[7] 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 the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[7.1] 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 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 id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

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



import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
```

```python
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
```

```
D:\Ancaonda3-3\lib\site-packages\gensim\utils.py:1197: UserWarning: detecte
d Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

[1]. Reading Data

In [2]:

```python
# using the 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 da
ta points
# you can change the number to any other number based on your computing power

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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 L
IMIT 5000""", con)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a ne
gative rating.
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 (5000, 10)

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulne
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

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	Text	COU

0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

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

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...

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

Out[6]: 393063

Exploratory Data Analysis

[2] 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	Helpfuln
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2

4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

As can be seen above the same user has multiple reviews of the with the 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, inp
lace=False, kind='quicksort', na_position='last')
```

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

Out[9]:
```
(4986, 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]:
```
99.72
```

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	HelpfulnessNumerator	Helpfuli
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

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

In [13]:
```
#Before starting the next phase of preprocessing lets see the number of entrie
s left
print(final.shape)
```

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

```
(4986, 10)
```

Out[13]:

```
1    4178
0     808
Name: Score, dtype: int64
```

[3]. Text Preprocessing.

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]:

```python
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

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

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

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

```
Why is this $[...] when the same product is available for $[...] here?<br />
>http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<br /><br
/>The Victor M380 and M502 traps are unreal, of course -- total fly genocid
e. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious these
chips are.  The best thing was that there were a lot of "brown" chips in th
e bsg (my favorite), so I bought some more through amazon and shared with f
amily and friends.  I am a little disappointed that there are not, so far,
very many brown chips in these bags, but the flavor is still very good.  I
like them better than the yogurt and green onion flavor because they do not
seem to be as salty, and the onion flavor is better.  If you haven't eaten
Kettle chips before, I recommend that you try a bag before buying bulk.  Th
ey are thicker and crunchier than Lays but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they we
re ordering; the other wants crispy cookies.  Hey, I'm sorry; but these rev
iews do nobody any good beyond reminding us to look  before ordering.<br />
<br />These are chocolate-oatmeal cookies.  If you don't like that combinat
ion, don't order this type of cookie.  I find the combo quite nice, really.
  The oatmeal sort of "calms" the rich chocolate flavor and gives the cooki
e sort of a coconut-type consistency.  Now let's also remember that tastes
differ; so, I've given my opinion.<br /><br />Then, these are soft, chewy c
ookies -- as advertised.  They are not "crispy" cookies, or the blurb would
say "crispy," rather than "chewy."  I happen to like raw cookie dough; howe
ver, I don't see where these taste like raw cookie dough.  Both are soft, h
owever, so is this the confusion?  And, yes, they stick together.  Soft coo
kies tend to do that.  They aren't individually wrapped, which would add to
the cost.  Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br />
<br />So, if you want something hard and crisp, I suggest Nabiso's Ginger S
naps.  If you want a cookie that's soft, chewy and tastes like a combinatio
n of chocolate and oatmeal, give these a try.  I'm here to place my second
order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />This k
cup is great coffee.  dcaf is very good as well
==================================================
```

In [15]:

```python
# 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)
```

```
Why is this $[...] when the same product is available for $[...] here?<br />
> /><br />The Victor M380 and M502 traps are unreal, of course -- total fly
genocide. Pretty stinky, but only right nearby.
```

In [16]:

```python
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-rem
ove-all-tags-from-an-element
from bs4 import BeautifulSoup

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

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

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

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

```
Why is this $[...] when the same product is available for $[...] here? />Th
e Victor M380 and M502 traps are unreal, of course -- total fly genocide. P
retty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious these
chips are.  The best thing was that there were a lot of "brown" chips in th
e bsg (my favorite), so I bought some more through amazon and shared with f
amily and friends.  I am a little disappointed that there are not, so far,
very many brown chips in these bags, but the flavor is still very good.  I
like them better than the yogurt and green onion flavor because they do not
seem to be as salty, and the onion flavor is better.  If you haven't eaten
Kettle chips before, I recommend that you try a bag before buying bulk.  Th
ey are thicker and crunchier than Lays but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they we
re ordering; the other wants crispy cookies.  Hey, I'm sorry; but these rev
iews do nobody any good beyond reminding us to look  before ordering.These
are chocolate-oatmeal cookies.  If you don't like that combination, don't o
rder this type of cookie.  I find the combo quite nice, really.  The oatmea
```

```
l sort of "calms" the rich chocolate flavor and gives the cookie sort of a
coconut-type consistency.  Now let's also remember that tastes differ; so,
I've given my opinion.Then, these are soft, chewy cookies -- as advertised.
  They are not "crispy" cookies, or the blurb would say "crispy," rather th
an "chewy."  I happen to like raw cookie dough; however, I don't see where
these taste like raw cookie dough.  Both are soft, however, so is this the
confusion?  And, yes, they stick together.  Soft cookies tend to do that.
They aren't individually wrapped, which would add to the cost.  Oh yeah, ch
ocolate chip cookies tend to be somewhat sweet.So, if you want something ha
rd and crisp, I suggest Nabiso's Ginger Snaps.  If you want a cookie that's
soft, chewy and tastes like a combination of chocolate and oatmeal, give th
ese a try.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cup is
great coffee.  dcaf is very good as well
```

In [17]:

```python
# 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]:

```python
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what they we
re ordering; the other wants crispy cookies.  Hey, I am sorry; but these re
views do nobody any good beyond reminding us to look  before ordering.<br /
><br />These are chocolate-oatmeal cookies.  If you do not like that combin
ation, do not order this type of cookie.  I find the combo quite nice, real
ly.  The oatmeal sort of "calms" the rich chocolate flavor and gives the co
```

```
okie sort of a coconut-type consistency.  Now let is also remember that tas
tes differ; so, I have given my opinion.<br /><br />Then, these are soft, c
hewy cookies -- as advertised.  They are not "crispy" cookies, or the blurb
would say "crispy," rather than "chewy."  I happen to like raw cookie doug
h; however, I do not see where these taste like raw cookie dough.  Both are
soft, however, so is this the confusion?  And, yes, they stick together.  S
oft cookies tend to do that.  They are not individually wrapped, which woul
d add to the cost.  Oh yeah, chocolate chip cookies tend to be somewhat swe
et.<br /><br />So, if you want something hard and crisp, I suggest Nabiso i
s Ginger Snaps.  If you want a cookie that is soft, chewy and tastes like a
combination of chocolate and oatmeal, give these a try.  I am here to place
my second order.
==================================================
```

In [19]:

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

```
Why is this $[...] when the same product is available for $[...] here?<br /
> /><br />The Victor  and  traps are unreal, of course -- total fly genocid
e. Pretty stinky, but only right nearby.
```

In [20]:

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

```
Wow So far two two star reviews One obviously had no idea what they were or
dering the other wants crispy cookies Hey I am sorry but these reviews do n
obody any good beyond reminding us to look before ordering br br These are
chocolate oatmeal cookies If you do not like that combination do not order
this type of cookie I find the combo quite nice really The oatmeal sort of
calms the rich chocolate flavor and gives the cookie sort of a coconut type
consistency Now let is also remember that tastes differ so I have given my
opinion br br Then these are soft chewy cookies as advertised They are not
crispy cookies or the blurb would say crispy rather than chewy I happen to
like raw cookie dough however I do not see where these taste like raw cooki
e dough Both are soft however so is this the confusion And yes they stick t
ogether Soft cookies tend to do that They are not individually wrapped whic
h would add to the cost Oh yeah chocolate chip cookies tend to be somewhat
sweet br br So if you want something hard and crisp I suggest Nabiso is Gin
ger Snaps If you want a cookie that is soft chewy and tastes like a combina
tion of chocolate and oatmeal give these a try I am here to place my second
order
```

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

In [22]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
```

```
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not i
n stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████| 4986/4986 [00:03<00:00, 1600.77i
t/s]
```

In [23]:
```
preprocessed_reviews[1500]
```

Out[23]:
```
'wow far two two star reviews one obviously no idea ordering wants crispy c
ookies hey sorry reviews nobody good beyond reminding us look ordering choc
olate oatmeal cookies not like combination not order type cookie find combo
quite nice really oatmeal sort calms rich chocolate flavor gives cookie sor
t coconut type consistency let also remember tastes differ given opinion so
ft chewy cookies advertised not crispy cookies blurb would say crispy rathe
r chewy happen like raw cookie dough however not see taste like raw cookie
dough soft however confusion yes stick together soft cookies tend not indiv
idually wrapped would add cost oh yeah chocolate chip cookies tend somewhat
sweet want something hard crisp suggest nabiso ginger snaps want cookie sof
t chewy tastes like combination chocolate oatmeal give try place second ord
er'
```

[3.2] Preprocess Summary

In [42]:
```
## Similartly you can do preprocessing for review summary also.
summary=[]
for sent in tqdm(final['Summary'].values):
    sent=re.sub(r'http\S+', '', sent)
    sent=BeautifulSoup(sent, 'lxml').get_text()
    sent = decontracted(sent)
    sent = re.sub("\S*\d\S*", "", sent).strip()
    sent = re.sub('[^A-Za-z]+', ' ', sent)
    #for word in sent.split():
    #   if (word.lower() not in stopwords):
    #       sent=' '.join(word.lower())
    sentance = ' '.join(e.lower() for e in sent.split() if e.lower() not in st
opwords)
    summary.append(sentance)
```

```
100%|██████████████████████████████| 4986/4986 [00:02<00:00, 2202.48i
```

```
t/s]
```

In [44]:
```
summary[0]
```

Out[44]:
```
'thirty bucks'
```

In [45]:
```
final['Summary'].values[0]
```

Out[45]:
```
'thirty bucks?'
```

[4] Featurization

[4.1] BAG OF WORDS

In [46]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abbot
t', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[4.2] Bi-Grams and n-Grams.

In [92]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/sta
ble/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html
```

```
# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000,
dtype='float64')
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final
_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.3] TF-IDF

In [48]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_featu
re_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", final
_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'able
find', 'able get', 'absolute', 'absolutely', 'absolutely delicious', 'absol
utely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.4] Word2Vec

In [49]:

```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())
```

In [50]:
```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZP
Y
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negati
ve300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v =
 True, to train your own w2v ")
```

```
[('excellent', 0.9961049556732178), ('overall', 0.9953181743621826), ('wond
erful', 0.9952445030212402), ('want', 0.9952048063278198), ('wanting', 0.99
50984120368958), ('looking', 0.995090663433075), ('either', 0.9950896501541
138), ('though', 0.9949077367782593), ('rather', 0.9949067831039429), ('ama
zing', 0.9948879480361938)]
==================================================
[('varieties', 0.9993524551391602), ('particular', 0.9992659091949463), ('c
```

```
ome', 0.9992481470108032), ('remember', 0.9992392063140869), ('popped', 0.9
992383718490601), ('yellow', 0.9992365837097168), ('kernels', 0.99921452999
11499), ('beverages', 0.9992142915725708), ('pods', 0.9992140531539917),
('donut', 0.9992039203643799)]
```

In [51]:

```
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  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'stink
y', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'received', 's
hipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'instead', 'rem
oved', 'easily', 'daughter', 'designed', 'printed', 'use', 'car', 'window
s', 'beautifully', 'shop', 'program', 'going', 'lot', 'fun', 'everywhere',
'like', 'tv', 'computer', 'really', 'good', 'idea', 'final', 'outstanding',
'window', 'everybody', 'asks', 'bought', 'made']
```

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

[4.4.1.1] Avg W2v

In [52]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
st
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 to change this to 300 if you use google's w2v
    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)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████████████████████████| 4986/4986 [00:08<00:00, 502.27i
```

```
t/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [53]:

```python
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
model.fit(preprocessed_reviews)
# 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 [54]:

```python
# 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 list
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%|██████████| 4986/4986 [00:40<00:00, 123.97i
t/s]
```

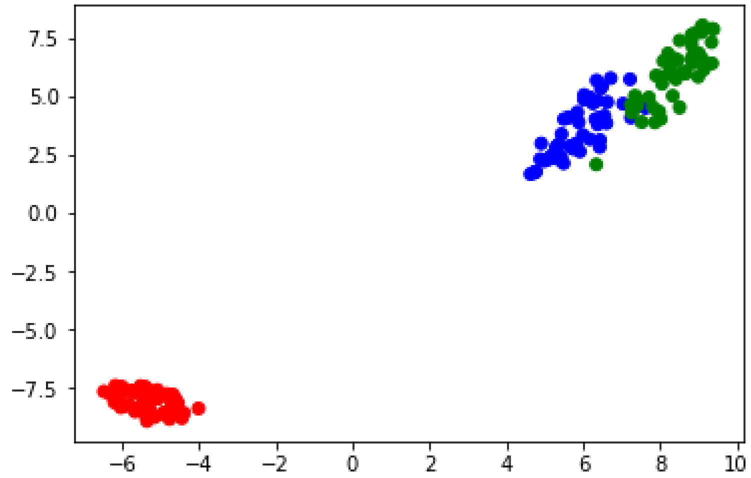
[5] Applying TSNE

1. you need to plot 4 tsne plots with each of these feature set
    A. Review text, preprocessed one converted into vectors using (BOW)
    B. Review text, preprocessed one converted into vectors using (TFIDF)
    C. Review text, preprocessed one converted into vectors using (AVG W2v)
    D. Review text, preprocessed one converted into vectors using (TFIDF W2v)
2. Note 1: The TSNE accepts only dense matrices
3. Note 2: Consider only 5k to 6k data points

In [74]:

```
# https://github.com/pavlin-policar/fastTSNE
import numpy as np
from sklearn import datasets
from sklearn.manifold import TSNE
iris = datasets.load_iris()
x, y = iris['data'], iris['target']

tsne = TSNE( n_components=2, perplexity=50, learning_rate=200, n_iter=2000)
#model = TSNE(n_components=2, random_state=0, perplexity=50)
#tsne_data = model.fit_transform(x)
X_embedding = tsne.fit_transform(x)
for_tsne=np.vstack((X_embedding.T, y)).T
#for_tsne = np.hstack((X_embedding, y.reshape(-1,1)))
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimension_y'
,'Score'])
colors = {0:'red', 1:'blue', 2:'green'}
plt.scatter(for_tsne_df['Dimension_x'], for_tsne_df['Dimension_y'], c=for_tsne
_df['Score'].apply(lambda x: colors[x]))
plt.show()
```



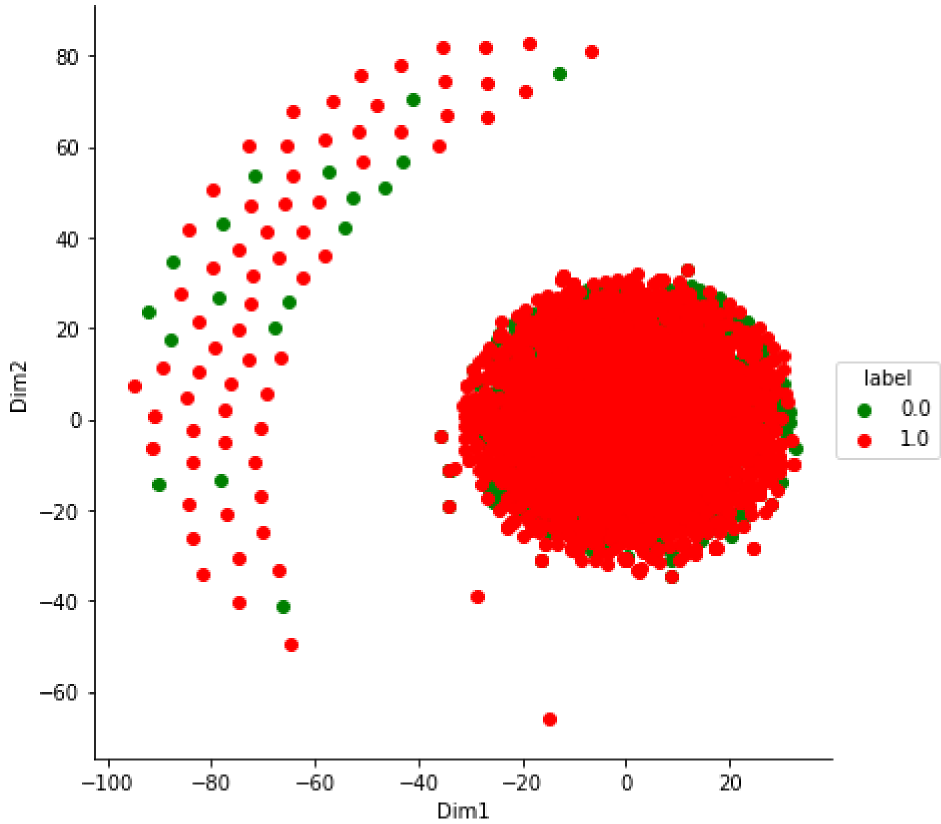
[5.1] Applying TNSE on Text BOW vectors

Datapoints-4500 and ngram_range=(1,2)

In [115]:
```
labels=final['Score']
lab=labels[0:4500]
from sklearn.preprocessing import StandardScaler
standard_data=StandardScaler(with_mean=False).fit_transform(final_bigram_count
s).todense()
#standard_data.shape
from sklearn.manifold import TSNE
tsne_model=TSNE(n_components=2, random_state=0, perplexity=30, n_iter=1000)
sample_data=standard_data[0:4500, :]
tsne_data=tsne_model.fit_transform(sample_data)
tsne_data.shape
```

Out[115]:
```
(4500, 2)
```

In [129]:
```
new_data=np.vstack((tsne_data.T, lab)).T
new_data.shape
new_df=pd.DataFrame(data=new_data, columns=('Dim1', 'Dim2', 'label'))
#new_df.shape
#new_df.head()
sns.FacetGrid(data=new_df, hue='label', palette={0:'green', 1:'red'}, size=6).
map(plt.scatter, 'Dim1', 'Dim2').add_legend()
plt.show()
```



Observations

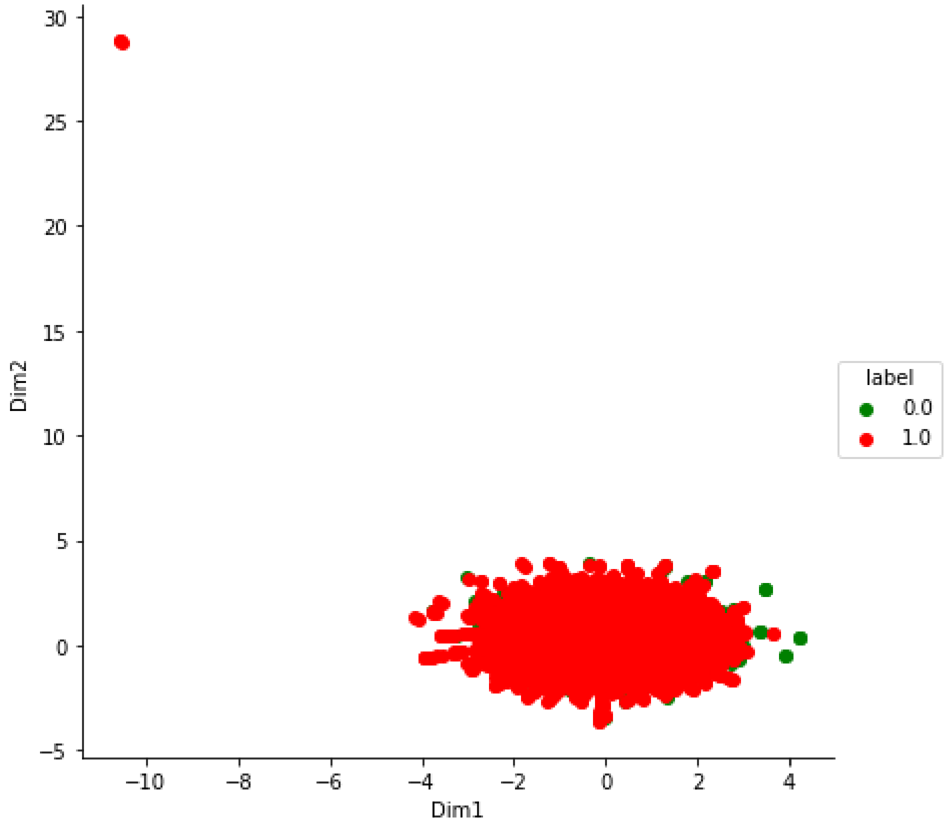
From the above observation we can say that both the classes of datapoints are not seperable. And almost all the datapoints lie in therange of -35 to +25 on x-axis.

[5.1] Applying TNSE on Text TFIDF vectors

Datapoints-4500 and ngram_range=(1,2)

In [130]:
```
standard_data=StandardScaler(with_mean=False).fit_transform(final_tf_idf).tode
nse()
tsne_model=TSNE(n_components=2, random_state=0, perplexity=30, n_iter=1000)
sample_data=standard_data[0:4500, :]
tsne_data=tsne_model.fit_transform(sample_data)
tsne_data.shape
```

```
new_data=np.vstack((tsne_data.T, lab)).T
new_data.shape
new_df=pd.DataFrame(data=new_data, columns=('Dim1', 'Dim2', 'label'))
sns.FacetGrid(data=new_df, hue='label', palette={0:'green', 1:'red'}, size=6).
map(plt.scatter, 'Dim1', 'Dim2').add_legend()
plt.show()
```



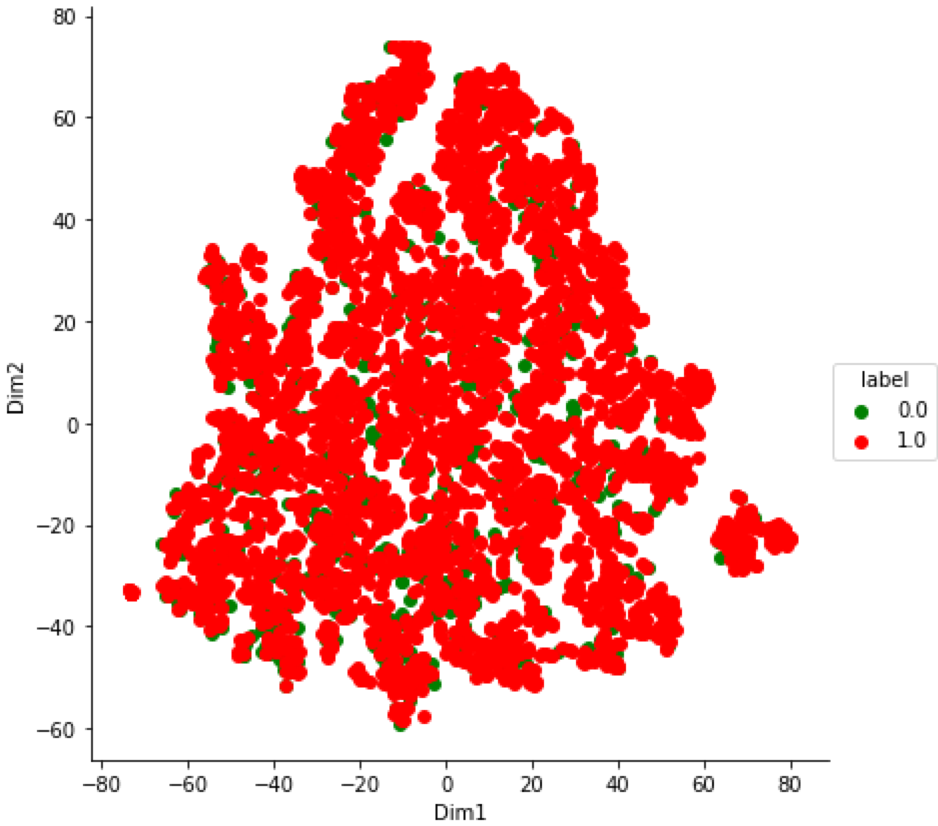
Observation

From the above observation we cannot seperate both the classes datapoints with a simple model. all 99 (approx) percent of points lie in the range of -4 to +4 on x-axis.

[5.3] Applying TNSE on Text Avg W2V vectors

Datapoints-4500 and ngram_range=(1,2)

In [134]:
```
standard_data=StandardScaler(with_mean=False).fit_transform(sent_vectors)
tsne_model=TSNE(n_components=2, random_state=0, perplexity=30, n_iter=1000)
sample_data=standard_data[0:4500, :]
tsne_data=tsne_model.fit_transform(sample_data)
tsne_data.shape
new_data=np.vstack((tsne_data.T, lab)).T
new_data.shape
new_df=pd.DataFrame(data=new_data, columns=('Dim1', 'Dim2', 'label'))
sns.FacetGrid(data=new_df, hue='label', palette={0:'green', 1:'red'}, size=6).
map(plt.scatter, 'Dim1', 'Dim2').add_legend()
plt.show()
```

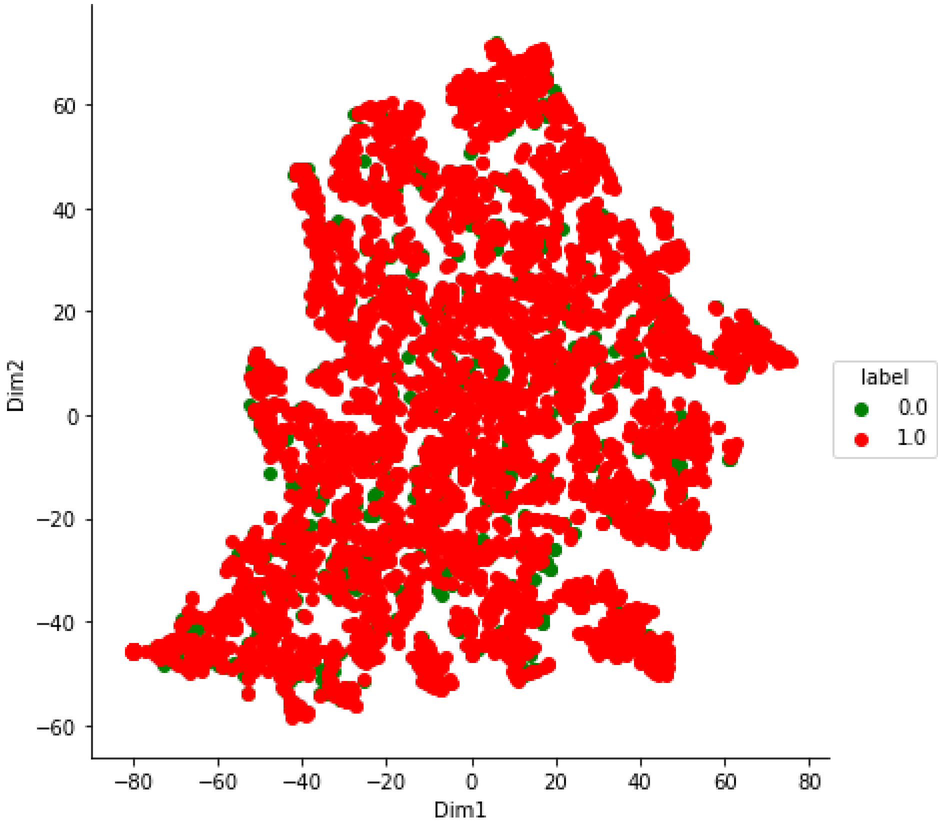


[5.4] Applying TNSE on Text TFIDF weighted W2V vectors

Datapoints-4500 and ngram_range=(1,2)

In [135]:
```
standard_data=StandardScaler(with_mean=False).fit_transform(tfidf_sent_vectors
```

```
)
tsne_model=TSNE(n_components=2, random_state=0, perplexity=30, n_iter=1000)
sample_data=standard_data[0:4500, :]
tsne_data=tsne_model.fit_transform(sample_data)
tsne_data.shape
new_data=np.vstack((tsne_data.T, lab)).T
new_data.shape
new_df=pd.DataFrame(data=new_data, columns=('Dim1', 'Dim2', 'label'))
sns.FacetGrid(data=new_df, hue='label', palette={0:'green', 1:'red'}, size=6).
map(plt.scatter, 'Dim1', 'Dim2').add_legend()
plt.show()
```



[6] Conclusions

From all the above vectroization techiques it is clear that we cannot seperate both the classes datapoints. The datapoints for all the techniques were spread randomly.