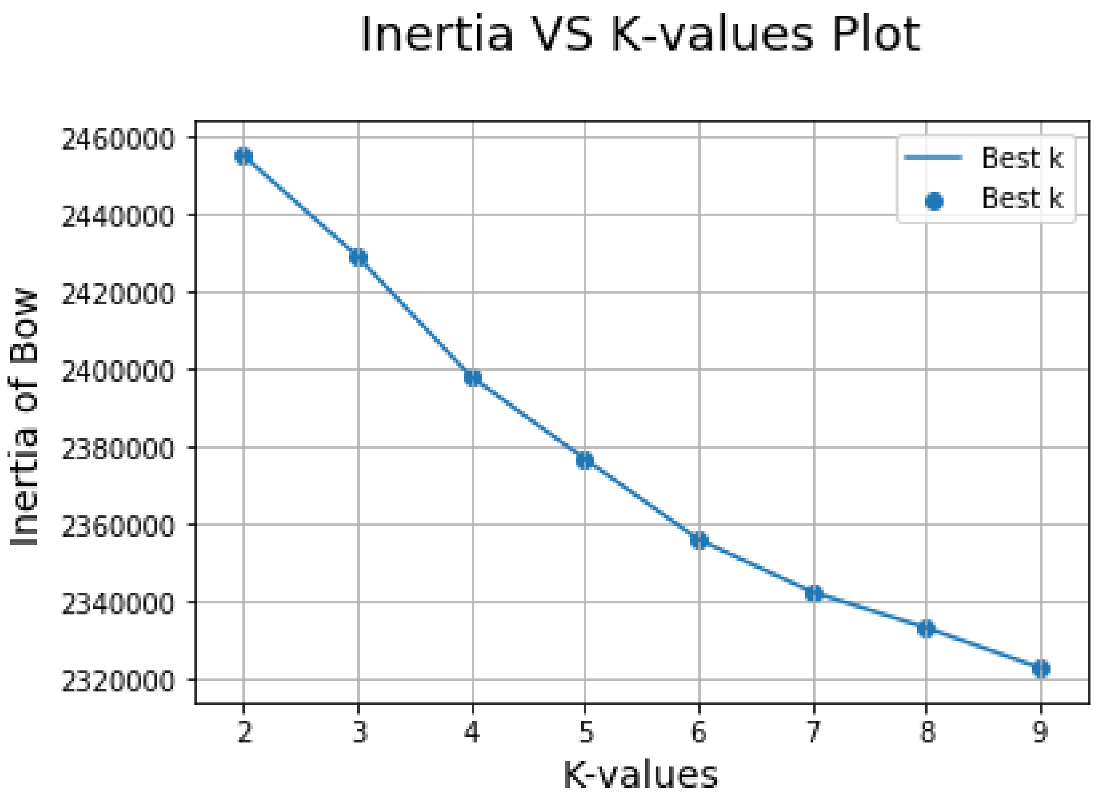
```
In [85]: from datetime import datetime
         start = datetime.now()

         k = [2,3,4,5,6,7,8,9]
         inertia_values_bow = []
         for i in k:
             k_means_bow = KMeans(random_state=0, n_clusters=i)
             k_means_bow = k_means_bow.fit(X_bow)
             inertia_values_bow.append(k_means_bow.inertia_)

         print("DONE")

         print("Time taken = ", datetime.now()-start)
```

```
DONE
Time taken =  1:30:41.395055
```

```
In [51]: print(len(inertia_values_bow))
```

```
8
```

```
In [87]: plt.plot(k, inertia_values_bow, label='Best k')
         plt.scatter(k, inertia_values_bow, label='Best k')

         plt.legend()
         plt.xlabel('K-values',size=14)
         plt.ylabel('Inertia of Bow',size=14)
         plt.title('Inertia VS K-values Plot\n',size=18)
         plt.grid()
         plt.show()
```



Here we are taking best value of k = 5

```
In [94]: kmeans_bow_best = KMeans(n_clusters=5, random_state=0)
         kmeans_bow_best = kmeans_bow_best.fit(X_bow)
```

```
In [109]: reviews = final['Text'].values
          # Getting all the reviews in different clusters
          cluster1 = []
          cluster2 = []
          cluster3 = []
          cluster4 = []
          cluster5 = []

          for i in range(kmeans_bow_best.labels_.shape[0]):
              if kmeans_bow_best.labels_[i] == 0:
                  cluster1.append(reviews[i])
              elif kmeans_bow_best.labels_[i] == 1:
                  cluster2.append(reviews[i])
              elif kmeans_bow_best.labels_[i] == 2:
                  cluster3.append(reviews[i])
              elif kmeans_bow_best.labels_[i] == 3:
```

```
                cluster4.append(reviews[i])
            else :
                cluster5.append(reviews[i])
```

In [111]:
```
type(cluster1)
```

Out[111]:
```
list
```

6.1.2 [5.1.2] Wordclouds of clusters obtained after applying k-means on BOW SET 1

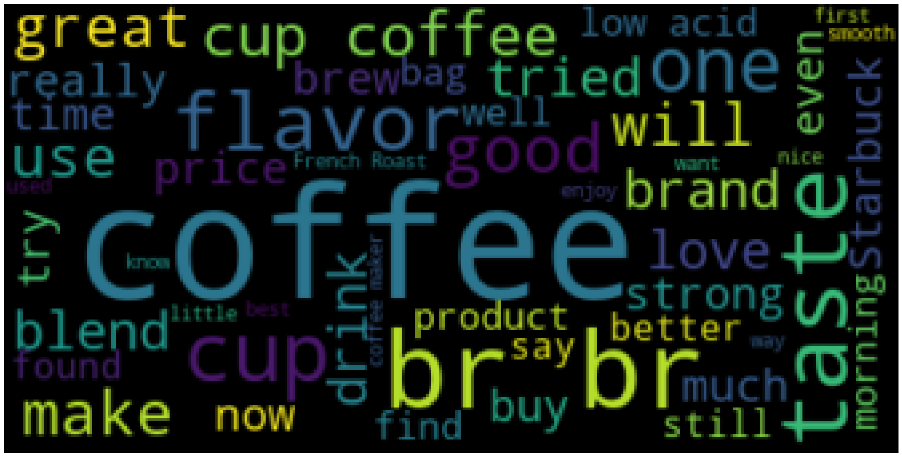
In [116]:
```
text=str(cluster1)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [110]:
```
type(text)
```

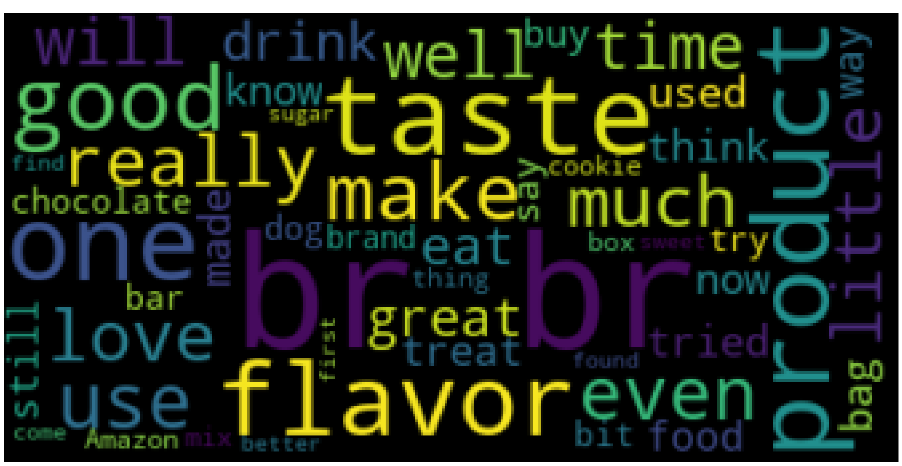
Out[110]:
```
str
```

In [104]:
```
text = str(cluster2)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene
```

```python
# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

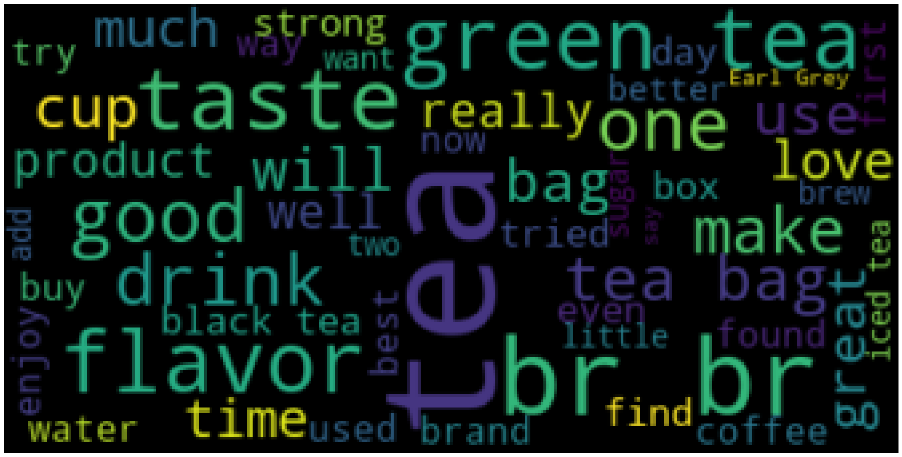



```python
In [105]: text = str(cluster3)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



```
In [106]: text = str(cluster4)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```


```
In [107]: text = str(cluster5)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```

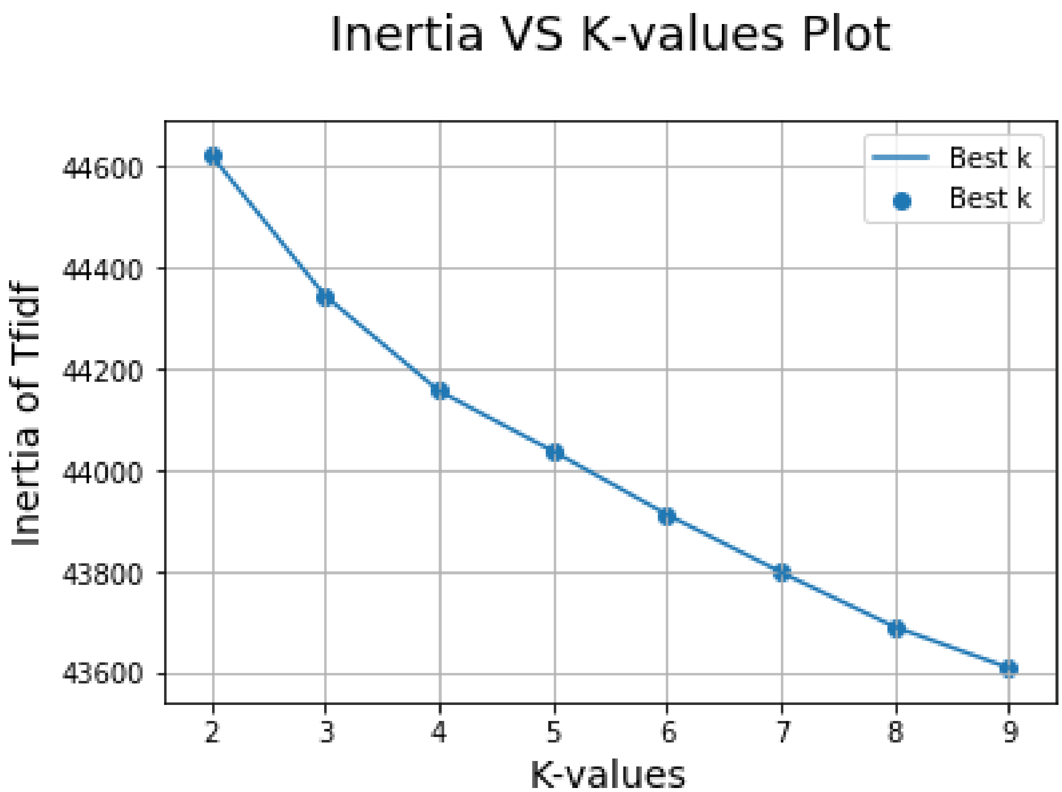


6.1.3 [5.1.3] Applying K-Means Clustering on TFIDF, SET 2

In [88]:
```
from datetime import datetime
start = datetime.now()

k = [2,3,4,5,6,7,8,9]
inertia_values_tfidf = []
for i in k:
    k_means_tfidf = KMeans(random_state=0, n_clusters=i)
    k_means_tfidf = k_means_tfidf.fit(X_tfidf)
    inertia_values_tfidf.append(k_means_tfidf.inertia_)

print("DONE")

print("Time taken = ", datetime.now()-start)
```

```
DONE
Time taken =  1:52:34.954290
```

In [89]:
```
plt.plot(k, inertia_values_tfidf , label='Best k')
plt.scatter(k, inertia_values_tfidf, label='Best k')

plt.legend()
plt.xlabel('K-values',size=14)
plt.ylabel('Inertia of Tfidf',size=14)
plt.title('Inertia VS K-values Plot\n',size=18)
plt.grid()
plt.show()
```



Here we are taking best value of k = 4

```
In [95]: kmeans_tfidf_best = KMeans(n_clusters=4, random_state=0)
         kmeans_tfidf_best = kmeans_tfidf_best.fit(X_tfidf)
```

```
In [125]: cluster_t1 = []
          cluster_t2 = []
          cluster_t3 = []
          cluster_t4 = []

          for i in range(kmeans_tfidf_best.labels_.shape[0]):
              if kmeans_tfidf_best.labels_[i] == 0:
                  cluster_t1.append(reviews[i])
              elif kmeans_tfidf_best.labels_[i] == 1:
                  cluster_t2.append(reviews[i])
              elif kmeans_tfidf_best.labels_[i] == 2:
                  cluster_t3.append(reviews[i])
              else :
                  cluster_t4.append(reviews[i])
```

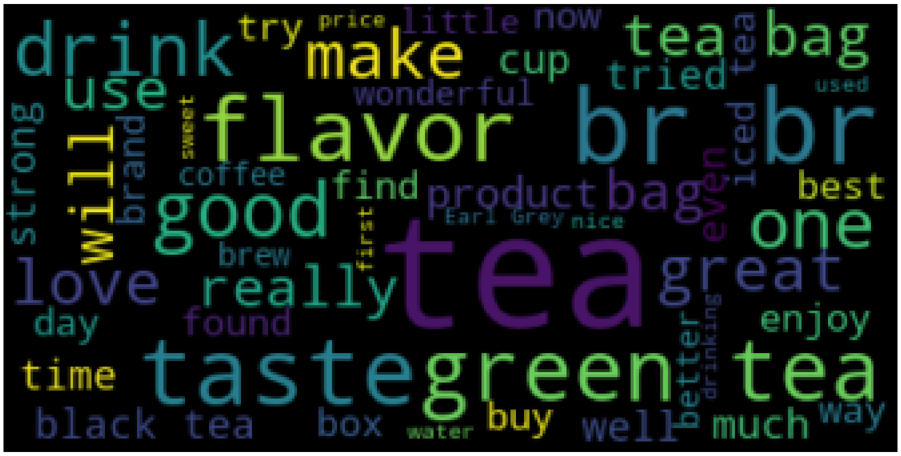
6.1.4 [5.1.4] Wordclouds of clusters obtained after applying k-means on TFIDF SET 2

In [119]:
```
text = str(cluster_t1)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [120]:
```
text = str(cluster_t2)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [121]:
```
text = str(cluster_t3)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

```
In [126]: text = str(cluster_t4)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```

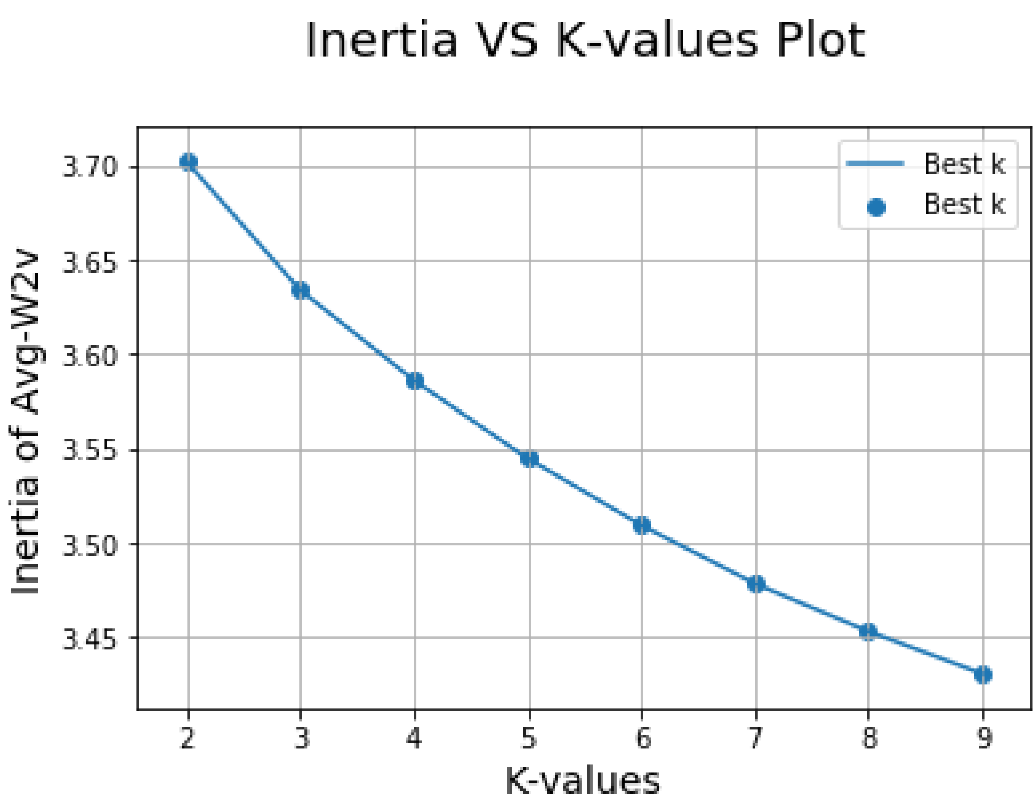


6.1.5 [5.1.5] Applying K-Means Clustering on AVG W2V, SET 3

```
In [90]: from datetime import datetime
         start = datetime.now()

         k = [2,3,4,5,6,7,8,9]
         inertia_values_aw2v = []
         for i in k:
             k_means_aw2v = KMeans(random_state=0, n_clusters=i)
             k_means_aw2v = k_means_aw2v.fit(sent_vectors)
             inertia_values_aw2v.append(k_means_aw2v.inertia_)

         print("DONE")

         print("Time taken = ", datetime.now()-start)
```

```
DONE
Time taken =  0:01:06.635534
```

```
In [91]: plt.plot(k, inertia_values_aw2v, label='Best k')
         plt.scatter(k, inertia_values_aw2v, label='Best k')

         plt.legend()
         plt.xlabel('K-values',size=14)
         plt.ylabel('Inertia of Avg-W2v',size=14)
         plt.title('Inertia VS K-values Plot\n',size=18)
         plt.grid()
         plt.show()
```



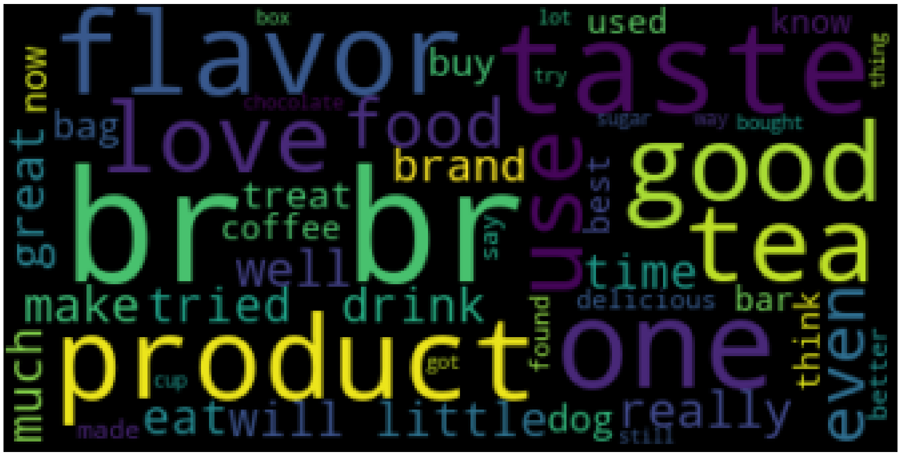
Here we are taking best value of k = 3

```
In [127]: kmeans_aw2v_best = KMeans(n_clusters=3, random_state=0)
          kmeans_aw2v_best = kmeans_aw2v_best.fit(sent_vectors)

In [138]: cluster_a1 = []
          cluster_a2 = []
          cluster_a3 = []

          for i in range(kmeans_aw2v_best.labels_.shape[0]):
              if kmeans_aw2v_best.labels_[i] == 0:
                  cluster_a1.append(reviews[i])
```

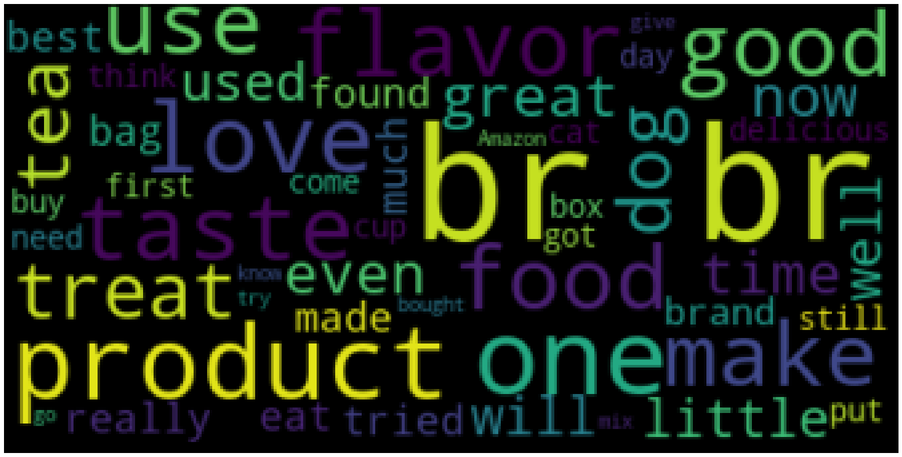
```
        elif kmeans_aw2v_best.labels_[i] == 1:
            cluster_a2.append(reviews[i])
        else :
            cluster_a3.append(reviews[i])
```

6.1.6 [5.1.6] Wordclouds of clusters obtained after applying k-means on AVG W2V SET 3

```
In [129]: text = str(cluster_a1)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```




```
In [130]: text = str(cluster_a2)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



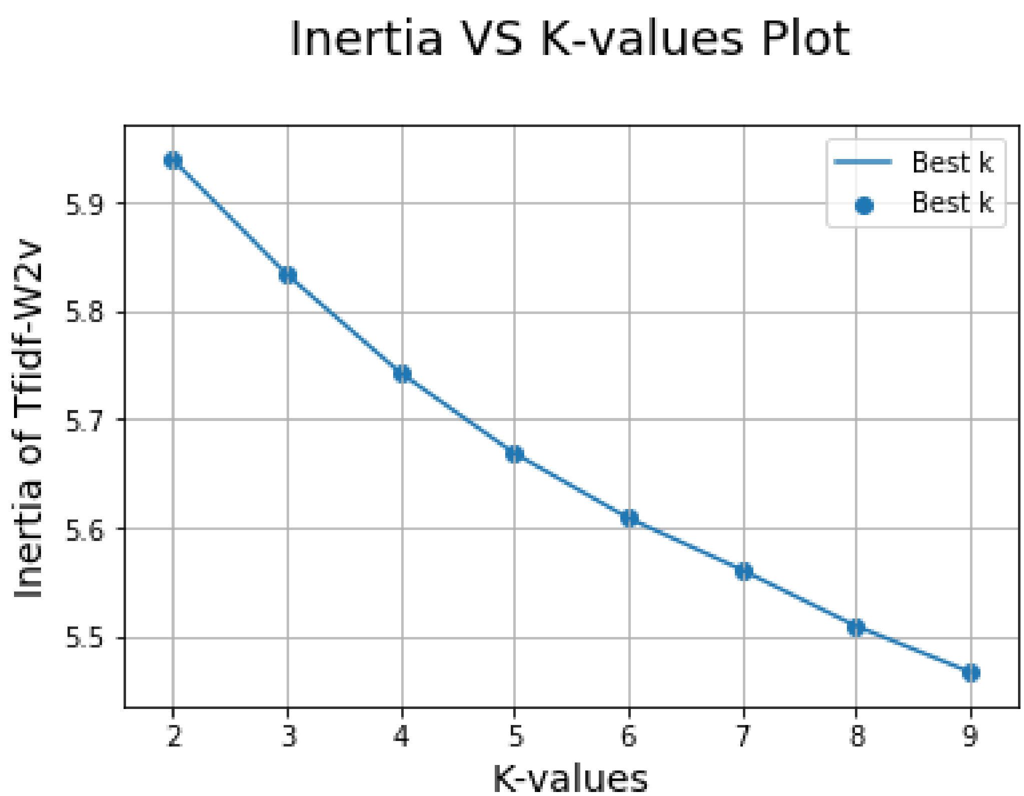
In [139]:
```
text = str(cluster_a3)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

6.1.7 [5.1.7] Applying K-Means Clustering on TFIDF W2V, SET 4

In [92]:
```
k = [2,3,4,5,6,7,8,9]
inertia_values_tfw2v = []
for i in k:
    k_means_tfw2v = KMeans(random_state=0, n_clusters=i)
    k_means_tfw2v = k_means_tfw2v.fit(tfidf_sent_vectors)
    inertia_values_tfw2v.append(k_means_tfw2v.inertia_)

print("DONE")
```

```
DONE
```

In [93]:
```
plt.plot(k, inertia_values_tfw2v, label='Best k')
plt.scatter(k, inertia_values_tfw2v, label='Best k')

plt.legend()
plt.xlabel('K-values',size=14)
plt.ylabel('Inertia of Tfidf-W2v',size=14)
plt.title('Inertia VS K-values Plot\n',size=18)
plt.grid()
plt.show()
```



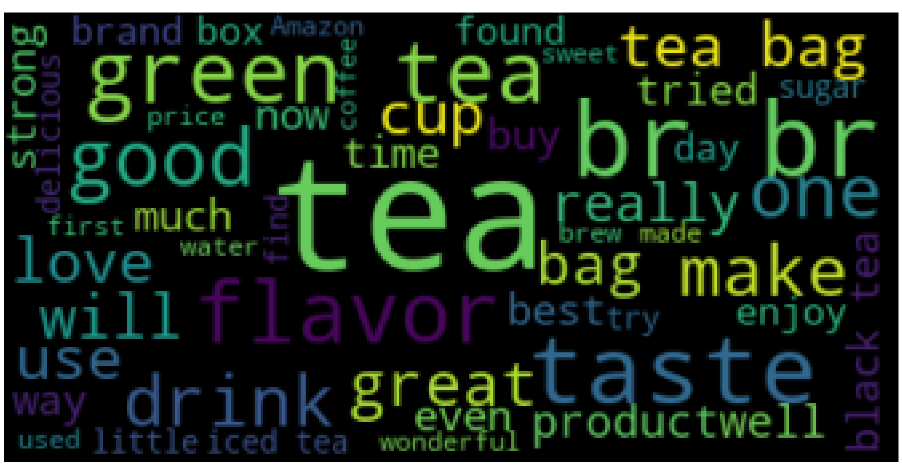
Here we are taking best value of k = 4

In [140]:
```
kmeans_tfw2v_best = KMeans(n_clusters=4, random_state=0)
kmeans_tfw2v_best = kmeans_tfw2v_best.fit(tfidf_sent_vectors)
```

In [141]:
```
cluster_w1 = []
cluster_w2 = []
cluster_w3 = []
cluster_w4 = []

for i in range(kmeans_tfw2v_best.labels_.shape[0]):
    if kmeans_tfw2v_best.labels_[i] == 0:
        cluster_w1.append(reviews[i])
    elif kmeans_tfw2v_best.labels_[i] == 1:
        cluster_w2.append(reviews[i])
    elif kmeans_tfw2v_best.labels_[i] == 2:
        cluster_w3.append(reviews[i])
    else :
        cluster_w4.append(reviews[i])
```

6.1.8 [5.1.8] Wordclouds of clusters obtained after applying k-means on TFIDF W2V SET 4

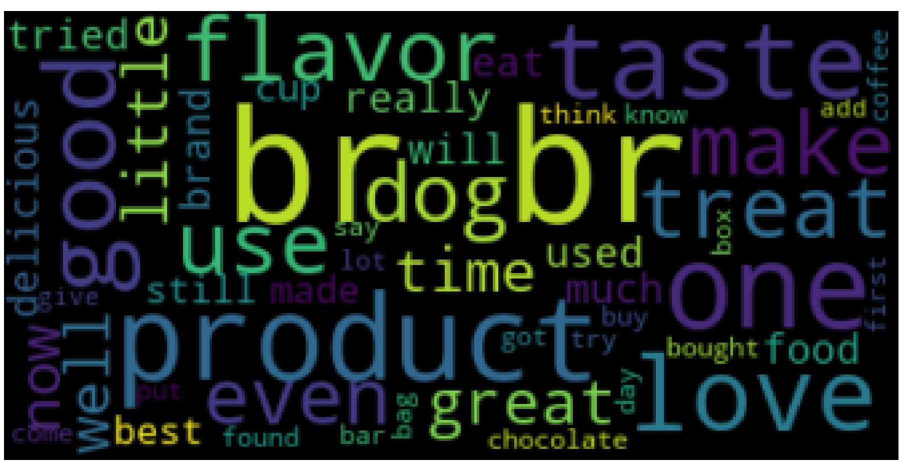
In [142]:
```
text = str(cluster_w1)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```



In [143]:
```python
text = str(cluster_w2)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [144]:
```python
text = str(cluster_w3)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```


```
In [145]: text = str(cluster_w4)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



6.2 [5.2] Agglomerative Clustering

6.2.1 [5.2.1] Applying Agglomerative Clustering on AVG W2V, SET 3

6.2.2 For Clusters = 2

In [214]:
```
agglo_aw2v_2 = AgglomerativeClustering(n_clusters=2)
agglo_aw2v_2 = agglo_aw2v_2.fit(sent_vectors)
```

In [225]:
```
cluster_a12 = []
cluster_a22 = []

for i in range(agglo_aw2v_2.labels_.shape[0]):
    if agglo_aw2v_2.labels_[i] == 0:
        cluster_a12.append(reviews[i])
    else :
        cluster_a22.append(reviews[i])
```

6.2.3 For Clusters = 4

In [215]:
```
agglo_aw2v_4 = AgglomerativeClustering(n_clusters=4)
agglo_aw2v_4 = agglo_aw2v_4.fit(sent_vectors)
```

In [228]:
```
cluster_a14 = []
cluster_a24 = []
cluster_a34 = []
cluster_a44 = []

for i in range(agglo_aw2v_4.labels_.shape[0]):
    if agglo_aw2v_4.labels_[i] == 0:
        cluster_a14.append(reviews[i])
    elif agglo_aw2v_4.labels_[i] == 1:
        cluster_a24.append(reviews[i])
    elif agglo_aw2v_4.labels_[i] == 2:
        cluster_a34.append(reviews[i])
    else :
        cluster_a44.append(reviews[i])
```

6.2.4 For Clusters = 5

In [216]:
```
agglo_aw2v_5 = AgglomerativeClustering(n_clusters=5)
agglo_aw2v_5 = agglo_aw2v_5.fit(sent_vectors)
```

In [233]:
```
cluster_a15 = []
cluster_a25 = []
cluster_a35 = []
cluster_a45 = []
cluster_a55 = []

for i in range(agglo_aw2v_5.labels_.shape[0]):
```

```
        if agglo_aw2v_5.labels_[i] == 0:
            cluster_a15.append(reviews[i])
        elif agglo_aw2v_5.labels_[i] == 1:
            cluster_a25.append(reviews[i])
        elif agglo_aw2v_5.labels_[i] == 2:
            cluster_a35.append(reviews[i])
        elif agglo_aw2v_5.labels_[i] == 3:
            cluster_a45.append(reviews[i])
        else :
            cluster_a55.append(reviews[i])
```

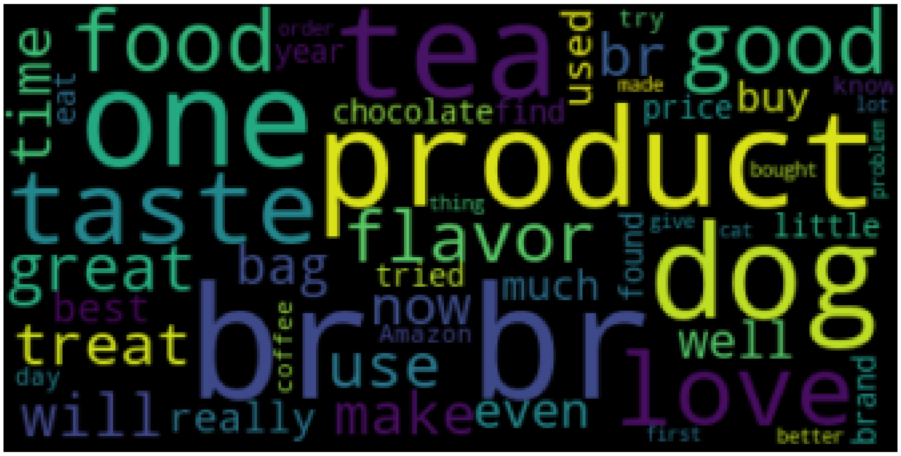
6.2.5 [5.2.2] Wordclouds of clusters obtained after applying Agglomerative Clustering on AVG W2V SET 3

For n_clusters=2

In [226]:
```
text = str(cluster_a12)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [227]:
```
text = str(cluster_a22)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene
```

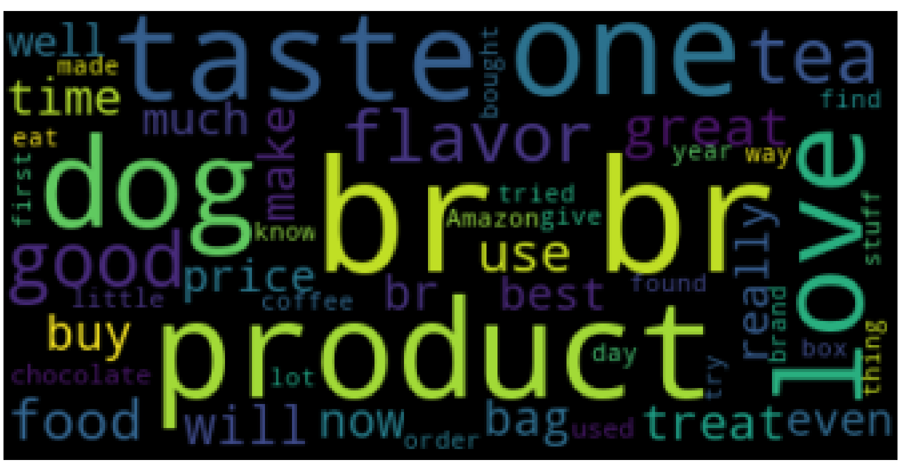
```
# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```



For n_clusters=4

In [229]:
```
text = str(cluster_a14)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```


```
In [230]: text = str(cluster_a24)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



In [231]:
```
text = str(cluster_a34)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [232]:
```
text = str(cluster_a44)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

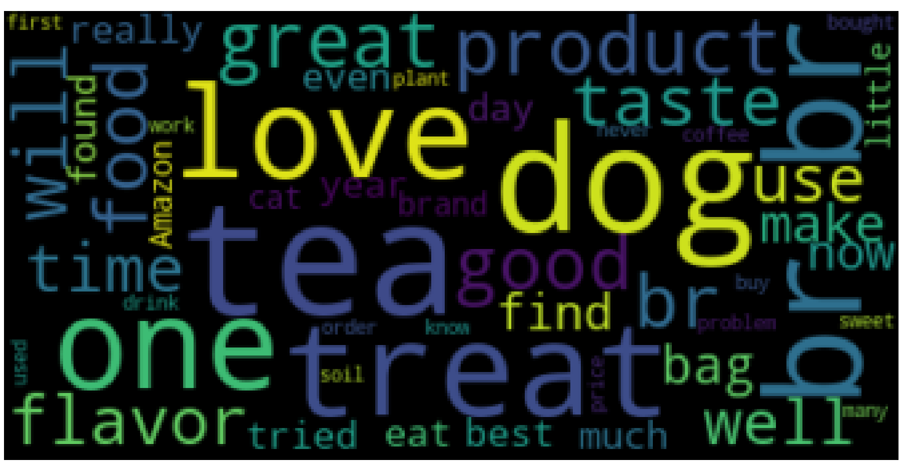
For n_clusters=5

```
In [234]: text = str(cluster_a15)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```

In [235]:
```
text = str(cluster_a25)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

In [236]:
```
text = str(cluster_a35)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```


```
In [237]: text = str(cluster_a45)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



```
In [238]: text = str(cluster_a55)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```

6.2.6 [5.2.3] Applying Agglomerative Clustering on TFIDF W2V, SET 4

6.2.7 For Clusters = 2

```
In [239]: agglo_tfw2v_2 = AgglomerativeClustering(n_clusters=2)
          agglo_tfw2v_2 = agglo_tfw2v_2.fit(tfidf_sent_vectors)

In [240]: cluster_w12 = []
          cluster_w22 = []

          for i in range(agglo_tfw2v_2.labels_.shape[0]):
              if agglo_tfw2v_2.labels_[i] == 0:
                  cluster_w12.append(reviews[i])
              else :
                  cluster_w22.append(reviews[i])
```

6.2.8 For Clusters = 3

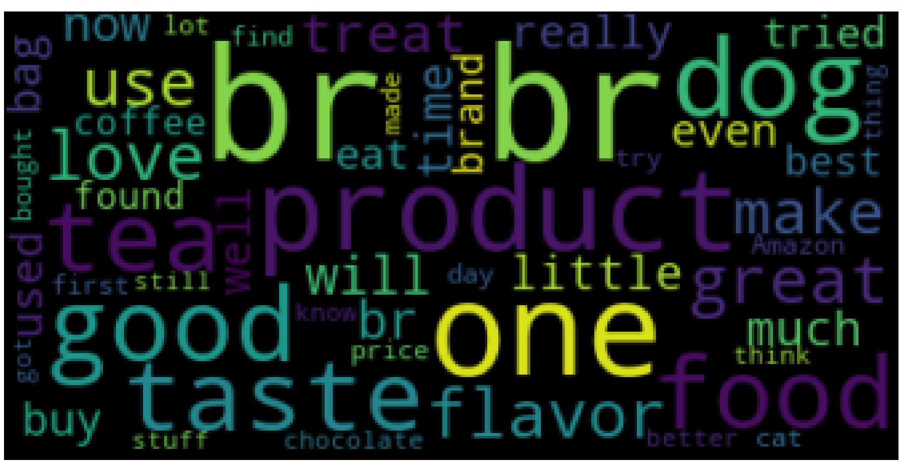
```
In [241]: agglo_tfw2v_3 = AgglomerativeClustering(n_clusters=3)
          agglo_tfw2v_3 = agglo_tfw2v_3.fit(tfidf_sent_vectors)
```

```
In [242]: cluster_w13 = []
          cluster_w23 = []
          cluster_w33 = []

          for i in range(agglo_tfw2v_3.labels_.shape[0]):
              if agglo_tfw2v_3.labels_[i] == 0:
                  cluster_w13.append(reviews[i])
              elif agglo_tfw2v_3.labels_[i] == 1:
                  cluster_w23.append(reviews[i])
              else :
                  cluster_w33.append(reviews[i])
```

6.2.9 [5.2.4] Wordclouds of clusters obtained after applying Agglomerative Clustering on TFIDF W2V SET 4

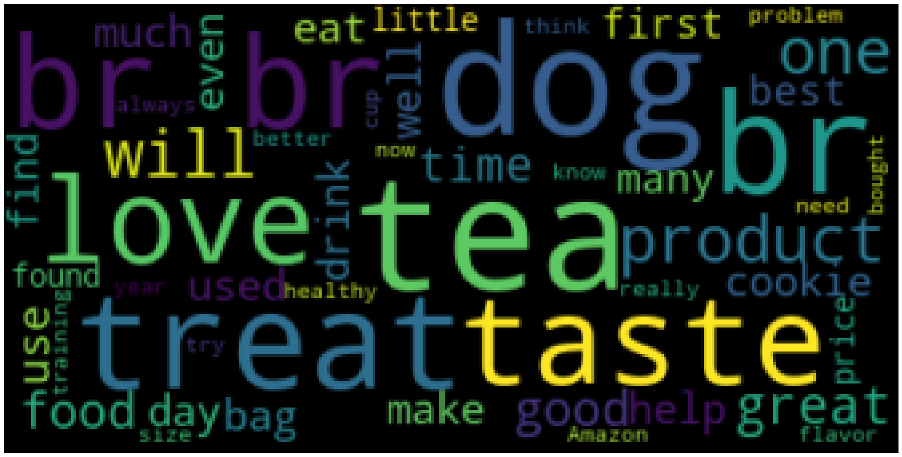
For n_clusters = 2

```
In [243]: text = str(cluster_w12)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



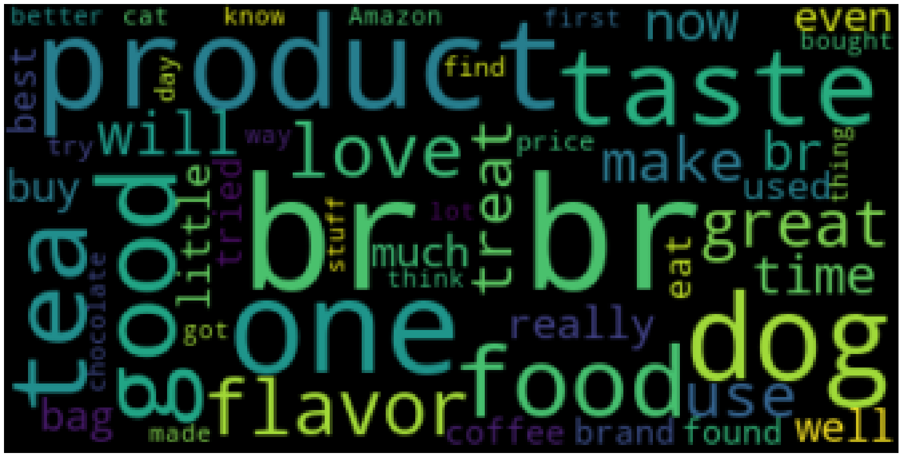

```
In [244]: text = str(cluster_w22)

          # Create and generate a word cloud image:
```

```
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

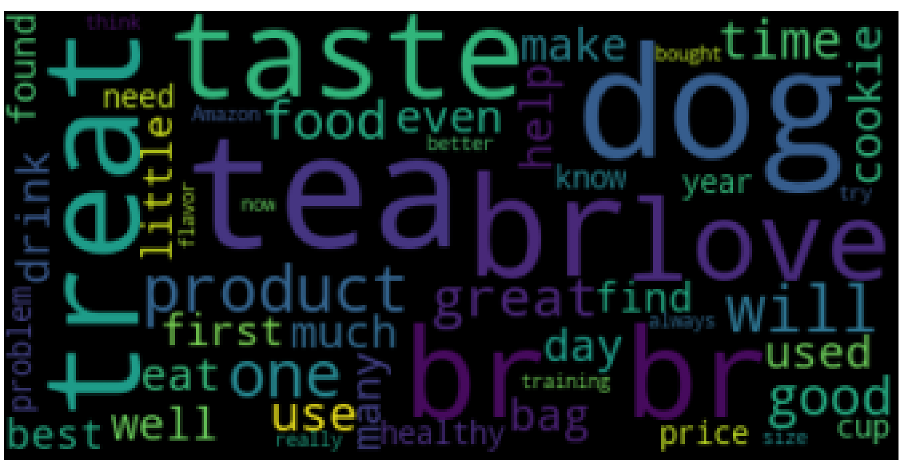


For n_clusters = 3

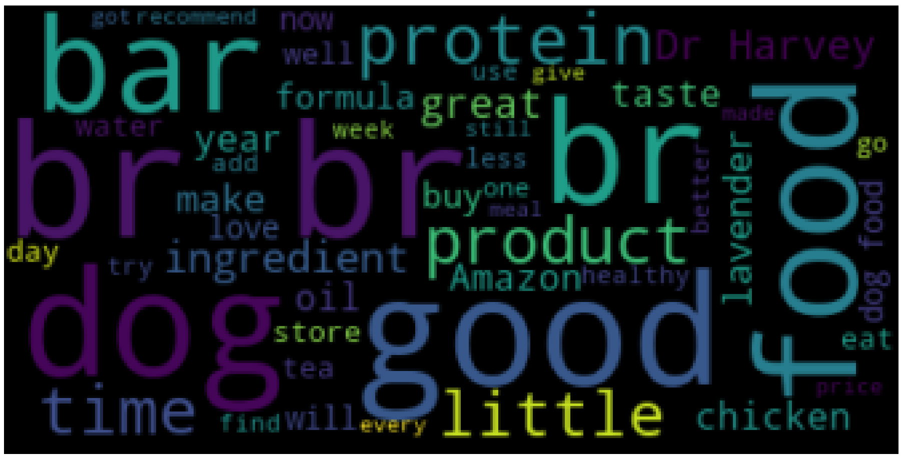
In [245]:
```
text = str(cluster_w13)

# Create and generate a word cloud image:
wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

# Display the generated image:
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```




```python
In [246]: text = str(cluster_w23)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



```
In [247]: text = str(cluster_w33)

          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").gene

          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```



6.3 [5.3] DBSCAN Clustering

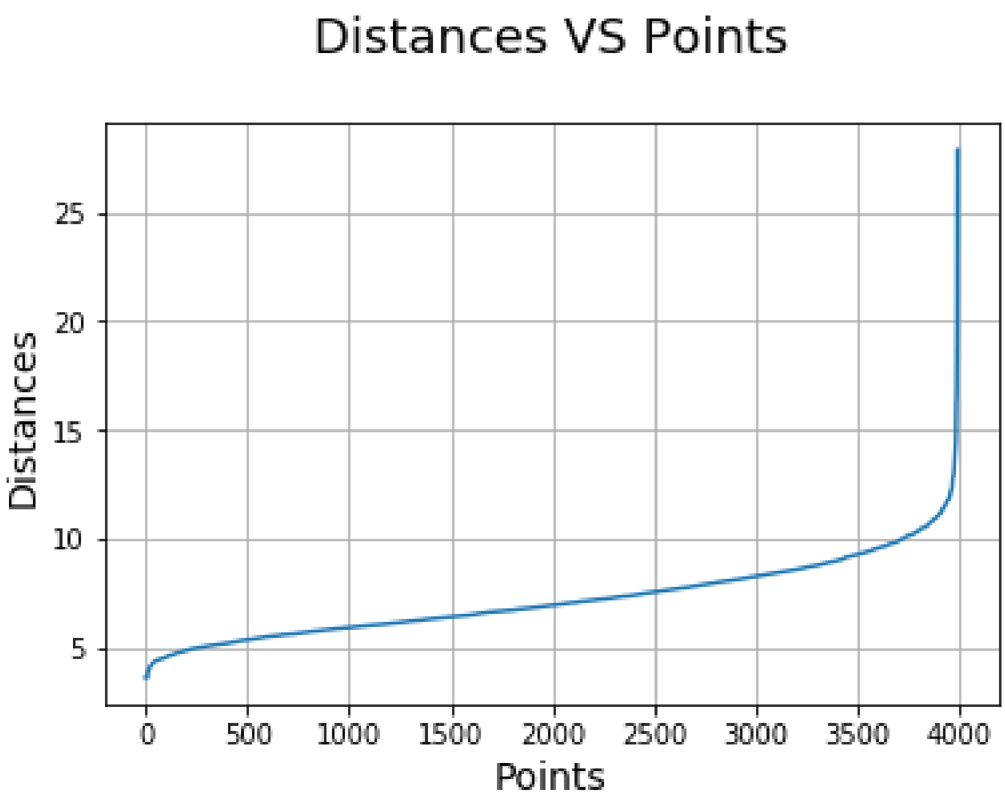
6.3.1 [5.3.1] Applying DBSCAN on AVG W2V, SET 3

To find correct eps

```
In [45]: scaler = preprocessing.StandardScaler()
         # Fit your data on the scaler object
         aw2v_data= scaler.fit_transform(sent_vectors)
```

```
In [46]: min_pts=2*aw2v_data.shape[1]
         distances=[]

         for data in aw2v_data:
             temp_dist=np.sort(np.sum((aw2v_data-data)**2,axis=1),axis=None)
             distances.append(temp_dist[100])

         sorted_distances=np.sort(distances)
         pt_index=[i for i in range(aw2v_data.shape[0])]
```

```
In [47]: # Plotting distances VS points
         import matplotlib.pyplot as plt
         plt.plot(pt_index, np.sqrt(sorted_distances))
         plt.xlabel('Points',size=14)
         plt.ylabel('Distances',size=14)
         plt.title('Distances VS Points\n',size=18)
         plt.grid()
         plt.show()
```



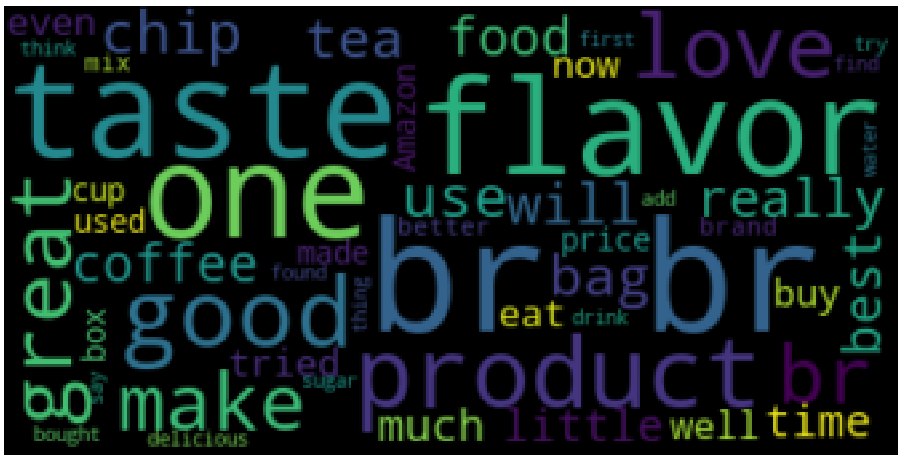
Here we are taking optimal value for eps = 11

```
In [39]: dbscan_aw2v_best = DBSCAN(eps=11, n_jobs=-1)
         dbscan_aw2v_best = dbscan_aw2v_best.fit(sent_vectors)
```

```
In [42]: reviews = final['Text'].values

         cluster_a1 = []

         for i in range(dbscan_aw2v_best.labels_.shape[0]):
             if dbscan_aw2v_best.labels_[i] == 0:
                 cluster_a1.append(reviews[i])
```

6.3.2 [5.3.2] Wordclouds of clusters obtained after applying DBSCAN on AVG W2V SET 3

```
In [43]: text = str(cluster_a1)

         # Create and generate a word cloud image:
         wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").genera

         # Display the generated image:
         plt.imshow(wordcloud, interpolation="bilinear")
         plt.axis("off")
         plt.show()
```

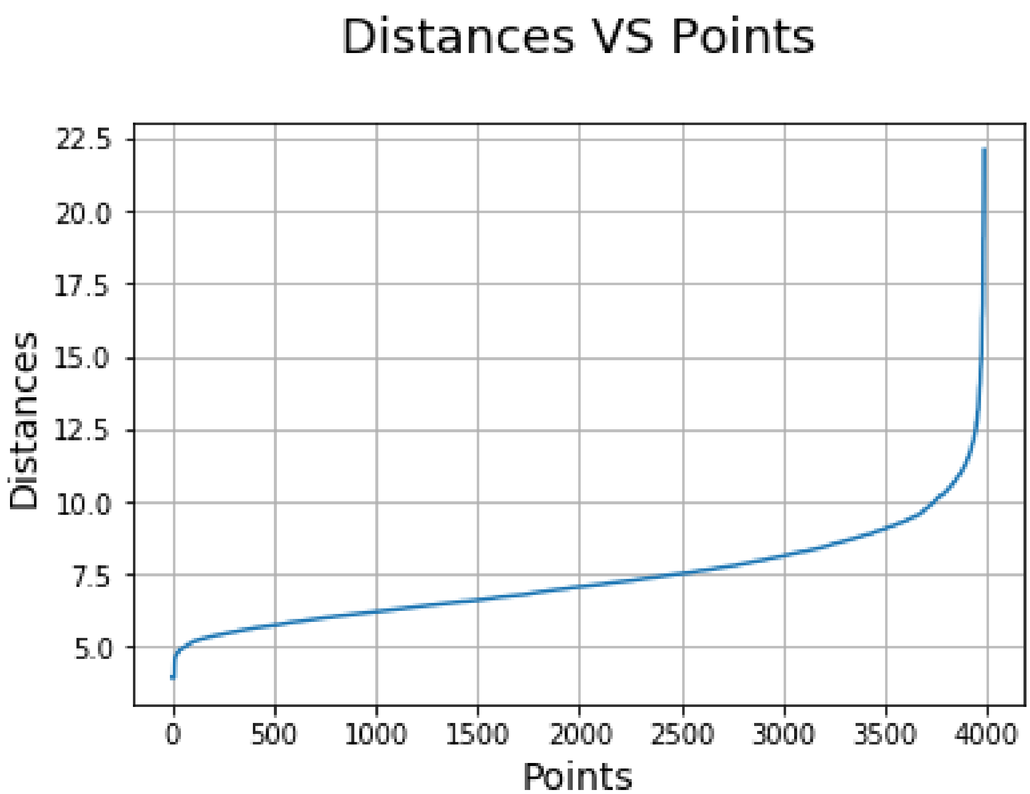


6.3.3 [5.3.3] Applying DBSCAN on TFIDF W2V, SET 4

To find correct eps

```
In [48]: scaler = preprocessing.StandardScaler()
         # Fit your data on the scaler object
         tfw2v_data= scaler.fit_transform(tfidf_sent_vectors)

In [49]: min_pts=2*tfw2v_data.shape[1]
         distances=[]

         for data in tfw2v_data:
             temp_dist=np.sort(np.sum((tfw2v_data-data)**2,axis=1),axis=None)
             distances.append(temp_dist[100])

         sorted_distances=np.sort(distances)
         pt_index=[i for i in range(tfw2v_data.shape[0])]
```

```
In [50]: # Plotting distances VS points
         import matplotlib.pyplot as plt
         plt.plot(pt_index, np.sqrt(sorted_distances))
         plt.xlabel('Points',size=14)
         plt.ylabel('Distances',size=14)
         plt.title('Distances VS Points\n',size=18)
         plt.grid()
         plt.show()
```



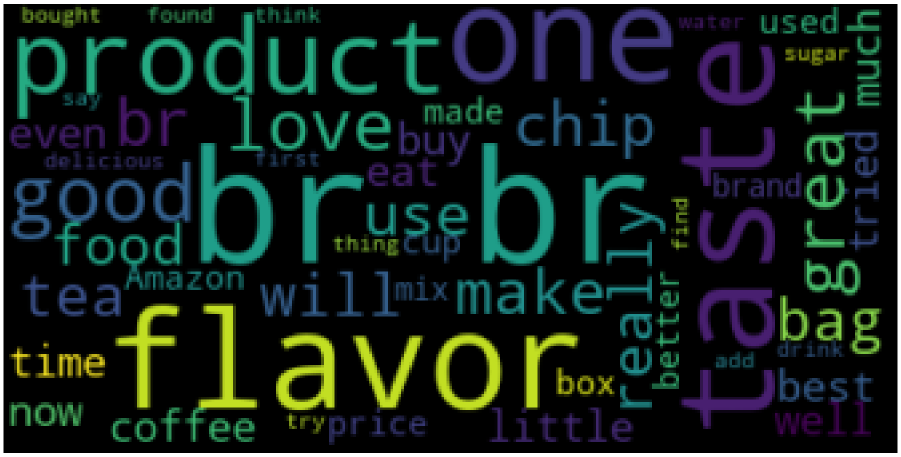
Here we are taking optimal value of eps = 10

```
In [51]: dbscan_tfw2v_best = DBSCAN(eps=10, n_jobs=-1)
         dbscan_tfw2v_best = dbscan_tfw2v_best.fit(tfidf_sent_vectors)
```

```
In [52]: cluster_w1 = []

         for i in range(dbscan_tfw2v_best.labels_.shape[0]):
             if dbscan_tfw2v_best.labels_[i] == 0:
                 cluster_w1.append(reviews[i])
```

6.3.4 [5.3.4] Wordclouds of clusters obtained after applying DBSCAN on TFIDF W2V SET 4

```
In [53]: text = str(cluster_w1)

         # Create and generate a word cloud image:
         wordcloud = WordCloud(max_font_size=70, max_words=50, background_color="black").genera

         # Display the generated image:
         plt.imshow(wordcloud, interpolation="bilinear")
         plt.axis("off")
         plt.show()
```



7 [6] Conclusions

```
In [276]: number= [1,2,3,4]
          cluster= ["K-means", "K-means", "K-means", "K-means"]
          model= ["Bow", "Tfidf", "Avg-w2v", "Tfidf-w2v"]
          k = ["5", "4", "3", "4"]

          #Initialize Prettytable
          ptable = PrettyTable()
          ptable.add_column("Index", number)
          ptable.add_column("Clustering", cluster)
          ptable.add_column("Model", model)
          ptable.add_column("n_clusters", k)

          print(ptable)

+-------+------------+-----------+------------+
| Index | Clustering |   Model   | n_clusters |
```

```
+--------+------------+-----------+------------+
|   1    |  K-means   |    Bow    |     5      |
|   2    |  K-means   |   Tfidf   |     4      |
|   3    |  K-means   |  Avg-w2v  |     3      |
|   4    |  K-means   | Tfidf-w2v |     4      |
+--------+------------+-----------+------------+
```

In [277]:
```python
number= [1,2]
cluster= ["Agglomerative", "Agglomerative"]
model= ["Avg-w2v", "Tfidf-w2v"]
k = ["2,4,5", "2,3"]

#Initialize Prettytable
ptable = PrettyTable()
ptable.add_column("Index", number)
ptable.add_column("Clustering", cluster)
ptable.add_column("Model", model)
ptable.add_column("n_clusters", k)

print(ptable)
```

```
+-------+---------------+-----------+------------+
| Index |   Clustering  |   Model   | n_clusters |
+-------+---------------+-----------+------------+
|   1   | Agglomerative |  Avg-w2v  |   2,4,5    |
|   2   | Agglomerative | Tfidf-w2v |    2,3     |
+-------+---------------+-----------+------------+
```

In [54]:
```python
number= [1,2]
cluster= ["DBSCAN", "DBSCAN"]
model= ["Avg-w2v", "Tfidf-w2v"]
e = ["11", "10"]

#Initialize Prettytable
ptable = PrettyTable()
ptable.add_column("Index", number)
ptable.add_column("Clustering", cluster)
ptable.add_column("Model", model)
ptable.add_column("Best eps", e)

print(ptable)
```

```
+-------+------------+-----------+----------+
| Index | Clustering |   Model   | Best eps |
+-------+------------+-----------+----------+
|   1   |   DBSCAN   |  Avg-w2v  |    11    |
|   2   |   DBSCAN   | Tfidf-w2v |    10    |
```

+--------+------------+-----------+----------+

1. For K-means we have taken 50000 datapoints and for Agglomerative and DBSCAN we have taken 4000 datapoints each.
2. While implementing K-means, best value for n_clusters for all models is find using elbow-knee method
3. For Agglomerative clustering, we have taken different values of n_clusters(2,3,4,5) for Avg-w2v model and tfidf-w2v.
4. Similarly in DBSCAN clustering, we have taken different values of eps(1,3,5,7) for both models.
5. For DBSCAN, just one cluster is plotted for each model.
6. Each cluster includes words related to some particular data.