```
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score, classification_report
import matplotlib.pyplot as plt
from wordcloud import WordCloud, STOPWORDS
from nltk.corpus import stopwords
from nltk.tokenize import word tokenize
import nltk
import string
import re
from tqdm.contrib.concurrent import process_map
nltk.download('stopwords')
from bs4 import BeautifulSoup
# import spacy
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')
      [nltk_data] Downloading package stopwords to /root/nltk_data...
      [nltk data]
                    Unzipping corpora/stopwords.zip.
      [nltk_data] Downloading package wordnet to /root/nltk_data...
      True
# mounting google drive to get the salite file
from google.colab import drive
drive_path = drive.mount('/content/drive/')
     Mounted at /content/drive/
# storing the file path in a variable
file_path = "/content/drive/MyDrive/foods.txt"
# Reading the content of the files using readlines
# readlines reads each line in a iteration
# Storing all the data in the variable file_data
with open(file_path, 'r', encoding='latin-1') as file:
    file data = file.readlines()
# Creating an empty lists of each column of the our dataframe
productIds, userIds, profileNames, helpfulness, scores, times, summaries, texts = ([] for _ in range(8))
# Going through each line of the data and appending them into different columns (separating the data column wise)
for line in file data:
    if line.startswith('product/productId:'):
         productIds.append(line.split(': ')[1].strip())
    elif line.startswith('review/userId:'):
         userIds.append(line.split(': ')[1].strip())
    elif line.startswith('review/profileName:'):
         profileNames.append(line.split(': ')[1].strip())
    elif line.startswith('review/helpfulness:'):
         helpfulness.append(line.split(': ')[1].strip())
    elif line.startswith('review/score:'):
         scores.append(line.split(': ')[1].strip())
    elif line.startswith('review/time:'):
         times.append(line.split(': ')[1].strip())
     elif line.startswith('review/summary:'):
         summaries.append(line.split(': ')[1].strip())
    elif line.startswith('review/text:'):
         texts.append(line.split(': ')[1].strip())
# checking if the data split correctly into different columns
print("Sameple data of productIds: ", productIds[:5])
print("Sameple data of userIds: ", userIds[:5])
print("Sameple data of profileNames: ", profileNames[:5])
print("Sameple data of helpfulness: ", helpfulness[:5])
print("Sameple data of scores: ", scores[:5])
print("Sameple data of times: ", times[:5])
print("Sameple data of summaries: ", summaries[:5])
print("Sameple data of texts: ", texts[:2])
     Sameple data of productIds: ['B001E4KFG0', 'B00813GRG4', 'B000LQOCH0', 'B000UA0QIQ', 'B006K2ZZ7K']
Sameple data of userIds: ['A3SGXH7AUHU8GW', 'A1D87F6ZCVE5NK', 'A8XLMWJIXXAIN', 'A395B0RC6FGVXV', 'A1UQRSCLF8GW1T']
Sameple data of profileNames: ['delmartian', 'dll pa', 'Natalia Corres "Natalia Corres"', 'Karl', 'Michael D. Bigham "M. Wassir"']
Sameple data of helpfulness: ['1/1', '0/0', '1/1', '3/3', '0/0']
Sameple data of scores: ['5.0', '1.0', '4.0', '2.0', '5.0']
Sameple data of times: ['1303862400', '1346976000', '1219017600', '1307923200', '1350777600']
```

Sameple data of summaries: ['Good Quality Dog Food', 'Not as Advertised', '"Delight" says it all', 'Cough Medicine', 'Great taffy' Sameple data of texts: ['I have bought several of the Vitality canned dog food products and have found them all to be of good quali

```
# Creating a data frame with the above column data
foods_df = pd.DataFrame({
    'product/productId': productIds,
    'review/userId': userIds,
    'review/profileName': profileNames,
   'review/helpfulness': helpfulness,
    'review/score': scores,
    'review/time': times,
    'review/summary': summaries,
    'review/text': texts
foods df.head()
        product/productId
                                review/userId review/profileName review/helpfulness rev
              B001E4KFG0 A3SGXH7AUHU8GW
     0
                                                         delmartian
                                                                                   1/1
              B00813GRG4
                            A1D87F6ZCVE5NK
                                                                                   0/0
                                                             dll pa
     1
                                                      Natalia Corres
     2
              B000LQOCH0
                              ABXLMWJIXXAIN
                                                                                   1/1
                                                     "Natalia Corres"
# converting all the data into lower case
foods_df['review/text'] = foods_df['review/text'].str.lower()
foods_df['review/summary'] = foods_df['review/summary'].str.lower()
foods_df['review/profileName'] = foods_df['review/profileName'].str.lower()
# checking if there is nan data
print(foods_df[foods_df == 'nan'].count())
    product/productId
     review/userId
    review/profileName
    review/helpfulness
                           0
    review/score
                            0
     review/time
     review/summary
                            2
     review/text
                            0
    dtype: int64
# checking if there is none data
print(foods_df[foods_df == 'none'].count())
     product/productId
                           0
     review/userId
                            a
     review/profileName
                           20
     review/helpfulness
                            0
     review/score
                            0
     review/time
                            0
     review/summary
     review/text
    dtype: int64
# the data which is nan
foods_df[foods_df['review/profileName'] == 'nan']
```

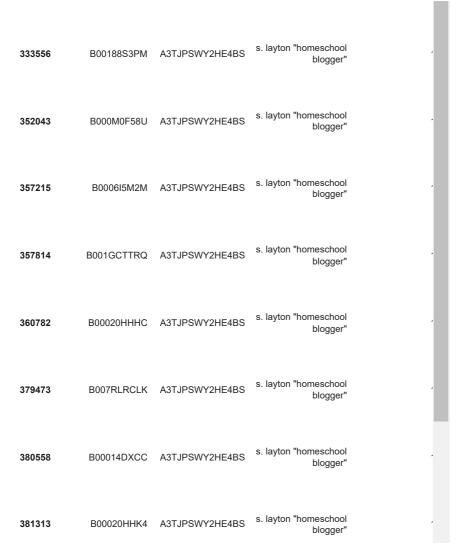
0.0+1 W			Data CCL accigi	mient + Oweta Bant
	product/productId	review/userId	review/profileName	review/helpfulne
25509	B000LKZB4Y	A36BVYD0NT7Z0F	nan	
29042	B000MPRP4C	A1DJV0XTCCSZ8F	nan	
38874	B000AYDGZ2	A36BVYD0NT7Z0F	nan	
49800	B000CRHQN0	A2LYFY32LXQDON	nan	
67077	B0006348H2	A2P0P67Y55SNOX	nan	
106550	B001EQ5DG0	A1P500QXEG3IUZ	nan	
110490	B00438XVGU	AOISTMMFDR9LU	nan	
113995	B000EYRHL2	AUQ465FVJ8ID8	nan	
137613	B000CQE3HS	AGT3BYX5P9SLH	nan	
163191	B000CQID1A	AGT3BYX5P9SLH	nan	
215456	B0014X5O1C	A1DJV0XTCCSZ8F	nan	
220566	B0034EDLS2	AOZHN8BHN0Y1O	nan	
235366	B0034EDMCW	AOZHN8BHN0Y1O	nan	
237199	B000EDM772	A29D3R6BWL2I88	nan	
291337	B004WJTMUE	A2XUKU2YKB9FHH	nan	
292867	B001E5DXH2	A20B063XORM0EG	nan	

DOOGTETOTIV ACIETMANTEDDOLLI

306751 B000R11W8E AGT3BYX5P9SLH nan  320131 B0003Z6W32E AGISTMMFDR9LU nan  327104 B001EQ54QE A3BJM4BT38KVQQ nan  373765 B004WTHCQ2 A59FXNKPGM2I4 nan  383570 B00451WLYI AGISTMMFDR9LU nan  425852 B0034EDMLI AOZHN8BHN0Y1O nan  431598 B000W5P0KI A36BVYDONT7Z0F nan 13  433664 B001LQCOIS A59FXNKPGM2I4 nan  440825 B008LFAS08 ACOE8TXIYABB5 nan  440825 B0034EDM2W AQZHN8BHN0Y1O nan  440826 B0034EDM2W AGZHN8BHN0Y1O nan  483361 B0006Z7NGK AGUUTD07ZXDOU nan  490412 B000CQE3IC AGT3BYX5P9SLH nan	8:34 PM			Data 602 - assignment 4 - Sweta Dant
320131 B003Z6W32E AOISTMMFDR9LU nan  327104 B001EQ54QE A3BJM4BT38KVOQ nan  373765 B004WTHCO2 A59FXNKPGM214 nan  383570 B00451WLYI AOISTMMFDR9LU nan  425852 B0034EDMLI AOZHN8BHN0Y1O nan  431598 B000W5P0KI A36BVYD0NT7Z0F nan 13  433664 B001LQCOIS A59FXNKPGM214 nan  440825 B008LFAS08 AC0E8TXIYABB5 nan  440825 B008LFAS08 AC0E8TXIYABB5 nan  443966 B0034EDM2W AOZHN8BHN0Y1O nan  483361 B0006Z7NOK AGUUTD07ZXD0U nan  490412 B000CQE3IC AGT3BYXSP9SLH nan	301147	DUUJZOZGZK	AOISTIMINIFDRAFO	пап
327104 B001EQ54QE A3BJM4BT38KVOQ nan  373765 B004WTHCO2 A59FXNKPGM2I4 nan  383570 B00451WLYI AOISTMMFDR9LU nan  425852 B0034EDMLI AOZHN8BHN0Y1O nan  431598 B000W5P0KI A36BVYD0NT7Z0F nan 13  433664 B001LQCOIS A59FXNKPGM2I4 nan  440825 B008LFAS08 AC0E8TXIYABB5 nan  443966 B0034EDM2W AOZHN8BHN0Y1O nan  483361 B0006Z7NOK AGUUTD07ZXD0U nan  490412 B000CQE3IC AGT3BYX5P9SLH nan  493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	306751	B000RI1W8E	AGT3BYX5P9SLH	nan
373765 B004WTHCO2 A59FXNKPGM2I4 nan  383570 B00451WLYI AOISTMMFDR9LU nan  425852 B0034EDMLI AOZHN8BHN0Y1O nan  431598 B000W5P0KI A36BVYD0NT7Z0F nan 13  433664 B001LQCOIS A59FXNKPGM2I4 nan  440825 B008LFAS08 AC0E8TXIYABB5 nan  440826 B0034EDM2W AOZHN8BHN0Y1O nan  483361 B0006Z7NOK AGUUTD07ZXD0U nan  490412 B000CQE3IC AGT3BYX5P9SLH nan  493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	320131	B003Z6W32E	AOISTMMFDR9LU	nan
383570 B00451WLYI AOISTMMFDR9LU nan 425852 B0034EDMLI AOZHN8BHN0Y1O nan 431598 B000W5P0KI A36BVYD0NT7Z0F nan 13 433664 B001LQCOIS A59FXNKPGM2I4 nan 440825 B008LFAS08 AC0E8TXIYABB5 nan 443966 B0034EDM2W AOZHN8BHN0Y1O nan 483361 B0006Z7NOK AGUUTD07ZXD0U nan 490412 B000CQE3IC AGT3BYX5P9SLH nan 493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	327104	B001EQ54QE	A3BJM4BT38KVOQ	nan
425852       B0034EDMLI       AOZHN8BHN0Y1O       nan         431598       B000W5P0KI       A36BVYD0NT7Z0F       nan       13         433664       B001LQCOIS       A59FXNKPGM2I4       nan         440825       B008LFAS08       AC0E8TXIYABB5       nan         443966       B0034EDM2W       AOZHN8BHN0Y1O       nan         483361       B0006Z7NOK       AGUUTD07ZXD0U       nan         490412       B000CQE3IC       AGT3BYX5P9SLH       nan         493563       B0028GWGY2       A2JOYB7DQTT0W6       nan	373765	B004WTHCO2	A59FXNKPGM2I4	nan
431598 B000W5P0KI A36BVYD0NT7Z0F nan 13 433664 B001LQCOIS A59FXNKPGM2I4 nan 440825 B008LFAS08 AC0E8TXIYABB5 nan 443966 B0034EDM2W AOZHN8BHN0Y1O nan 483361 B0006Z7NOK AGUUTD07ZXD0U nan 490412 B000CQE3IC AGT3BYX5P9SLH nan 493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	383570	B00451WLYI	AOISTMMFDR9LU	nan
433664       B001LQCOIS       A59FXNKPGM2I4       nan         440825       B008LFAS08       AC0E8TXIYABB5       nan         443966       B0034EDM2W       AOZHN8BHN0Y10       nan         483361       B0006Z7NOK       AGUUTD07ZXD0U       nan         490412       B000CQE3IC       AGT3BYX5P9SLH       nan         493563       B0028GWGY2       A2JOYB7DQTT0W6       nan	425852	B0034EDMLI	AOZHN8BHN0Y1O	nan
440825       B008LFAS08       AC0E8TXIYABB5       nan         443966       B0034EDM2W       AOZHN8BHN0Y1O       nan         483361       B0006Z7NOK       AGUUTD07ZXD0U       nan         490412       B000CQE3IC       AGT3BYX5P9SLH       nan         493563       B0028GWGY2       A2JOYB7DQTT0W6       nan	431598	B000W5P0KI	A36BVYD0NT7Z0F	nan 13
443966       B0034EDM2W       AOZHN8BHN0Y1O       nan         483361       B0006Z7NOK       AGUUTD07ZXD0U       nan         490412       B000CQE3IC       AGT3BYX5P9SLH       nan         493563       B0028GWGY2       A2JOYB7DQTT0W6       nan	433664	B001LQCOIS	A59FXNKPGM2I4	nan
483361 B0006Z7NOK AGUUTD07ZXD0U nan  490412 B000CQE3IC AGT3BYX5P9SLH nan  493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	440825	B008LFAS08	AC0E8TXIYABB5	nan
490412 B000CQE3IC AGT3BYX5P9SLH nan  493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	443966	B0034EDM2W	AOZHN8BHN0Y1O	nan
493563 B0028GWGY2 A2JOYB7DQTT0W6 nan	483361	B0006Z7NOK	AGUUTD07ZXD0U	nan
POOLE DOOLDOVA/EQ ACCOUNTS 1	490412	B000CQE3IC	AGT3BYX5P9SLH	nan
	493563	B0028GWGY2	A2JOYB7DQTT0W6	nan
. d+l(+00dc d+l;b0/10m/cummab/:  ;bab;)   (+00dc d+l;b0/10m/cummab/:  ;5050;)				

 $foods\_df[(foods\_df['review/summary'] == 'nan') \mid (foods\_df['review/summary'] == 'none') \mid (foods\_df['review/summary'] == '1') \mid (foods\_df['revie$ 

, 0.0-1 IVI			Data 002 doolgin	mont i owota bank
	product/productId	review/userId	review/profileName	review/helpfuln
33958	B00412W76S	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
40548	B00020HHRW	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
101106	B0014B0HWK	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
102979	B000FVDWU4	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
117515	B0016B7Z32	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
119242	B000E1DSTK	A20EAC7J61W08W	hollis mccollum	
144396	B001TNXSZG	A3JYBMJJWX5ABL	rbeccaboopsie	
155712	B0009VO58S	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
178290	B00073IVAQ	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
198474	B000FVBYCW	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
212691	В00020ННАО	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
223957	B004H6MV28	A11OJJ3SJK5P5C	nancy m. clement caron	
237565	B000ELGPAO	A15AMT9T9A1309	film-friend	
293906	В00020ННМ2	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
299495	B00142BX68	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	
300961	B000VJYTZM	A3TJPSWY2HE4BS	s. layton "homeschool blogger"	

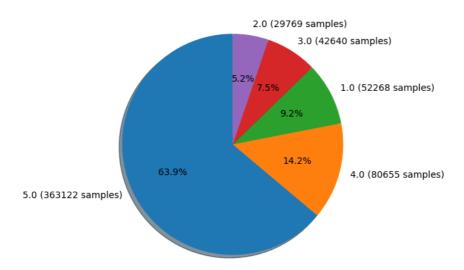


We can see a lot of data missing in the summaries column but there is an associated text column present. But, if we see the data carefully we observe that there is a lot of duplicate data.

```
BUUU/3JVFU A31JPSWY2HE4BS
      386283
                                                                 bloggor"
# we replaced all the profile names that were nan with anonymous
foods_df['review/profileName'] = foods_df['review/profileName'].replace('nan', 'anonymous')
print(foods_df[foods_df['review/profileName'] == 'nan'].count())
     product/productId
                           0
     review/userId
     review/profileName
                           0
     review/helpfulness
                           0
                           0
     review/score
     review/time
                           0
     review/summary
                           0
     review/text
                           0
     dtype: int64
\ensuremath{\text{\#}} we replaced all the summarires that were nan with anonymous
foods_df['review/summary'] = foods_df['review/summary'].replace('nan', 'no summary')
print(foods_df[foods_df['review/summary'] == 'nan'].count())
     product/productId
     review/userId
                           0
     review/profileName
     review/helpfulness
                           0
     review/score
     review/time
                           0
     review/summary
                           0
     review/text
                           0
     dtype: int64
```

We can plot to see how many of our reviews are postive(>3), negative(<3) and neutral(=3)

### Distribution of ratings in reviews



We can see a lot of positive reviews and a very little neutral reviews

- 1. positive reviews: 78% (approximately)
- 2. Negative reviews: 14% (approximately)
- 3. Neutral reviews: 8% (approximately)

```
# foods_df.dropna(inplace=True)
# foods_df = foods_df.drop_duplicates()
# foods_df
```

Now since we want to classify if a data is positive or negative we have to decide which scores are positive and negative. considerations:

- 1. score = 4, 5 as positive
- 2. score = 1, 2 as negative
- 3. score = 3 as neutral So, we can remove the data with score = 3 to make the data even cleaner

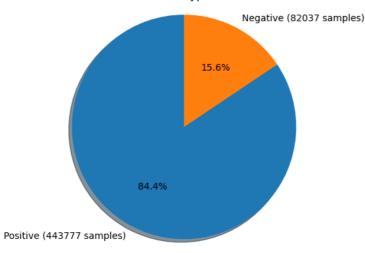
```
# converting score into float
foods_df['review/score'] = foods_df['review/score'].astype(float)

foods_df = foods_df[foods_df['review/score'] != 3]
foods_df
```

review/helpfulness	review/profileName	review/userId	product/productId	
1/1	delmartian	A3SGXH7AUHU8GW	B001E4KFG0	0
0/C	dll pa	A1D87F6ZCVE5NK	B00813GRG4	1
1/1	natalia corres "natalia corres"	ABXLMWJIXXAIN	B000LQOCH0	2
3/3	karl	A395BORC6FGVXV	B000UA0QIQ	3
O/C	michael d. bigham "m. wassir"	A1UQRSCLF8GW1T	B006K2ZZ7K	4
O/C	lettie d. carter	A28KG5XORO54AY	B001E07N10	568449

<sup>#</sup> Assigning review type based on score
foods\_df.loc[foods\_df["review/score"] > 3, 'review/type'] = 'Positive'
foods\_df.loc[foods\_df["review/score"] < 3, 'review/type'] = 'Negative'
foods\_df</pre>

## Distribution of type of review



We can see that most of the reviews are positive. The postive reviews comprise almost 85% of the total data we have.

We can use word cloud to understand the frequently used words depending on the type of review

```
positive_review = foods_df[foods_df["review/type"] == "Positive"]

text = " ".join(review for review in positive_review['review/summary'] + positive_review['review/text'])

print ("There are {} words in the combination of all review.".format(len(text)))

# Create stopword list:

default_stopwords=set(stopwords.words('english'))

# Generate a word cloud image

wordcloud = WordCloud(stopwords=default_stopwords, background_color="white", width=1200, height=600).generate(text)

# Display the generated image:

plt.figure()

plt.itile('Positive reviews wordcloud')

plt.imshow(wordcloud, interpolation='bilinear')

plt.axis("off")

plt.show()
```

There are 185505236 words in the combination of all review.

#### Positive reviews wordcloud



The words like like, delicious, great, good, best have appeared very frequently. We can also see that there are lot of words that are not helpful for our classification. It has a lot of html tag related data that can be seen in the above word cloud. We can also infer that the number 1 has also very frequently occured in our data which has to be cleaned.

```
negative_review = foods_df[foods_df["review/type"] == "Negative"]

text = " ".join(review for review in negative_review['review/summary'] + negative_review['review/text'])

print ("There are {} words in the combination of all review.".format(len(text)))

# Create stopword list:

default_stopwords=set(stopwords.words('english'))

# Generate a word cloud image

wordcloud = WordCloud(stopwords=default_stopwords, background_color="white", width=1200, height=600).generate(text)

# Display the generated image:

plt.figure()

plt.title('Negative reviews wordcloud')

plt.imshow(wordcloud, interpolation='bilinear')

plt.axis("off")

plt.show()
```

There are 38844364 words in the combination of all review.



Words like bad, don't like can be seen Similar to the postive review wordcloud we can observe the dominance of the html tag data that has to be cleaned.

We have to check if there was redundant data, the data that might have been duplicated. There are rows of data that have the same information.

```
# duplicate rows
mask_duplicated_reviews = foods_df.duplicated(subset=["review/userId","product/productId","review/time"], keep='first')
count_duplicated_reviews = mask_duplicated_reviews.value_counts()
sum_reviews = count_duplicated_reviews.sum()
perc_duplicated_reviews = (count_duplicated_reviews/sum_reviews) * 100
print(sum_reviews)
print(perc_duplicated_reviews)
     525814
              99.299182
     False
     True
               0.700818
     dtype: float64
# removing duplicate rows in a data frame
duplicate = foods_df[mask_duplicated_reviews]
duplicate.sort_values(by = ['review/profileName'])
```

	product/productId	review/userId	review/profileName	review/helpfulness
359571	B007M832YY	A3A1OA237FOZFK	#1 amazon fan	0/0
359572	B007M832YY	A3A1OA237FOZFK	#1 amazon fan	0/0
30985	B007M83302	A3A1OA237FOZFK	#1 amazon fan	0/0
30984	B007M83302	A3A1OA237FOZFK	#1 amazon fan	0/0
547610	B006HYLW32	A3A1OA237FOZFK	#1 amazon fan	0/0
247331	B000EOXQS0	A1JLE30SBP6J3A	zefran	0/0
445314	B000ODH4BG	A1JLE30SBP6J3A	zefran	0/0
445315	B000ODH4BG	A1JLE30SBP6J3A	zefran	0/0
445313	B000ODH4BG	A1JLE30SBP6J3A	zefran	0/0

<sup>#</sup> delete the duplicate rows

 $foods\_df = foods\_df[\sim\!mask\_duplicated\_reviews]$ 

foods\_df

```
review/userId review/profileName review/helpfulu
     product/productId
0
           B001E4KFG0 A3SGXH7AUHU8GW
                                                   delmartian
          B00813GRG4
1
                         A1D87F6ZCVE5NK
                                                       dll pa
                                          natalia corres "natalia
                          ABXLMWJIXXAIN
2
          B000LQOCH0
                                                      corres"
3
           B000UA0QIQ A395BORC6FGVXV
                                                         karl
```

```
# duplicate
mask_duplicated_reviews = foods_df.duplicated(subset=["review/userId","product/productId","review/summary"], keep='first')
count_duplicated_reviews = mask_duplicated_reviews.value_counts()

sum_reviews = count_duplicated_reviews.sum()
perc_duplicated_reviews = (count_duplicated_reviews/sum_reviews) * 100
print(sum_reviews)
print(perc_duplicated_reviews)

# removing duplicate rows in a data frame
duplicate = foods_df[mask_duplicated_reviews]
duplicate.sort_values(by = ['review/profileName'])
```

```
False 99.950395
True 0.049605
dtype: float64
    product/productId review/userId review/profileName review/helpfulne

435906 B000LKXQCS AWM1KZ2MDOVWJ a. winters "be good humans."
```

# delete the duplicate rows
foods\_df = foods\_df[~mask\_duplicated\_reviews]
foods\_df

	product/productId	review/userId	review/profileName	review/helpful
0	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	
1	B00813GRG4	A1D87F6ZCVE5NK	dll pa	
2	B000LQOCH0	ABXLMWJIXXAIN	natalia corres "natalia corres"	
3	B000UA0QIQ	A395BORC6FGVXV	karl	
4	B006K2ZZ7K	A1UQRSCLF8GW1T	michael d. bigham "m. wassir"	
568449	B001E07N10	A28KG5XORO54AY	lettie d. carter	
568450	B003S1WTCU	A3I8AFVPEE8KI5	r. sawyer	
568451	B004l613EE	A121AA1GQV751Z	pksd "pk_007"	
568452	B004l613EE	A3IBEVCTXKNOH	kathy a. welch "katwel"	
568453	B001LR2CU2	A3LGQPJCZVL9UC	srfell17	
21870 rc	ows × 9 columns			

```
# duplicate
mask_duplicated_reviews = foods_df.duplicated(subset=["review/userId","product/productId","review/text"], keep='first')
count_duplicated_reviews = mask_duplicated_reviews.value_counts()

sum_reviews = count_duplicated_reviews.sum()
perc_duplicated_reviews = (count_duplicated_reviews/sum_reviews) * 100
print(sum_reviews)
print(perc_duplicated_reviews)

# removing duplicate rows in a data frame
duplicate = foods_df[mask_duplicated_reviews]
duplicate.sort_values(by = ['review/profileName'])
```

True	99.990994 0.009006			
dtype:	float64 <pre>product/productId</pre>	review/userId	review/profileName	review/helpfulr
488254	B0013A0QXC	A3K5C7JVGRD7EM	b. van gelder "senseo"	
464614	B000UBD88A	A3K5C7JVGRD7EM	b. van gelder "senseo"	
126174	B000XQ5HDQ	A21Z8B8XSZ4R17	eric r. dierks	
463539	B000GW67KY	A21Z8B8XSZ4R17	eric r. dierks	
302871	B000GW0UGG	A21Z8B8XSZ4R17	eric r. dierks	
10884	B0034KP00S	A1TMAVN4CEM8U8	gunner	
562165	B004HOSGWE	A1TMAVN4CEM8U8	gunner	
225034	B001LNTY70	A1TMAVN4CEM8U8	gunner	
229970	B000ZSX4GE	A1TMAVN4CEM8U8	gunner	
307041	B004HOOZEW	A1TMAVN4CEM8U8	gunner	
307043	B004HOOZEW	A1TMAVN4CEM8U8	gunner	
351106	B0034KN29O	A1TMAVN4CEM8U8	gunner	
221975	B0049Z9ANU	A1TMAVN4CEM8U8	gunner	
370161	B000ZSZ5S4	A1TMAVN4CEM8U8	gunner	
370163	B000ZSZ5S4	A1TMAVN4CEM8U8	gunner	

491262	B008114GDW	A1TMAVN4CEM8U8	gunner
513329	B004HOLD60	A1TMAVN4CEM8U8	gunner
513331	B004HOLD60	A1TMAVN4CEM8U8	gunner
562163	B004HOSGWE	A1TMAVN4CEM8U8	gunner
347897	B000ZT15EQ	A1TMAVN4CEM8U8	gunner
195161	B0049Z5OSK	A1TMAVN4CEM8U8	gunner
225032	B001LNTY70	A1TMAVN4CEM8U8	gunner
134893	B004HOQE64	A1TMAVN4CEM8U8	gunner
43719	B0049ZCF9G	A1TMAVN4CEM8U8	gunner
43464	B001EQ4P2I	A1TMAVN4CEM8U8	gunner
43462	B001EQ4P2I	A1TMAVN4CEM8U8	gunner
158908	B001TH4C2A	A1TMAVN4CEM8U8	gunner
78166	B004MC0CNW	A1TMAVN4CEM8U8	gunner
81453	B001EQ4RBM	A1TMAVN4CEM8U8	gunner
81455	B001EQ4RBM	A1TMAVN4CEM8U8	gunner

12/5/23, 8:34 PM

96132

B004HOLD4W A1TMAVN4CEM8U8

96134 B004HOLD4W A1TMAVN4CEM8U8 gunner

As we observed in the word cloud there is a lot of data with the html tags. So, using beautiful soup we are deleting the data that includes words like br, .com

```
# Function to remove HTML tags from a string
def remove_html_tags(text):
   soup = BeautifulSoup(text, 'html.parser')
   return soup.get_text()
    # Replace <br> tags with spaces
   for br in soup.find_all('br'):
       br.replace_with(' ')
   return soup.get_text()
foods_df['review/text'] = foods_df['review/text'].apply(remove_html_tags)
foods_df['review/summary'] = foods_df['review/summary'].apply(remove_html_tags)
foods_df
```

```
<ipython-input-27-2164b4b2f235>:3: MarkupResemblesLocatorWarning: The input looks
    soup = BeautifulSoup(text, 'html.parser')
<ipython-input-27-2164b4b2f235>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stablefoods_df['review/text'] = foods_df['review/text'].apply(remove_html_tags)
<ipython-input-27-2164b4b2f235>:3: MarkupResemblesLocatorWarning: The input looks
    soup = BeautifulSoup(text, 'html.parser')
<ipython-input-27-2164b4b2f235>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using lacfore indexer call indexed = value instead
```

There are a lot of times when humans express emotions with a lot of charaters where not necessary like soooo goooddd. We are trying to eliminate those characters by deleting the characters which have the same repeated character for more than 3 times.

```
review/userId review/nrofileName review/helnful
               product/productId
# removing words with repeated alphabets
def remove_words_with_repeated_characters(sentence):
    pattern = re.compile("\s*\b(?=\w*(\w)\1{2,})\w*\b")
    clean_text = re.sub(pattern,' ',sentence)
    return (clean_text)
# apply the function:
foods_df['review/summary'] = foods_df['review/summary'].apply(remove_words_with_repeated_characters)
foods_df['review/text'] = foods_df['review/text'].apply(remove_words_with_repeated_characters)
foods df.head()
     <ipython-input-28-0c3f8c00e636>:9: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/us">https://pandas.pydata.org/pandas-docs/stable/us</a>
       foods df['review/summary'] = foods_df['review/summary'].apply(remove_words_with_rep
     <ipython-input-28-0c3f8c00e636>:10: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/us">https://pandas.pydata.org/pandas-docs/stable/us</a>
       foods_df['review/text'] = foods_df['review/text'].apply(remove_words_with_repeated_
         product/productId
                                  review/userId review/profileName review/helpfulness rev
               B001F4KFG0 A3SGXH7AUHU8GW
      0
                                                                                         1/1
                                                             delmartian
               B00813GRG4
                               A1D87F6ZCVE5NK
                                                                                         0/0
                                                                 dll pa
                                                   natalia corres "natalia
               B000LQOCH0
                                 ABXLMWJIXXAIN
                                                                                         1/1
      2
                                                                corres'
      3
               B000UA0QIQ
                              A395BORC6FGVXV
                                                                   karl
                                                                                         3/3
                B006K2ZZ7K A1UQRSCLF8GW1T michael d. bigham "m.
                                                                                         0/0
     5218/U rows × 9 columns
```

We observed in our word cloud that the number 1 was repeated a lot of times. There might be a lot of numerical data in the text columns like that which are noise for us. So, we are cleaning numerical data.

```
# removing digits
def remove_digits(text):
    pattern = r'[^a-zA-z.,!?/:;\"\'\s]'
    return re.sub(pattern, '', text)

# apply the function:
foods_df['review/summary'] = foods_df['review/summary'].apply(remove_digits)
foods_df['review/text'] = foods_df['review/text'].apply(remove_digits)
foods_df.head()
```

Try using .loc[row\_indexer,col\_indexer] = value instead

```
<ipython-input-29-dleabc9a2ba0>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-foods_df['review/summary'] = foods_df['review/summary'].apply(remove_digits)
<ipython-input-29-dleabc9a2ba0>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-foods\_df['review/text'] = foods\_df['review/text'].apply(remove\_digits)</a>

review/	review/summary	review/time	review/score	review/helpfulness	review/profileName	review/userId	product/productId	
i have bo several o vi canneo	good quality dog food	1303862400	5.0	1/1	delmartian	A3SGXH7AUHU8GW	B001E4KFG0	0
pro ari labele jumbo sa peai	not as advertised	1346976000	1.0	0/0	dll pa	A1D87F6ZCVE5NK	B00813GRG4	1
this confe that been are	"delight" says it all	1219017600	4.0	1/1	natalia corres "natalia corres"	ABXLMWJIXXAIN	B000LQOCH0	2
if you lookin the se ingredie	cough medicine	1307923200	2.0	3/3	karl	A395BORC6FGVXV	B000UA0QIQ	3
great ta a great p there w	great taffy	1350777600	5.0	0/0	michael d. bigham "m. wassir"	A1UQRSCLF8GW1T	B006K2ZZ7K	4

While classifying data having punctutaions and special charcters just increases the amount of data but not useful data.

```
# create function for punctuation and special characters removal:
def remove_special_chars_punctuations(sentence):
    # match a single character not present in the set (basically anything other than a-z and A-Z)
    pattern = re.compile("[^a-zA-Z]+")
    clean_text = re.sub(pattern,' ',sentence).strip()
    return clean_text

# apply the function:
foods_df['review/summary'] = foods_df['review/summary'].apply(remove_special_chars_punctuations)
foods_df['review/text'] = foods_df['review/text'].apply(remove_special_chars_punctuations)
foods_df.head()
```

```
cipython-input-30-24e128c81ff2>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us foods_df['review/summary'] = foods_df['review/summary'].apply(remove_special_chars_cipython-input-30-24e128c81ff2>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
```

DOUBTIN OU MOUGHIMOHOUT

STOP words are a major thing than can be eliminated while cleaning text data. Stop words are a set of commomly used word in a language. These words include 'a', 'the', 'is', 'are' etc. These words usually have a very little almost no importance in our classification. Eliminating these words will give us only the useful words in a big sentence which will help us better classify.

```
# cleaning the stop words
stop_words = set(stopwords.words('english'))
foods_df['review/text'] = foods_df['review/text'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop_words)]))
foods_df['review/summary'] = foods_df['review/summary'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop_words)])
foods_df
```

```
cipython-input-31-bf2535701b8d>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stablefoods_df['review/text'] = foods_df['review/text'].apply(lambda x: ' '.join([word cipython-input-31-bf2535701b8d>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stablefoods_df['review/summary'] = foods_df['review/summary'].apply(lambda x: ' '.join product/productId review/userId review/profileName review/helpfulic
```

We are plotting the word cloud after cleaning the data to see how well we were able to clean the data.

```
positive_review = foods_df[foods_df["review/type"] == "Positive"]
text = " ".join(review for review in positive_review['review/text'] + ' ' + positive_review['review/summary'])
print ("There are {} words in the combination of all review.".format(len(text)))

# Create stopword list:
default_stopwords=set(stopwords.words('english'))

# Generate a word cloud image
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)

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

There are 111719718 words in the combination of all review.

#### Positive reviews wordcloud



After cleaning the data and removing the unnecessary data we can see that our word cloud has words that are relavent to the positive feedback. We can see that the html data and numerical data that was present in the plot before is eliminated.

```
negative_review = foods_df[foods_df["review/type"] == "Negative"]
text = " ".join(review for review in negative_review['review/text'] + ' ' + negative_review['review/summary'])
print ("There are {} words in the combination of all review.".format(len(text)))

# Create stopword list:
default_stopwords=set(stopwords.words('english'))

# Generate a word cloud image
wordcloud = WordCloud(background_color="white", width=1200, height=600).generate(text)

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

There are 22594232 words in the combination of all review.

# Negative reviews wordcloud

```
Coffee is bought surviving and control of the contr
```

```
# downloading the needed resources
# Download necessary resources
nltk.download('punkt')
nltk.download('wordnet')

# lemmatizing the data
def lemmatize_text(text):
    lemmatizer = WordNetLemmatizer()
    tokens = word_tokenize(text)
    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in tokens]
    return ' '.join(lemmatized_tokens)

foods_df['lemmatized_text'] = foods_df['review/text'].apply(lemmatize_text)
foods_df['lemmatized_summary'] = foods_df['review/summary'].apply(lemmatize_text)

# after lemmatizing
foods_df.head(10)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
     [nltk_data]
                    Unzipping tokenizers/punkt.zip.
     [nltk_data] Downloading package wordnet to /root/nltk_data...
                    Package wordnet is already up-to-date!
     [nltk data]
     <ipython-input-34-0314e85d9ffa>:13: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable">https://pandas.pydata.org/pandas-docs/stable</a>
        foods_df['lemmatized_text'] = foods_df['review/text'].apply(lemmatize_text)
      <ipython-input-34-0314e85d9ffa>:14: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable">https://pandas.pydata.org/pandas-docs/stable</a>
# making a new column
foods_df['clean_combined_text'] = foods_df['lemmatized_summary'] + ' ' + foods_df['lemmatized_text']
foods_df.head()
     <ipython-input-35-10ad7eefa6ad>:2: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/us">https://pandas.pydata.org/pandas-docs/stable/us</a> foods_df['clean_combined_text'] = foods_df['lemmatized_summary'] + ' ' + foods_df['
          product/productId
                                    review/userId review/profileName review/helpfulness rev
      0
                B001E4KFG0 A3SGXH7AUHU8GW
                                                                                             1/1
                                                                delmartian
      1
                B00813GRG4
                                A1D87F6ZCVE5NK
                                                                     dll pa
                                                                                             0/0
                                                      natalia corres "natalia
      2
               BOOOL QOCHO
                                  ABXI MW.IIXXAIN
                                                                                             1/1
                                                                   corres"
      3
                B000UA0QIQ
                                A395BORC6FGVXV
                                                                      karl
                                                                                             3/3
                 B006K2ZZ7K A1UQRSCLF8GW1T michael d. bigham "m.
                                                                                             0/0
                                                                   wassir
# Splitting the data into train and test data
X_train, X_test, y_train, y_test = train_test_split(foods_df['clean_combined_text'], foods_df['review/score'], test_size=0.2, random_sta
# Vectorizing the text
# Bags of words
vectorizer = CountVectorizer()
X_train_text = vectorizer.fit_transform(X_train)
X_test_text = vectorizer.transform(X_test)
                                                                                                  Naive Bayes classifier
# creating a naive bayes classifier
classifier = MultinomialNB(force alpha=True)
# fit the data to the classifier
classifier.fit(X_train_text, y_train)
                 MultinomialNB
      MultinomialNB(force_alpha=True)
```

```
# Evaluating the model
y_prediction = classifier.predict(X_test_text)
# accuracy
accuracy = accuracy_score(y_test, y_prediction)
print("Accuracy", accuracy)
Logistic regression
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(max_iter=1000, random_state=42)
classifier.fit(X_train_text, y_train)
y pred = classifier.predict(X test text)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
# print(classification_report(y_test, y_pred))
     Accuracy: 0.8196294096230862
     /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=
     STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
     Increase the number of iterations (max_iter) or scale the data as shown in:
         https://scikit-learn.org/stable/modules/preprocessing.html
     Please also refer to the documentation for alternative solver options:
         https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
       n_iter_i = _check_optimize_result(
```

To classify the score using reviews we have to first clean the data to ensure that we give our classifier clean data to make sure we build a good model.

After reading the data into a pandas Data Frame we are cleaning the data. These are the ways the data has been cleaned.

- 1. We made all the data into lower case to ensure that data is read similarly.
- 2. We removed duplicate rows of data to ensure there is no redundant data.
- 3. HTML tags data is being as deleted as the given data has been scraped from a website and contains a lot of html tag data.
- 4. There was a lot of data where one character has been repeated more than once to express emotions those type of data has been cleaned.
- 5. Removed punctuations and special cravings to eliminate excess data that has no importance for our classification.
- 6. Removed digits from textual data.
- 7. STOP words take up a lot of space that is not required. English words that are used to make sentences gramatically correct. These words are not needed for our classification.

Before and after cleaning the data a word cloud is plotted to see the frequency of the words in our data. We can see the clear distinction of the data difference between the wordclouds that are plotted.

Naive Bayes and logistic regression have been used to classify the data. We can see that logistic regression predicted the data more accurately than naive bayes.

Accuracy of Naive Bayes: 77.13%

Accuracy of logistic regression: 81.96%