Amazon Fine Foods Review Analysis

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:

```
Id - Row Id
ProductId - unique identifier for the product
UserId - unqiue identifier for the user
ProfileName - Profile name of the user
HelpfulnessNumerator - number of users who found the review helpful
HelpfulnessDenominator - number of users who indicated whether they found the revie
w helpful or not
Score - rating between 1 and 5
Time - timestamp for the review
Summary - brief summary of the review
Text - text of the review
```

In [1]:

```
# Import the relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import re
import nltk
import string
from nltk.corpus import stopwords
import string
from nltk.stem import PorterStemmer
from nltk.stem import SnowballStemmer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn import preprocessing
from sklearn.manifold import TSNE
from sklearn.feature_extraction.text import TfidfVectorizer
import gensim
import warnings
warnings.filterwarnings('ignore')
```

Act_data = Actual data that is available in dataset

In [2]:
```
# Loading the dataset
Act_data = pd.read_csv('/home/kirankumar_yeddala/Reviews.csv')
print("Actual Shape of data:",Act_data.shape)
#Structure of 5 rows of data
Act_data.head()
```

```
Actual Shape of data: (568454, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Sco
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	

In [3]:
```
Act_data.describe()
```

Out[3]:

	Id	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
count	568454.000000	568454.000000	568454.00000	568454.000000	5.684540e+05
mean	284227.500000	1.743817	2.22881	4.183199	1.296257e+09
std	164098.679298	7.636513	8.28974	1.310436	4.804331e+07
min	1.000000	0.000000	0.00000	1.000000	9.393408e+08
25%	142114.250000	0.000000	0.00000	4.000000	1.271290e+09
50%	284227.500000	0.000000	1.00000	5.000000	1.311120e+09
75%	426340.750000	2.000000	2.00000	5.000000	1.332720e+09
max	568454.000000	866.000000	923.00000	5.000000	1.351210e+09

My average rating of all the dataset is approx 4.18 out of (1 to 5)

Data Cleaning

In [4]:
```
# Removing the data for which score is not equal to 3
Act_data = Act_data[Act_data['Score'] != 3]
Act_data.shape
```

Out[4]:
```
(525814, 10)
```

In [5]:
```
# Now splitting the data based on score as Positive or Negative
# If my score is above 3 it is positive otherwise it is Negative.
# As the dataset contains more than 50000 plus records, due to computational tim
e we will work on 15000K records
sample_act_data = Act_data.head(5000)
sample_act_data['Score'] = ['Positive' if (int(score)>3) else 'Negative' for sco
re in sample_act_data['Score']]
```

In [6]:
```
#Checking after converting the Score values to Positive or Negative
sample_act_data.head()
```

Out[6]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	S
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Po:
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Neg
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Po:
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	Neg
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Po:

In [7]:
```
#Percentage of Scores after modification
sample_act_data['Score'].value_counts(normalize = True)
```

Out[7]:
```
Positive    0.8374
Negative    0.1626
Name: Score, dtype: float64
```

With the sample dataset of 5000 positive score is 83.74% and Negative score is 16.26%

Now Deleting the Duplicate entries and sorting the considered dataset for further processing

In [8]:
```
sorted_data = sample_act_data.sort_values('ProductId', ascending=True, inplace=F
alse, kind='quicksort', na_position='last')

final_data = sample_act_data.drop_duplicates(subset = {'UserId','ProfileName','T
ime','Text'}, keep='first', inplace=False)
```

Data Preprocessing

Methods used in Preprocessing

1. Stop words removal
2. Removal of HTML tags
3. Stemming using porter stemming - removing affixes from words
4. Tokenizing - Splitting sentences and words from the body of text
5. Lemmatization - synonym or a different word with the same meaning

In [9]:
```
#nltk.download('stopwords')
#set of stop words
stop = set(stopwords.words('english'))

#Initializing snowball stemmer
snow_stem = nltk.stem.SnowballStemmer('english')

#function to clean the word of any html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

#function to clean the word of any punctuation or special characters
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [10]:
```
#Preprocessing the text like cleaning HTML tags, removal of stopwords, punctuati
ons removal...
Preproc_text = []
cleanedtext = []
for sent in final_data['Text']:
    row_text=[]
    sent = cleanhtml(sent)
    for words in sent.split():
        clean_word = cleanpunc(words)
        if (clean_word.isalpha()) & (len(clean_word)>2):
            if(clean_word.lower() is not stop):
                finalword = (snow_stem.stem(clean_word.lower()).encode('utf8'))
                row_text.append(finalword)
            else:
                continue
        else:
            continue

    Preproc_text.append( b' '.join(row_text).decode('utf8'))
```

BOW

The bag-of-words model is a way of representing text data when modeling text with machine learning algorithms

The bag-of-words model is simple to understand and implement and has seen great success in problems such as language modeling and document classification.

In a nutshell, A bag-of-words is a representation of text that describes the occurrence of words within a document. It involves two things:

1. A vocabulary of known words.
2. A measure of the presence of known words.

In [11]:

```
#Converting the cleaned text to sparse matrix
count_vec = CountVectorizer()
bow = count_vec.fit_transform(Preproc_text)
```

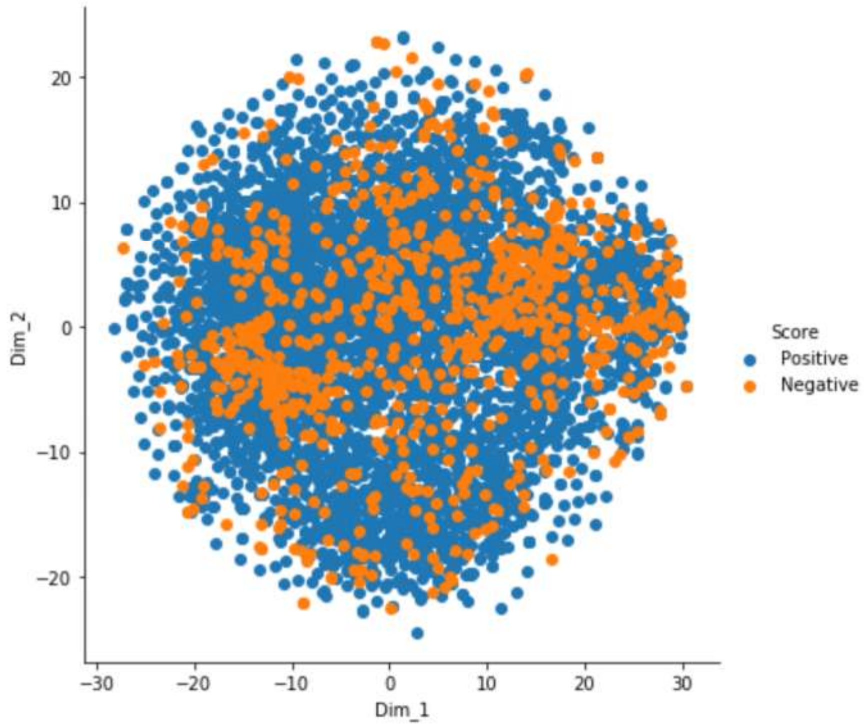
In [12]:

```
#converting sparse matrix to dense matrix
bow = bow.todense()
```

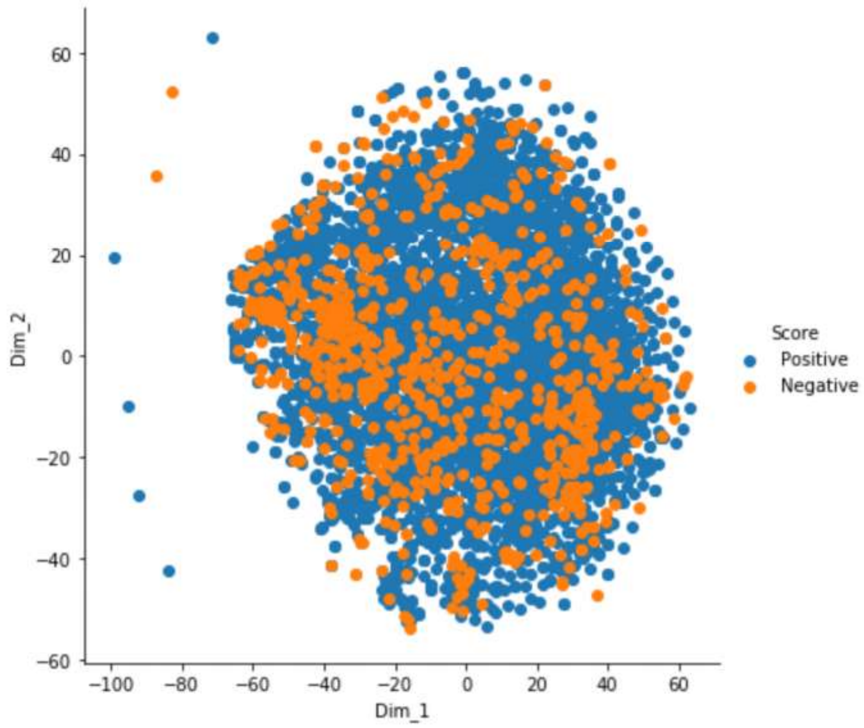
Now applying BOW data on TSNE

In [13]:

```
#Applying TSNE with default perplexity and iterations
bow_TSNE = TSNE(n_components = 2, random_state = 0).fit_transform(bow)
label = final_data['Score']
tsne_data = np.vstack((bow_TSNE.T, label)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=('Dim_1', 'Dim_2', 'Score'))
sns.FacetGrid(tsne_df, hue = 'Score', size = 6).map(plt.scatter, 'Dim_1', 'Dim_2
').add_legend()
plt.show()
```



In [14]:
```
bow_TSNE = TSNE(perplexity = 10, n_iter = 1000).fit_transform(bow)
label = final_data['Score']
tsne_data = np.vstack((bow_TSNE.T, label)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=('Dim_1', 'Dim_2', 'Score'))
sns.FacetGrid(tsne_df, hue = 'Score', size = 6).map(plt.scatter, 'Dim_1', 'Dim_2
').add_legend()
plt.show()
```



Increae in Iterations does not produce any favourable solution as positive and negative are still overlapping

TF-IDF

TF-IDF stands for term frequency-inverse document frequency. TF-IDF weight is a statistical measure used to evaluate how important a word is to a document in a collection or corpus. The importance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus.

Term_frequency(TF) = (number of times word occur in document) / (Total number of words in the document).

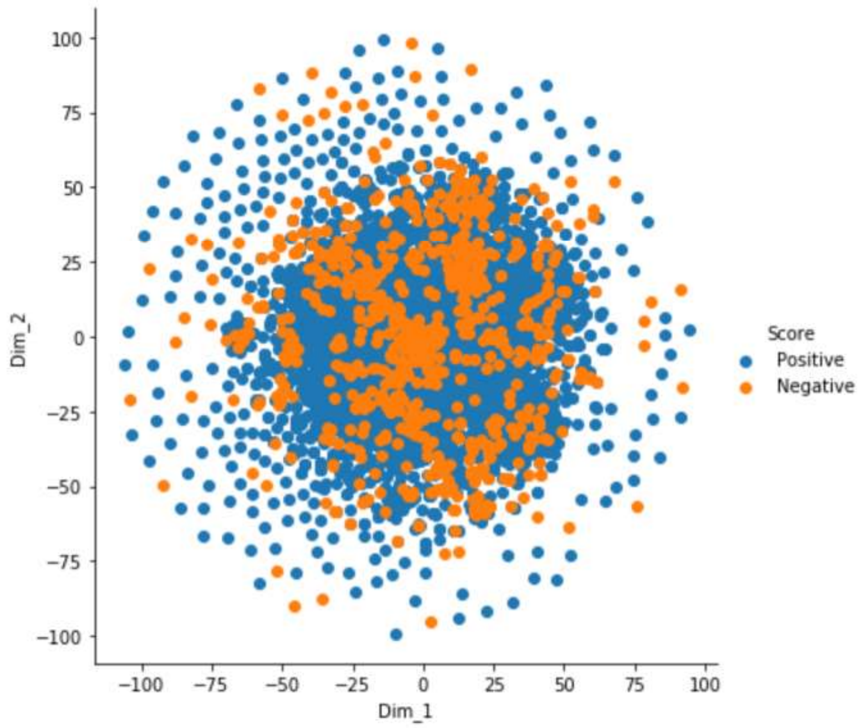
Inverse_Document_freqency(IDF) = log((total number of documents) / In which documents a word occurs))

```
So, TF-IDF(word) = TF(wor) * IDF(word)
```

In [12]:
```
#Vectorize the data
tfidf_vect = TfidfVectorizer(ngram_range=(1,2))
tfidf = tfidf_vect.fit_transform(Preproc_text)
```

In [13]:
```
#Converting from sparse matrix to dense matric
tfidf = tfidf.todense()
```

In [13]:
```
#Plotting the tfidf with default iterations
tfidf_TSNE = TSNE(n_components = 2, random_state = 0).fit_transform(tfidf)
label = final_data['Score']
tsne_data = np.vstack((tfidf_TSNE.T, label)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=('Dim_1', 'Dim_2', 'Score'))
sns.FacetGrid(tsne_df, hue = 'Score', size = 6).map(plt.scatter, 'Dim_1', 'Dim_2
').add_legend()
plt.show()
```



W2V and AvgW2V

w2v --> It considers semantic meaning of a sentence/word. It learns all relationships automatically from rawtext

Avgw2v --> It will calculate the weighted schemas of each word to the total no. of words

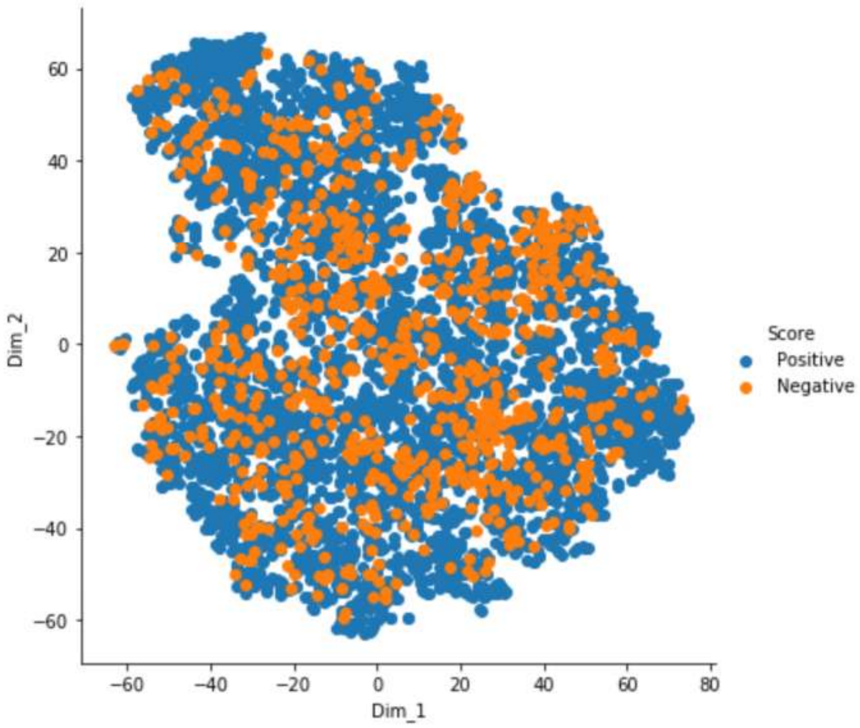
In [15]:
```
#Splitting each sentence in to words
sent_words = []
for sent in Preproc_text:
    sent_words.append(sent.split())
```

In [16]:
```
#Converting each word into vector
from gensim.models import Word2Vec
w2v = Word2Vec(sent_words,min_count=5,size=50,workers=4)
```

In [17]:
```
#fining w2v_words
w2v_words = list(w2v.wv.vocab)
```

In [18]:
```
#Avg_W2V for all Reviews
avg_w2vs = []
for sent in Preproc_text:
    #initializing number of words
    n_words = 0
    #initializing vector of size of 50
    sent_vec = np.zeros(50)
    for word in sent.split():
        if word in w2v_words:
            #creating for each word is an vector
            vec = w2v.wv[word]
            sent_vec += vec
            n_words += 1
    if n_words != 0:
        sent_vec /= n_words
        avg_w2vs.append(sent_vec)
```

In [18]:
```
w2v_tsne = TSNE(n_components = 2, random_state = 0).fit_transform(avg_w2vs)
label = final_data['Score']
tsne_data = np.vstack((w2v_tsne.T, label)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=('Dim_1', 'Dim_2', 'Score'))
sns.FacetGrid(tsne_df, hue = 'Score', size = 6).map(plt.scatter, 'Dim_1', 'Dim_2
').add_legend()
plt.show()
```



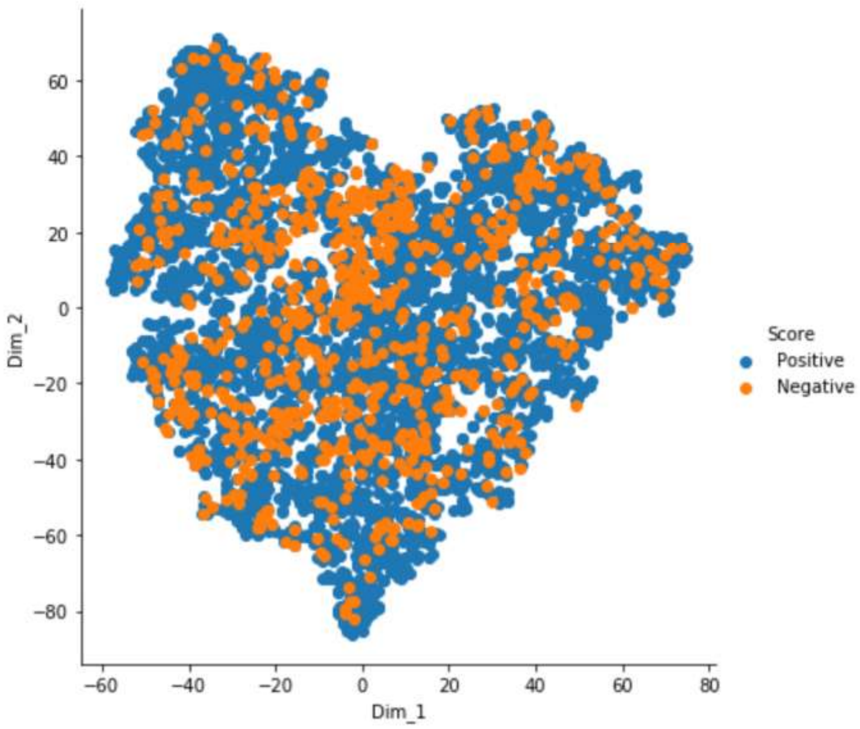
TFIDF-W2V

It will considers the term frequency and w2v of each word to the sum of all the term frequencies

tfidf-w2v = [t1*(w2v(w1)) + t2*(w2v(w2))+-----]/t1+t2+-----

In [19]:
```
features = tfidf_vect.get_feature_names()
tfidf_w2vs = []
row = 0
for sent in Preproc_text:
    sent_vec = np.zeros(50)
    tfidf_sum = 0
    for word in sent.split():
        if(word in w2v_words):
            vec = w2v.wv[word]
            tfidf_value = tfidf[row, features.index(word)]
            sent_vec += (vec * tfidf_value)
            tfidf_sum += tfidf_value
    if(tfidf_sum != 0):
        sent_vec /= tfidf_sum
        tfidf_w2vs.append(sent_vec)
    row += 1
```

In [20]:
```
tfidf_w2vs_tsne = TSNE(n_components = 2, random_state = 0).fit_transform(tfidf_w
2vs)
label = final_data['Score']
tsne_data = np.vstack((tfidf_w2vs_tsne.T, label)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=('Dim_1', 'Dim_2', 'Score'))
sns.FacetGrid(tsne_df, hue = 'Score', size = 6).map(plt.scatter, 'Dim_1', 'Dim_2
').add_legend()
plt.show()
```



In [ ]: