Amazon_Fine_Food_Review_Assignment-2

February 3, 2019

1 Assignment-2 : Apply T-SNE on Amazon Fine Food Review Dataset

In [48]:
```
# Importing all the necessary libraries

%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 nltk.stem.porter import PorterStemmer

import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer


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


from tqdm import tqdm
import os
```

```
In [3]: # Reading data from SQLite Table

        con=sqlite3.connect("database.sqlite")
        Data=pd.read_sql_query("select * from Reviews",con)
```

```
In [4]: print("\nNumber of Reviews: ",Data["Text"].count())
        print("\nNumber of Users: ",len(Data["UserId"].unique())) # Unique returns 1-D array o
        print("\nNumber of Products: ",len(Data["ProductId"].unique()))
        print("\nShape of Data: ",Data.shape)
        print("\n",Data.columns)
```

```
Number of Reviews:  568454

Number of Users:  256059

Number of Products:  74258

Shape of Data:  (568454, 10)

 Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

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

2 Inforamtion about data

3 1.1 Attribute Information of the Dataset:

Id - A unique value starts from 1
ProductId - unique identifier for the product
UserId - unqiue identifier for the user
ProfileName - Name of user profile
HelpfulnessNumerator - number of users who found the review helpful
HelpfulnessDenominator - number of users who indicated whether they found the review 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

4 2.0 Objective :

Apply TSNE on Bag Of Word,TF-IDF, Word2Vec, TF-IDF Word2Vec

In [5]:
```
Data['Score'].unique()
```

Out[5]:
```
array([5, 1, 4, 2, 3], dtype=int64)
```

In [6]:
```
# For negative review (Score=1 or 2)
# For positive review (Score = 4 or 5)
# considering review with Score = 3 as neutral
# Let's check how many have score value equal to 3
print(pd.read_sql_query("select score,count(score) as Total_Count from Reviews where s
```

```
   Score  Total_Count
0      3        42640
```

In [7]:
```
# Since 42,640 Data are having score of 3
# removing reviews having Score = 3

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

In [8]:
```
# Giving reviews with Score>3 a positive rating (1),and reviews with a score<3 a negat

def change_discrite_to_numerical(x):
    if x < 3:
        return 0
    return 1

actualScore = filtered_data['Score']
positiveNegative = actualScore.map(change_discrite_to_numerical)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(2)
```

```
Number of data points in our data (525814, 10)
```

Out[8]:
```
   Id   ProductId          UserId ProfileName  HelpfulnessNumerator  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                     1
1   2  B00813GRG4  A1D87F6ZCVE5NK      dll pa                     0

   HelpfulnessDenominator  Score        Time                Summary  \
0                       1      1  1303862400  Good Quality Dog Food
1                       0      0  1346976000      Not as Advertised

                                                Text
0  I have bought several of the Vitality canned d...
1  Product arrived labeled as Jumbo Salted Peanut...
```

5 3.0 Exploratory Data Analysis

```
In [9]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
```

```
Out[9]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
        1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
        2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
        3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
        4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2

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

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

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

6 3.1 Data Cleaning: Deduplication

(i). It is observed (as shown in the table above) 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.

(ii). 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

(iii). ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) (iv). ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

(v). 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.

(vi). 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 [10]: #Sorting data according to ProductId in ascending order
         sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal
         sorted_data.head(2)
```

```
Out[10]:            Id   ProductId          UserId      ProfileName  \
         138706  150524  0006641040   ACITT7DI6IDDL  shari zychinski
         138688  150506  0006641040  A2IW4PEEKO2R0U            Tracy

                 HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         138706                     0                       0      1   939340800
         138688                     1                       1      1  1194739200

                                                   Summary  \
         138706                     EVERY book is educational
         138688  Love the book, miss the hard cover version

                                                             Text
         138706  this witty little book makes my son laugh at l...
         138688  I grew up reading these Sendak books, and watc...
```

```
In [11]: # Removal of Duplicate entries (Deduplication of entries).
         # It will find duplicates on the basis of element contained by subset by default it u

         final=sorted_data.drop_duplicates(subset={'UserId','ProfileName','Time','Text'},keep=
         print(final.shape)
```

```
(364173, 10)
```

```
In [12]: #Checking to see how much % of data still remains

         print("% of Data present in Dataset: {:.2f}".format((final['Id'].size*1.0)/(filtered_c
```

```
% of Data present in Dataset: 69.26
```

```
In [13]: display= pd.read_sql_query("""
         SELECT *
```

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

        display.head()
```

```
Out[13]:       Id   ProductId          UserId              ProfileName  \
         0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
         1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

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

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

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

7 Observation :

1. In the above table It can be seen that in two rows given the value of HelpfulnessNumerator is greater than
HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions.

2. HelpfulnessNumerator : No of people given yes HelpfulnessDenominator : No of people given yes and no both included.

3. So HelpfulnessNumerator sholud be always less than HelpfulnessDenominator

```
In [14]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [15]: print("Shape of the DataSet: ",final.shape)

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

```
Shape of the DataSet:  (364171, 10)

 1    307061
0     57110
Name: Score, dtype: int64
```

8 4.0 Text Preprocessing

In the Preprocessing phase we will perform the following in the given 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)

```
In [16]: # find number of sentences containing HTML tags
         import re
         i=0;
         for sent in final['Text']:
             if (len(re.findall('<.*?>', sent))):
                  i += 1;
         print("Number of Sentence Containing HTML Tags : ",i)
```

```
Number of Sentence Containing HTML Tags :  93153
```

```
In [17]: stop = set(stopwords.words('english')) #set of stopwords
         sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

         def cleanhtml(sentence): #function to clean the word of any html-tags
             cleanr = re.compile('<.*?>')
             cleantext = re.sub(cleanr, ' ', sentence)
             return cleantext
         def cleanpunc(sentence): #function to clean the word of any punctuation or special ch
             cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
             cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
             return  cleaned
```

```
In [18]: #Code for implementing step-by-step the checks mentioned in the pre-processing phase
         # this code takes a while to run as it needs to run on 500k sentences.
         if not os.path.isfile('final.sqlite'):
             final_string=[]
             all_positive_words=[] # store words from +ve reviews here
             all_negative_words=[] # store words from -ve reviews here.
             for i, sent in enumerate(tqdm(final['Text'].values)):
                 filtered_sentence=[]
                 #print(sent);
```

```
            sent=cleanhtml(sent) # remove HTMl tags
            for w in sent.split():
                # we have used cleanpunc(w).split(), one more split function here because
                # if we dont use .split() function then we will be considring "abc def" a
                for cleaned_words in cleanpunc(w).split():
                    if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                        if(cleaned_words.lower() not in stop):
                            s=(sno.stem(cleaned_words.lower())).encode('utf8')
                            filtered_sentence.append(s)
                            if (final['Score'].values)[i] == 1:
                                all_positive_words.append(s) #list of all words used to d
                            if(final['Score'].values)[i] == 0:
                                all_negative_words.append(s) #list of all words used to d
            str1 = b" ".join(filtered_sentence) #final string of cleaned words
            final_string.append(str1)


        #adding a column of CleanedText which displays the data after pre-processing of th

        final['CleanedText']=final_string
        final['CleanedText']=final['CleanedText'].str.decode("utf-8")

        # store final table into an SQlLite table for future.

        conn = sqlite3.connect('final.sqlite')
        c=conn.cursor()
        conn.text_factory = str
        final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
                     index=True, index_label=None, chunksize=None, dtype=None)
        conn.close()

        # we need not to call close() to close because it will automatically close.

        with open('positive_words.pkl', 'wb') as f:
            pickle.dump(all_positive_words, f)
        with open('negitive_words.pkl', 'wb') as f:
            pickle.dump(all_negative_words, f)
```

```
In [19]: if os.path.isfile('final.sqlite'):
             conn = sqlite3.connect('final.sqlite')
             final = pd.read_sql_query("SELECT * FROM Reviews WHERE Score != 3 ", conn)
             conn.close()
         else:
             print("Please the above cell")
```

```
In [20]: # Extracting equal number of random sample of positive and negative score

         dfn=final[final.Score==0].sample(n=2500)
```

```
dfp=final[final.Score==1].sample(n=2500)
print("Shape of Data \n",dfn.shape,dfp.shape,sep="\n")
```

```
Shape of Data

(2500, 12)
(2500, 12)
```

```
In [21]: # Concatenating positive and negative score DataFrame into one DataFrame
         frames=[dfp,dfn]
         new_df=pd.concat(frames)
         new_df.shape
```

```
Out[21]: (5000, 12)
```

```
In [22]: # Displaying two Value of DataFrame
         new_df.head(2)
```

```
Out[22]:          index      Id   ProductId          UserId       ProfileName  \
         210311  464095  501805  B001OOYNDG   AN7VS5F3XPAQ4  Gretchen E. Paul
         276980  455587  492563  B003M6HHBE  A2H6IUQM2A99DA           maurypb

                 HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         210311                     2                       3      1  1241654400
         276980                     0                       0      1  1326672000

                                                           Summary  \
         210311                                   milton's crackers
         276980  HiChew: The love child of Gummy Bears and Star...

                                                              Text  \
         210311  We enjoy these crackers so much we are willing...
         276980  Mmmm... a cross between Starburst fruit chews ...

                                                       CleanedText
         210311  enjoy cracker much will order line els buy upp...
         276980  mmmm cross starburst fruit chew gummi bear gre...
```

9 5.0 Bag Of Words

1. To perform Bag of Words CountVectorizer() function is used.
2. It convert a collection of text documents to a matirx of token counts.
3. It returns sparse matrix which contain that (row no , column no and value) corresponding to non zero value in matrix.
4. Example

[0 0 3 0 4

0 0 5 7 0

]
Row No 0 0 1 1
Column No 2 4 2 3
Value 3 4 5 7

5. Representing a sparse matrix by a 2D array leads to wastage of lots of memory as zeroes in the matrix are of no use in most of the cases. So, instead of storing zeroes with non-zero elements, we only store non-zero elements.

```
In [23]: count_vect=CountVectorizer()
         Bow_counts=count_vect.fit_transform(new_df['CleanedText'].values)
         print("the type of count vectorizer ",type(Bow_counts))
         print("\nthe shape of out text BOW vectorizer ",Bow_counts.get_shape())
         print("\nthe number of unique words ", Bow_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>

the shape of out text BOW vectorizer  (5000, 9986)

the number of unique words  9986
```

```
In [24]: # Converting Sparse matrix to Dense Matrix
         y=Bow_counts.todense()
```

```
In [25]: # Displaying the shape
         y.shape
```

```
Out[25]: (5000, 9986)
```

10 5.1 Applying TSNE On Bag Of Words Data

```
In [26]: from fastTSNE import TSNE
         model= TSNE(n_components=2,random_state=0,perplexity=50)
         tsne_data= model.fit(y)
```

```
In [27]: # Checking Shape of Data
         tsne_data.shape
```

```
Out[27]: (5000, 2)
```

```
In [28]: # Extracting Label from Data

         label = new_df['Score']

         # Checking Shape of Label
         label.shape
```

Out[28]: (5000,)

In [29]:
```
# Adding Label to data obtained after applying TSNE

data = np.vstack((tsne_data.T,label)).T

# Checking Shape of Data
data.shape
```

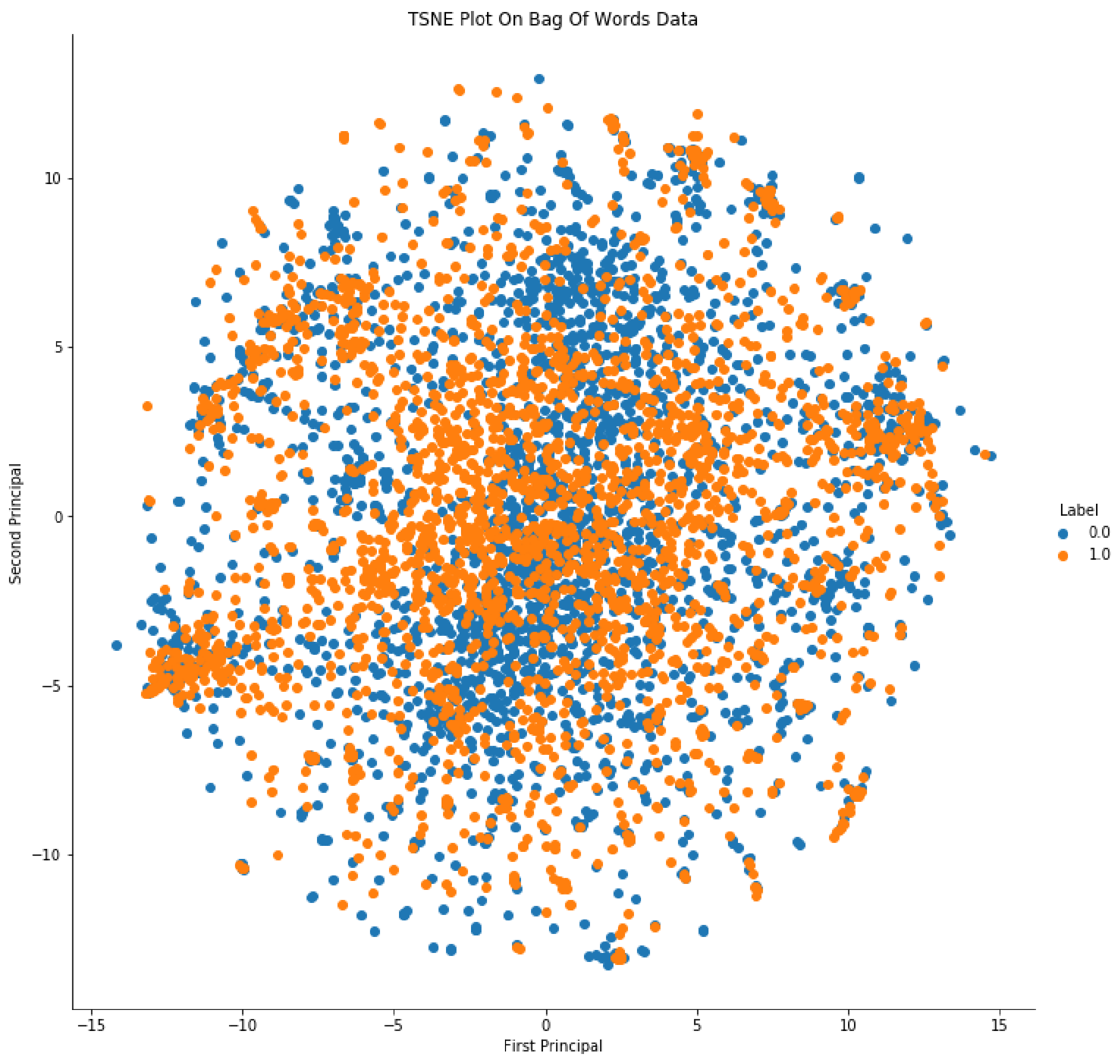
Out[29]: (5000, 3)

In [30]:
```
# Creating DataFrame from data obtained after Adding Label To Data obtained after app
BOW_df=pd.DataFrame(data,columns=['X','Y','Label'])

# Counting different types of label

BOW_df['Label'].value_counts()
```

Out[30]:
```
0.0    2500
1.0    2500
Name: Label, dtype: int64
```

11 5.2 TSNE Plot On Bag Of Words

In [31]:
```
# Plotting

sns.FacetGrid(data=BOW_df,hue='Label',height=10).map(plt.scatter,'X','Y').add_legend(
plt.title("TSNE Plot On Bag Of Words Data")
plt.xlabel("First Principal")
plt.ylabel("Second Principal")
plt.show()
```



12 5.3 Conclusion :

1. In the above plot data are overlapping so we can not say it is linearly seperable or not.

. # 6.0 TF-IDF

```
In [32]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf = tf_idf_vect.fit_transform(new_df['CleanedText'].values)
         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
```

```
The type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
The shape of out text TFIDF vectorizer  (5000, 141385)
```

```
The number of unique words including both unigrams and bigrams  141385
```

```
In [33]: # Tranforming Sparse Matrix to Dense Matrix

         y = final_tf_idf.todense()
         y.shape
```

```
Out[33]: (5000, 141385)
```

13 6.1 Applying TSNE On TF-IDF Data

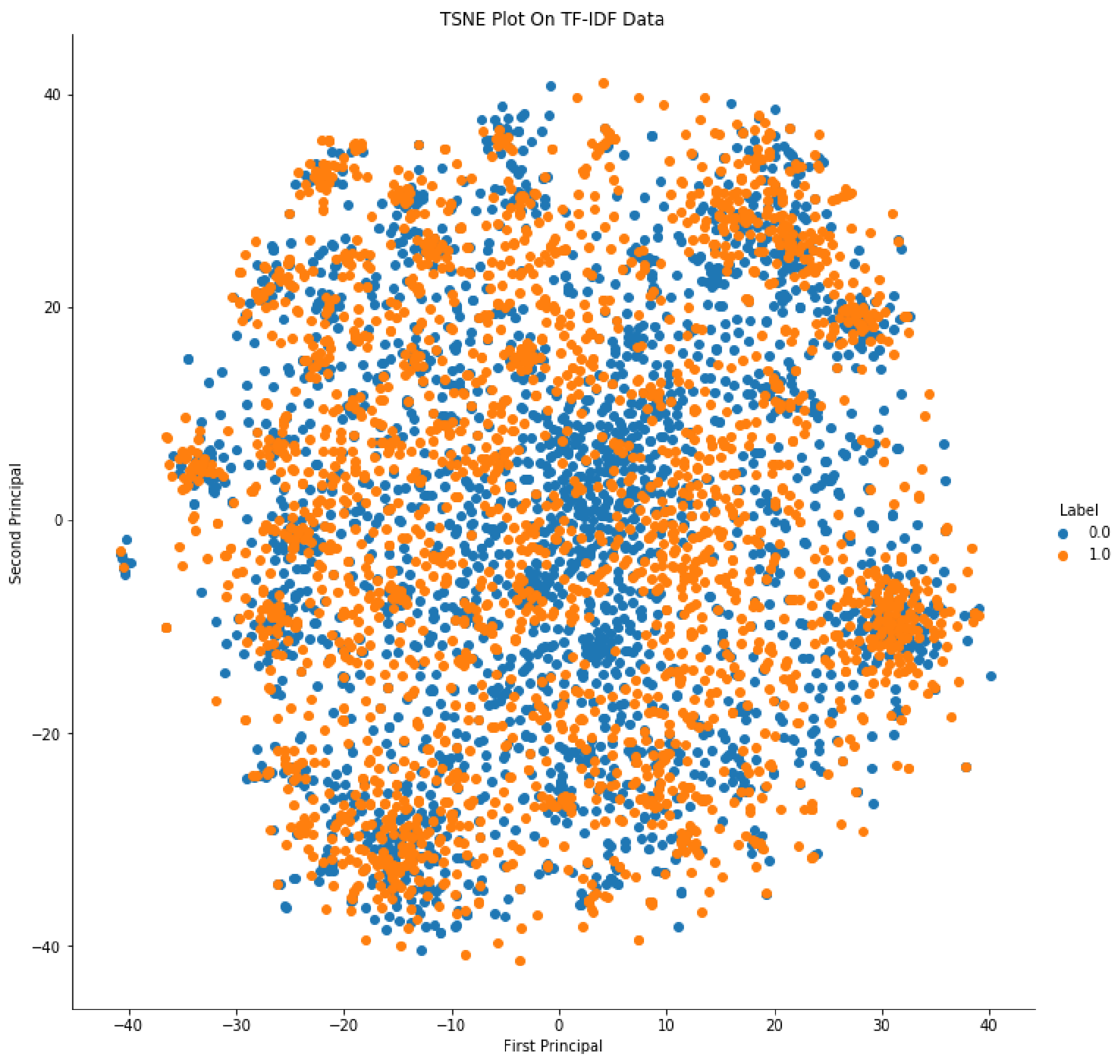
```
In [34]: from fastTSNE import TSNE
         model=TSNE(n_components=2,random_state=0)
         tsne_data= model.fit(y)
```

```
In [35]: label = new_df['Score']
         data = np.vstack((tsne_data.T,label)).T
         TFIDF_df=pd.DataFrame(data,columns=['X','Y','Label'])
         TFIDF_df['Label'].value_counts()
```

```
Out[35]: 0.0    2500
         1.0    2500
         Name: Label, dtype: int64
```

14 6.2 TSNE Plot On TF-IDF

```
In [36]: sns.FacetGrid(data=TFIDF_df,hue='Label',height=10).map(plt.scatter,'X','Y').add_legend
         plt.title("TSNE Plot On TF-IDF Data")
         plt.xlabel("First Principal")
         plt.ylabel("Second Principal")
         plt.show()
```



15 6.3 Conclusion :

1. In this plot also data are overlapping.

16 7.0 Word-To-Vector

In [37]:
```
# Loading Google News Word2Vector

Ram_gt_16GB=True
want_to_read_sub_set_of_google_w2v = True
want_to_read_whole_google_w2v = True

if not Ram_gt_16GB:
```

```
        if want_to_read_sub_set_of_google_w2v and  os.path.isfile('/content/drive/My Drive
            with open('/content/drive/My Drive/AmazonFineFoodReviews/google_w2v_for_amazon
                # model is dict object, you can directly access any word vector using mod
                model = pickle.load(f)
    else:
        if want_to_read_whole_google_w2v and os.path.isfile('/content/drive/My Drive/Colab
            model = KeyedVectors.load_word2vec_format('/content/drive/My Drive/Colab Noteb
```

In [38]:
```
# Training Word2Vec model using own text corpus
i=0
list_of_sent=[]
for sent in new_df['CleanedText']:
    list_of_sent.append(sent.split())
```

In [39]:
```
print(new_df['CleanedText'].values[0])
print("*****************************************************************")
print(list_of_sent[1:3])
```

```
enjoy cracker much will order line els buy upper peninsula michigan
*****************************************************************
[['mmmm', 'cross', 'starburst', 'fruit', 'chew', 'gummi', 'bear', 'great', 'theyr', 'avail', 'r
```

In [40]:
```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [41]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:10])
```

```
number of words that occured minimum 5 times  3365
sample words  ['enjoy', 'cracker', 'much', 'will', 'order', 'line', 'els', 'buy', 'upper', 'mic
```

In [42]:
```
w2v_model.wv.most_similar('tasti')
```

Out[42]:
```
[('overal', 0.9994135499000549),
 ('blueberri', 0.9993277788162231),
 ('prefer', 0.9993239045143127),
 ('your', 0.9992917776107788),
 ('thin', 0.9992701411247253),
 ('lack', 0.9992452263832092),
 ('punch', 0.9992323517799377),
 ('tooth', 0.9992275834083557),
 ('garlic', 0.9991897940635681),
 ('kick', 0.9991853833198547)]
```

17 7.1 Applying TSNE On Word-To-Vector

```
In [49]: token=[]
         label=[]

         for word in w2v_model.wv.vocab :
             token.append(w2v_model[word])
             label.append(word)

         print(len(token))
```

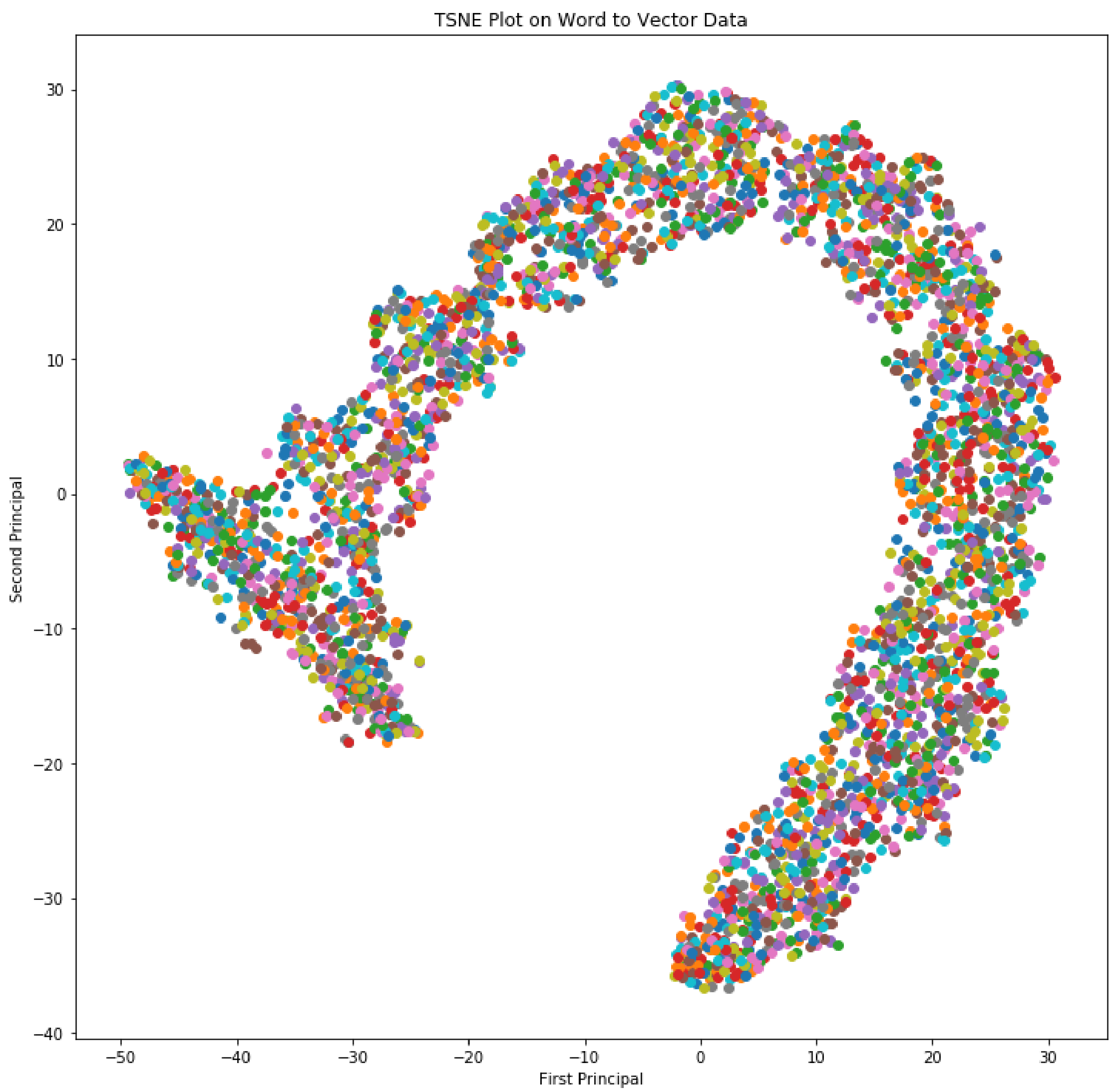
```
3365
```

```
In [50]: from sklearn.manifold import TSNE
         model=TSNE(perplexity=100,n_components=2,random_state=0)
         tsne_data=model.fit_transform(token)
```

18 7.2 TSNE Plot On Word-To-Vector

```
In [51]: x = []
         y = []
         for value in tsne_data:
             x.append(value[0])
             y.append(value[1])
```

```
In [52]: plt.figure(figsize=(12, 12))
         for i in range(len(x)):
             plt.scatter(x[i],y[i])
         plt.title("TSNE Plot on Word to Vector Data")
         plt.xlabel("First Principal")
         plt.ylabel("Second Principal")
         plt.show()
```



19 7.3 Conclusion :

1. Due to overlapping nature of data we can not say anything.
2. We are also not able to see cluster of similar words here.

20 8.0 Average Word to Vector

1. Let r1 is review of a given corpus
2. r1 : w1 w2 w3 w4 w5.....wn
3. Average w2v for r1=V1=(w2v(w1)+w2v(w2)+.....+w2v(wn))/n

In [53]:
```
sent_vectors = []; # List containing the avg-w2v for each sentence/review is stored i

for sent in tqdm(new_df['CleanedText']):

    sent_vec = np.zeros(50) # Initialisation of vector so that we could add
    cnt_words =0; # counting num of words with a valid vector in the sentence/review
    for word in sent.split():
        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%|| 5000/5000 [00:05<00:00, 780.11it/s]


5000
50
```

21 8.1 Applying TSNE On Average Word-To-Vector

In [54]:
```
from sklearn.manifold import TSNE
model=TSNE(n_components=2,random_state=0)
tsne_data= model.fit_transform(sent_vectors)
```

In [55]:
```
tsne_data.shape
```

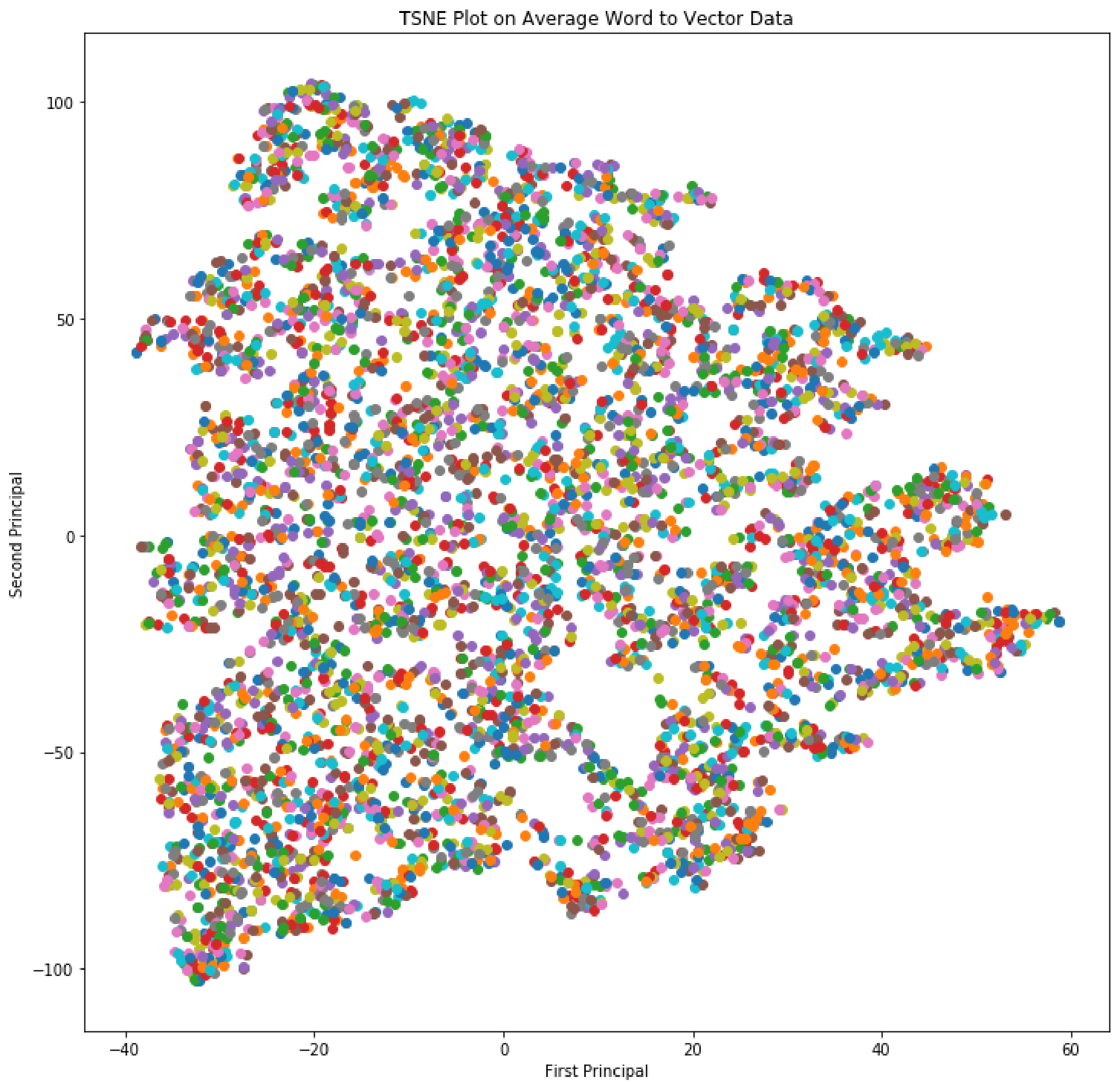
Out[55]:
```
(5000, 2)
```

22 8.2 TSNE Plot On Average Word-To-Vector

In [56]:
```
x = []
y = []
for value in tsne_data:
    x.append(value[0])
    y.append(value[1])
```

In [57]:
```
plt.figure(figsize=(12, 12))
for i in range(len(x)):
    plt.scatter(x[i],y[i])
plt.title("TSNE Plot on Average Word to Vector Data")
plt.xlabel("First Principal")
```

```
plt.ylabel("Second Principal")
plt.show()
```



23 8.3 Conclusion :

1. In this plot also data are overlapping.

24 9.0 TF-IDF Word-To-Vector

```
In [58]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
         model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(new_df['CleanedText'].values)
```

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

        tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
        row=0;
        for sent in tqdm(list_of_sent): # 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:
                    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%|| 5000/5000 [00:07<00:00, 699.11it/s]
```

25 9.1 Applying TSNE On TF-IDF Word-To-Vector

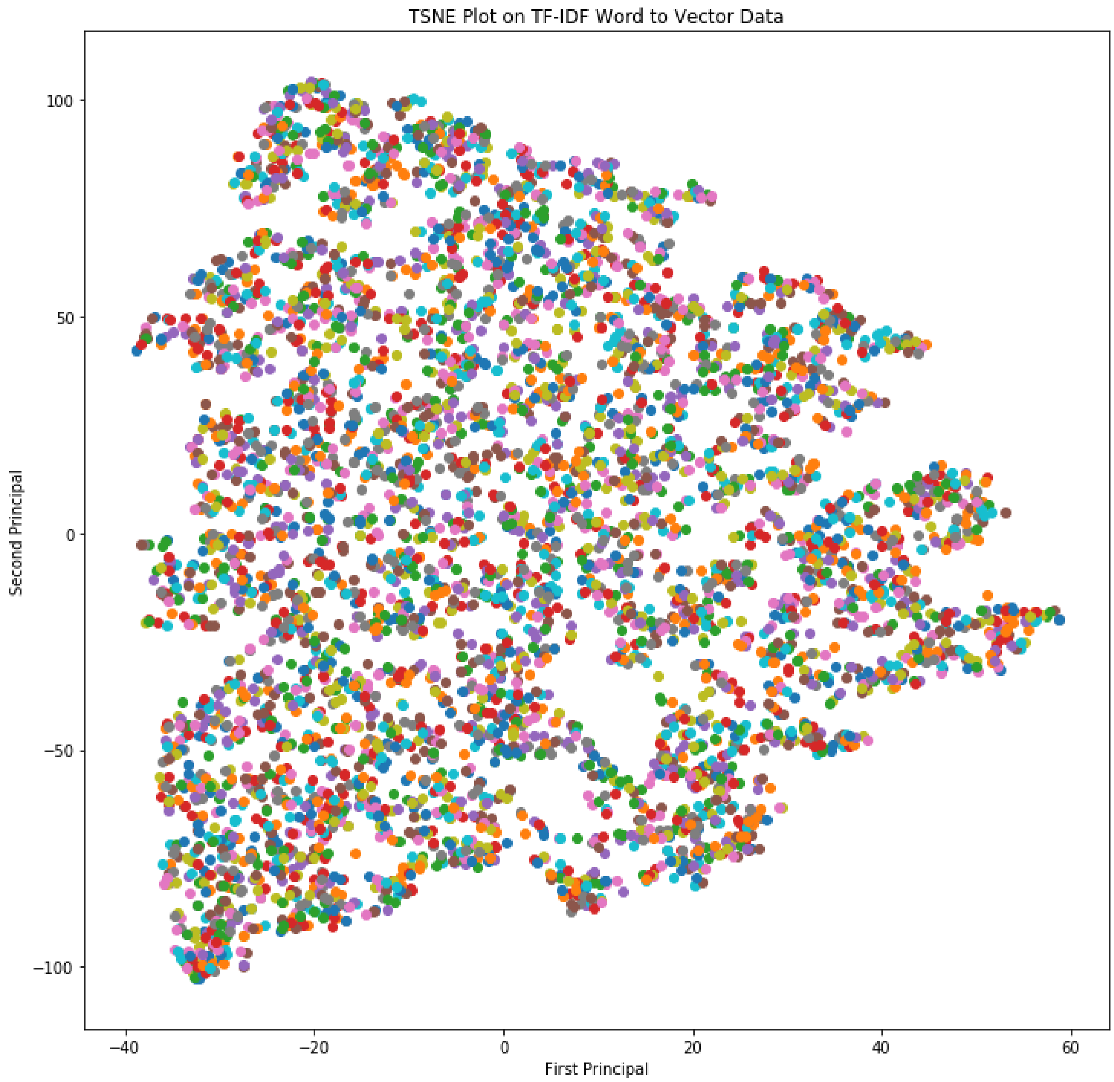
```
In [60]: from sklearn.manifold import TSNE
        model=TSNE(n_components=2,random_state=0)
        tsne_data= model.fit_transform(sent_vectors)
```

26 9.2 TSNE Plot On TF-IDF Word-To-Vector

```
In [61]: x = []
        y = []
        for value in tsne_data:
            x.append(value[0])
            y.append(value[1])
```

```
In [62]: plt.figure(figsize=(12, 12))
        for i in range(len(x)):
            plt.scatter(x[i],y[i])
```

```
plt.title("TSNE Plot on TF-IDF Word to Vector Data")
plt.xlabel("First Principal")
plt.ylabel("Second Principal")
plt.show()
```



27 9.3 Conclusion :

1. In this plot also we have same problem of data overlapping.