Assignment - 2 (t-SNE visualization of Amazon reviews with polarity based color-coding)

August 19, 2018

OBJECTIVE : Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2).

```
In [1]: # Importing libraries
        %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
In [3]: 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
        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
        import warnings
        warnings.filterwarnings("ignore")
```

1 (1). Loading Data

```
In [4]: # using the SQLite Table to read data.
        con1 = sqlite3.connect('database.sqlite')
In [5]: # Eliminating neutral reviews i.e. those reviews with Score = 3
        filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)
In [6]: # Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
        def polarity(x):
            if x < 3:
                return 'negative'
            return 'positive'
        # Applying polarity function on Score column of filtered_data
        filtered_data['Score'] = filtered_data['Score'].map(polarity)
In [7]: print(filtered_data.shape)
        filtered_data.head()
(525814, 10)
Out[7]:
                                                               ProfileName \
           Ιd
               ProductId
                                   UserId
        0
            1 B001E4KFG0 A3SGXH7AUHU8GW
                                                                 delmartian
           2 B00813GRG4 A1D87F6ZCVE5NK
                                                                    dll pa
            3 BOOOLQOCHO
                            ABXLMWJIXXAIN
                                           Natalia Corres "Natalia Corres"
            4 BOOOUAOQIQ A395BORC6FGVXV
            5 B006K2ZZ7K A1UQRSCLF8GW1T
                                             Michael D. Bigham "M. Wassir"
           HelpfulnessNumerator
                                 HelpfulnessDenominator
                                                            Score
                                                                         Time
        0
                                                                   1303862400
                                                      1 positive
                              0
        1
                                                         negative
                                                                   1346976000
        2
                              1
                                                         positive
                                                                   1219017600
        3
                              3
                                                         negative
                                                                   1307923200
        4
                                                         positive
                                                                   1350777600
                                                                               Text
                         Summary
        0
           Good Quality Dog Food I have bought several of the Vitality canned d...
        1
               Not as Advertised Product arrived labeled as Jumbo Salted Peanut...
          "Delight" says it all This is a confection that has been around a fe...
        3
                  Cough Medicine If you are looking for the secret ingredient i...
        4
                     Great taffy Great taffy at a great price. There was a wid...
```

2 Data Cleaning: Deduplication

```
In [9]: #Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
        final.shape
Out[9]: (364173, 10)
In [10]: #Checking to see how much % of data still remains
         ((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
Out[10]: 69.25890143662969
\textbf{In [11]:} \textit{ \# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator}
        final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]</pre>
In [12]: print(final.shape)
(364171, 10)
In [13]: final[30:50]
Out [13]:
                    Ιd
                         ProductId
                                             UserId \
                150501
                        0006641040 AJ46FKXOVC7NR
         138683
         138676
                150493
                        0006641040
                                    AMXOPJKV4PPNJ
               150500
                        0006641040 A1IJKK6Q1GTEAY
         138682
         138681
                150499 0006641040 A3E7R866M94L0C
        476617 515426 141278509X
                                     AB1A5EGHHVA9M
                 24751 2734888454 A1C298ITT645B6
        22621
         22620
                 24750 2734888454 A13ISQV0U9GZIC
         284375 308077
                        2841233731 A3QD68022M2XHQ
         157850 171161 7310172001
                                   AFXMWPNS1BLU4
         157849 171160 7310172001
                                    A74C7IARQEM1R
         157833 171144 7310172001 A1V5MY8V9AWUQB
         157832 171143 7310172001 A2SW060IW01VPX
         157837 171148 7310172001 A3TFTWTG2CC1GA
         157831 171142 7310172001 A2Z01AYFVQYG44
         157830 171141 7310172001
                                    AZ40270J4JBZN
         157829 171140 7310172001
                                    ADXXVGRCGQQUO
                        7310172001 A13MS1JQG2AD0J
         157828 171139
         157827 171138 7310172001 A13LAE0YTXA11B
                                    A16GY2RCF410DT
         157848
               171159
                        7310172001
         157834 171145 7310172001 A1L8DNQYY69L2Z
                                                      ProfileName
                                               Nicholas A Mesiano
         138683
                                        E. R. Bird "Ramseelbird"
         138676
         138682
                                                       A Customer
         138681
                                          L. Barker "simienwolf"
                                                          CHelmic
         476617
```

```
22621
                                         Hugh G. Pritchard
22620
                                                 Sandikaye
284375
                                                    LABRNTH
157850
                                                H. Sandler
157849
                                                    stucker
                           Cheryl Sapper "champagne girl"
157833
157832
157837
                                                J. Umphress
                                     Cindy Rellie "Rellie"
157831
        Zhinka Chunmee "gamer from way back in the 70's"
157830
                                        Richard Pearlstein
157829
157828
                                                C. Perrone
                                  Dita Vyslouzilova "dita"
157827
157848
                                                         LB
157834
                                                  R. Flores
        {\tt HelpfulnessNumerator}
                               HelpfulnessDenominator
                                                            Score
                                                                          Time
138683
                            2
                                                                     940809600
                                                         positive
                           71
                                                     72
                                                         positive
                                                                   1096416000
138676
138682
                            2
                                                         positive
                                                                    1009324800
138681
                            2
                                                         positive
                                                                    1065830400
476617
                            1
                                                         positive
                                                                    1332547200
22621
                            0
                                                         positive
                                                                   1195948800
                                                         negative
22620
                            1
                                                                   1192060800
284375
                            0
                                                         positive
                                                                    1345852800
157850
                            0
                                                         positive
                                                                    1229385600
                            0
157849
                                                         positive
                                                                    1230076800
157833
                            0
                                                         positive
                                                                    1244764800
157832
                            0
                                                         positive
                                                                    1252022400
157837
                            0
                                                         positive
                                                                   1240272000
157831
                            0
                                                                   1254960000
                                                         positive
157830
                            0
                                                         positive
                                                                    1264291200
157829
                            0
                                                         positive
                                                                   1264377600
                            0
                                                         positive
157828
                                                                   1265760000
                            0
                                                         positive
                                                                    1269216000
157827
157848
                            0
                                                         positive
                                                                    1231718400
                            0
157834
                                                         positive
                                                                   1243728000
                                                     Summary \
        This whole series is great way to spend time w...
138683
        Read it once. Read it twice. Reading Chicken S...
138676
                                         It Was a favorite!
138682
138681
                                          Can't explain why
476617
                                         The best drink mix
22621
                                          Dog Lover Delites
22620
                                              made in china
284375
                         Great recipe book for my babycook
157850
                                           Excellent treats
```

```
157849
                                          Sophie's Treats
157833
                              THE BEST healthy dog treat!
157832
                         My Alaskan Malamute Loves Them!!
157837
                                         Best treat ever!
157831
           my 12 year old maltese has always loved these
157830
                        Dogs, Cats, Ferrets all love this
157829
                                                5 snouts!
157828
                                      Best dog treat ever
157827
                                 Great for puppy training
157848
                                                   Great!
157834
                                          Terrific Treats
                                                     Text
138683 I can remember seeing the show when it aired o...
138676 These days, when a person says, "chicken soup"...
138682 This was a favorite book of mine when I was a ...
138681 This book has been a favorite of mine since I ...
476617 This product by Archer Farms is the best drink...
22621
        Our dogs just love them. I saw them in a pet ...
22620
        My dogs loves this chicken but its a product f...
284375 This book is easy to read and the ingredients ...
157850 I have been feeding my greyhounds these treats...
157849 This is one product that my welsh terrier can ...
157833 This is the ONLY dog treat that my Lhasa Apso ...
157832 These liver treas are phenomenal. When i recei...
157837 This was the only treat my dog liked during ob...
157831 No waste, even if she is having a day when s...
157830 I wanted a treat that was accepted and well li...
157829 My Westie loves these things! She loves anyth...
157828 This is the only dog treat that my terrier wil...
157827 New puppy loves this, only treat he will pay a...
157848 My dog loves these treats! We started using t...
157834 This is a great treat which all three of my do...
```

OBSERVATION: - Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

```
In [14]: final = final[final['ProductId'] != '2841233731']
In [15]: final = final[final['ProductId'] != '0006641040']
In [16]: final.shape
Out[16]: (364136, 10)
```

3 Text Preprocessing: Stemming, stop-word removal and Lemmatization.

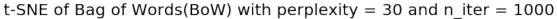
```
stop = set(stopwords.words('english'))
In [18]: words_to_keep = set(('not'))
        stop -= words_to_keep
In [19]: #initialising the snowball stemmer
         sno = nltk.stem.SnowballStemmer('english')
In [20]: #function to clean the word of any html-tags
         def cleanhtml(sentence):
             cleanr = re.compile('<.*?>')
             cleantext = re.sub(cleanr, ' ', sentence)
             return cleantext
In [21]: #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 [22]: #Code for removing HTML tags , punctuations . Code for removing stopwords . Code for
         # also greater than 2 . Code for stemming and also to convert them to lowercase lette
         i=0
         str1=' '
         final_string=[]
         all_positive_words=[] # store words from +ve reviews here
         all_negative_words=[] # store words from -ve reviews here.
         s=' '
         for sent in final['Text'].values:
             filtered_sentence=[]
             #print(sent);
             sent=cleanhtml(sent) # remove HTMl tags
             for w in sent.split():
                 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] == 'positive':
                                 all_positive_words.append(s) #list of all words used to descr
                             if(final['Score'].values)[i] == 'negative':
                                 all_negative_words.append(s) #list of all words used to descr
                         else:
                             continue
                     else:
                         continue
             str1 = b" ".join(filtered_sentence) #final string of cleaned words
```

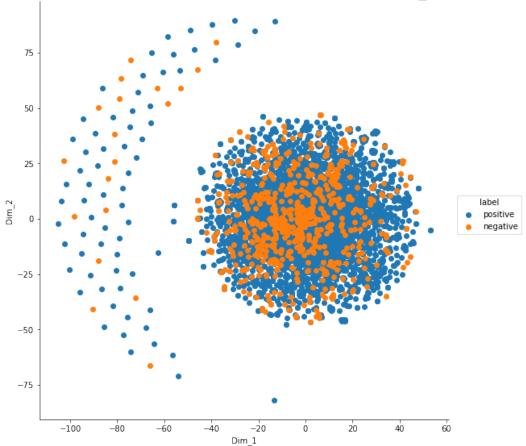
```
i+=1
In [23]: #adding a column of CleanedText which displays the data after pre-processing of the r
        final['CleanedText']=final_string
         final['CleanedText']=final['CleanedText'].str.decode("utf-8")
         #below the processed review can be seen in the CleanedText Column
         print('Shape of final',final.shape)
        final.head()
Shape of final (364136, 11)
Out [23]:
                         ProductId
                                             UserId
                                                           ProfileName \
        476617 515426 141278509X
                                     AB1A5EGHHVA9M
                                                               CHelmic
         22621
                  24751 2734888454 A1C298ITT645B6
                                                    Hugh G. Pritchard
        22620
                 24750 2734888454 A13ISQV0U9GZIC
                                                             Sandikaye
         157850 171161 7310172001 AFXMWPNS1BLU4
                                                            H. Sandler
                                                               stucker
         157849 171160 7310172001
                                     A74C7IARQEM1R
                 HelpfulnessNumerator
                                      HelpfulnessDenominator
                                                                  Score
                                                                               Time
        476617
                                                              positive
                                                                         1332547200
                                    1
         22621
                                    0
                                                              positive
                                                                         1195948800
         22620
                                                                         1192060800
                                    1
                                                            1
                                                              negative
         157850
                                    0
                                                              positive
                                                                         1229385600
         157849
                                    0
                                                              positive
                                                                         1230076800
                            Summary
                                                                                  Text \
                The best drink mix This product by Archer Farms is the best drink...
         476617
                 Dog Lover Delites Our dogs just love them. I saw them in a pet ...
         22621
         22620
                      made in china My dogs loves this chicken but its a product f...
         157850
                  Excellent treats I have been feeding my greyhounds these treats...
         157849
                   Sophie's Treats This is one product that my welsh terrier can ...
                                                       CleanedText
         476617
                product archer farm best drink mix ever mix fl...
         22621
                 dog love saw pet store tag attach regard made ...
         22620
                 dog love chicken product china wont buy anymor...
         157850
                feed greyhound treat year hound littl finicki ...
         157849
                one product welsh terrier eat sophi food alerg...
   (1). Bag of Words (BoW)
In [27]: # Using only 4K (4000) rows for further analysis as my RAM is only 8 GB
        my_final = final[0:4000]
In [29]: my_final.shape
```

final_string.append(str1)

```
Out [29]: (4000, 11)
In [34]: my_final['Score'].value_counts()
Out[34]: positive
                     3327
        negative
                      673
         Name: Score, dtype: int64
In [35]: my_final['CleanedText'].values.shape
Out[35]: (4000,)
In [65]: #BoW
         count_vect = CountVectorizer(min_df=10) #in scikit-learn
         final_counts = count_vect.fit_transform(my_final['CleanedText'].values)
         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])
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (4000, 2010)
the number of unique words 2010
In [66]: # Change sparse matrix to dense matrix
         final_counts = final_counts.toarray()
In [67]: final_counts.shape
Out[67]: (4000, 2010)
In [40]: import warnings
         warnings.filterwarnings('ignore')
         # Data-preprocessing: Standardizing the data
         from sklearn.preprocessing import StandardScaler
         standardized_data = StandardScaler().fit_transform(final_counts)
         print(standardized_data.shape)
(4000, 2010)
   t-SNE of Bag Of Words
In [41]: my_final['Score'].shape
Out [41]: (4000,)
```

```
In [42]: # TSNE
        from sklearn.manifold import TSNE
        model = TSNE(n_components=2, random_state=0)
         # configuring the parameteres
        # the number of components = 2
         # default perplexity = 30
         # default learning rate = 200
         # default Maximum number of iterations for the optimization = 1000
        tsne_data = model.fit_transform(standardized_data)
         # creating a new data frame which help us in ploting the result data
        tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
        tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
         # Ploting the result of tsne
        sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_le
        plt.title('t-SNE of Bag of Words(BoW) with perplexity = 30 and n_iter = 1000',size=20
        plt.show()
```



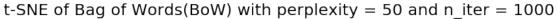


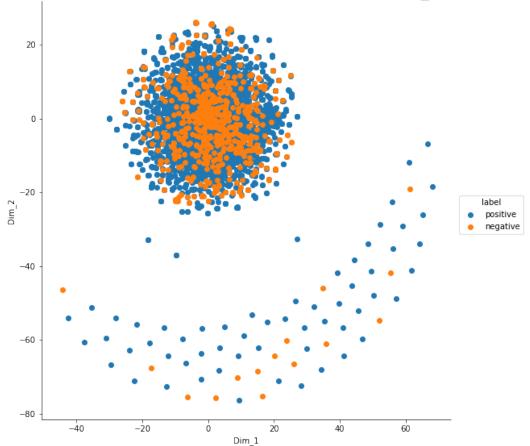
```
In [43]: # t-SNE with perplexity = 50 and n_iter = 1000
    model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=1000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 1000', size=20 plt.show()
```



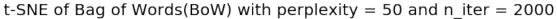


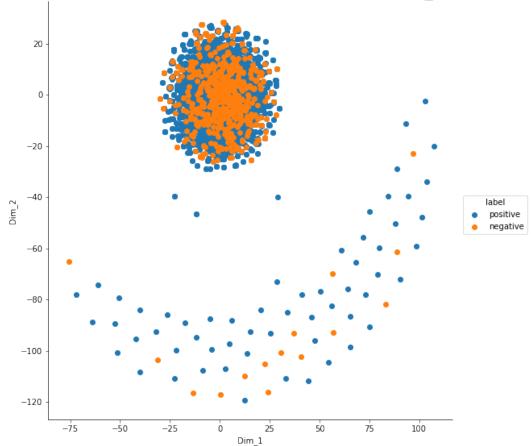
```
In [44]: # t-SNE with perplexity = 50 and n_iter = 2000
    model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=2000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 2000', size=20 plt.show()
```



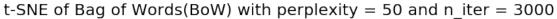


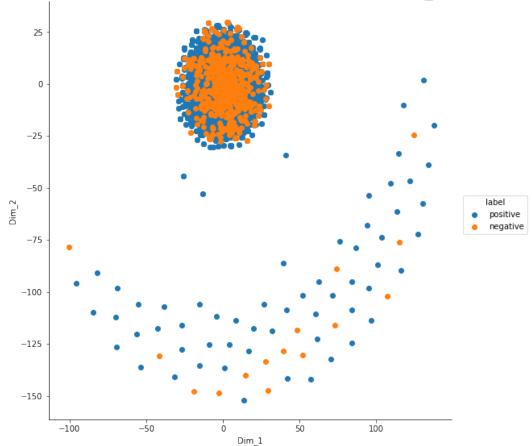
```
In [45]: # t-SNE with perplexity = 50 and n_iter = 3000
    model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=3000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 3000', size=20 plt.show()
```



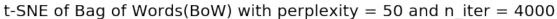


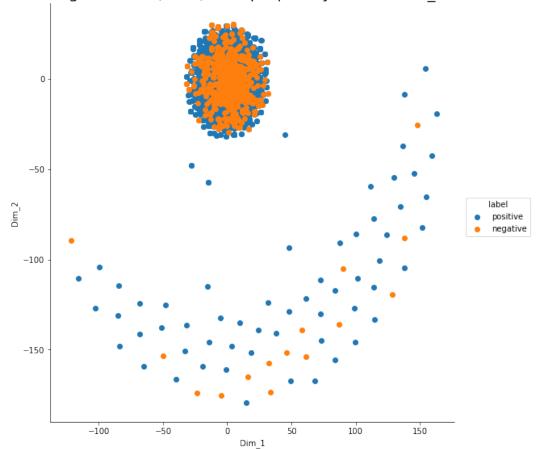
```
In [46]: # t-SNE with perplexity = 50 and n_iter = 4000
    model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=4000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 4000', size=20 plt.show()
```



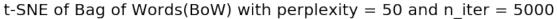


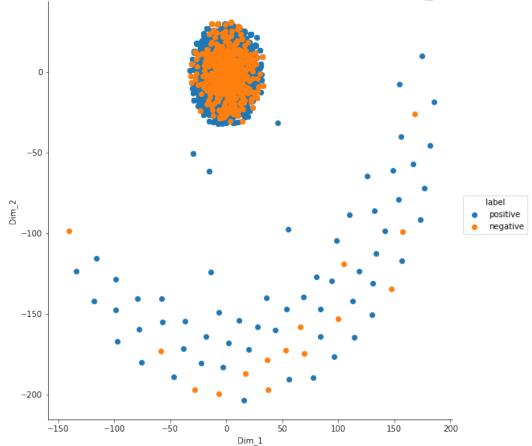
```
In [47]: # t-SNE with perplexity = 50 and n_iter = 5000
    model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 5000', size=20 plt.show()
```



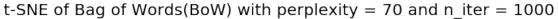


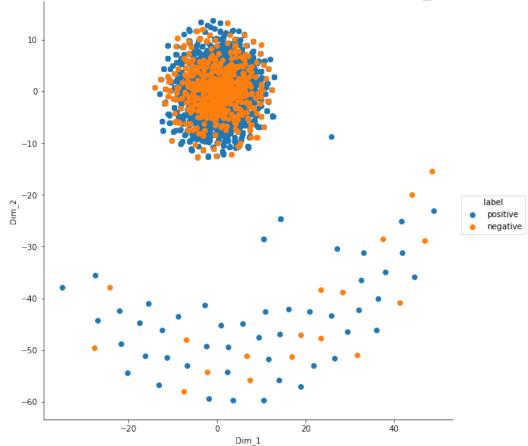
```
In [48]: # t-SNE with perplexity = 70 and n_iter = 1000
    model = TSNE(n_components=2, random_state=0, perplexity=70, n_iter=1000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 70 and n_iter = 1000', size=20 plt.show()
```



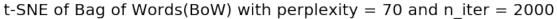


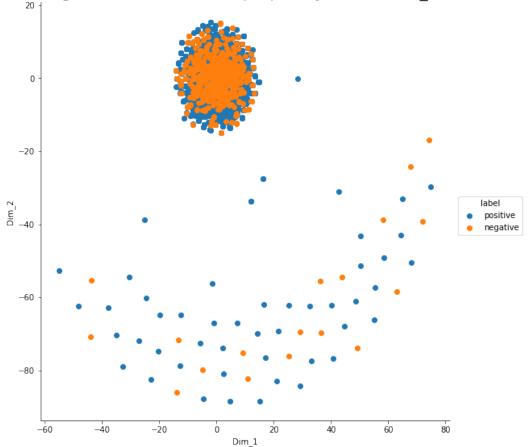
```
In [49]: # t-SNE with perplexity = 70 and n_iter = 2000
    model = TSNE(n_components=2, random_state=0, perplexity=70, n_iter=2000)

tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 70 and n_iter = 2000', size=20 plt.show()
```



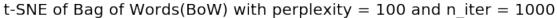


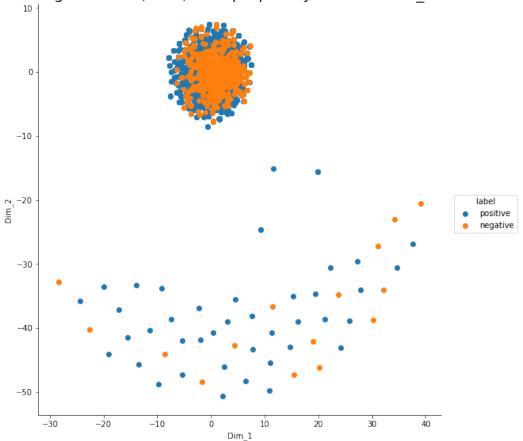
```
In [50]: # t-SNE with perplexity = 100 and n_iter = 1000
    model = TSNE(n_components=2, random_state=0, perplexity=100, n_iter=1000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 100 and n_iter = 1000', size=20 plt.show()
```



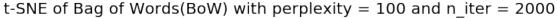


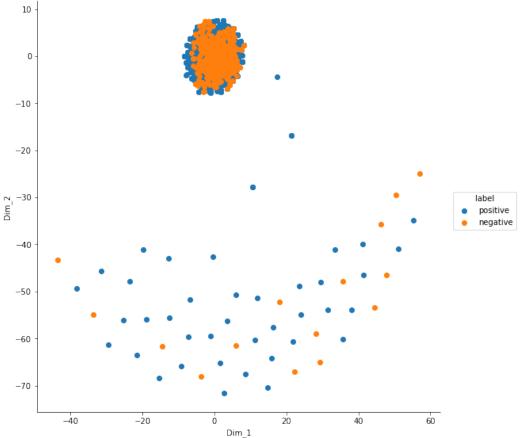
```
In [51]: # t-SNE with perplexity = 100 and n_iter = 2000
    model = TSNE(n_components=2, random_state=0, perplexity=100, n_iter=2000)

    tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
    sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legelt.title('t-SNE of Bag of Words(BoW) with perplexity = 100 and n_iter = 2000', size=20 plt.show()
```





OBSERVATIONS:- After drawing and observing t-SNE plots for different values of perplexity and n_iter. It is good to draw t-SNE plots for further techniques using following hyperparameters:

(1). perplexity = 50

the shape of out text BOW vectorizer

(2). $n_{iter} = 3000$

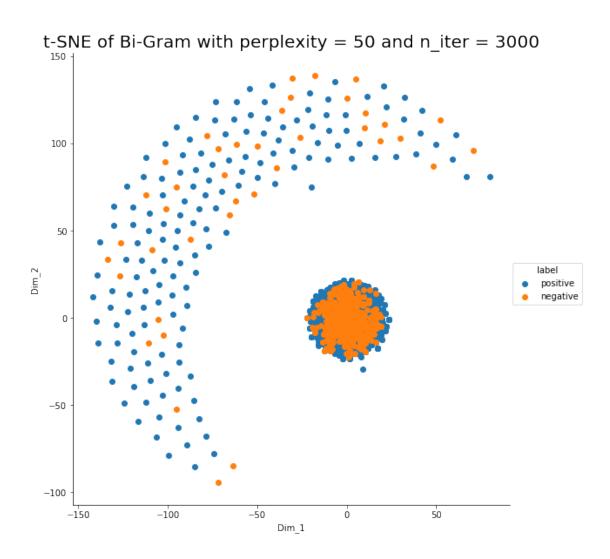
OBSERVATION FOR ABOVE PLOTS: From above plots it is clear that they are overlapping almost 90%-95% and it is very difficult to draw a line to classify the polarity of the reviews.

6 Bi-Grams

(4000, 6369)

```
In [69]: # Change sparse matrix to dense matrix
         final_bigram_counts = final_bigram_counts.toarray()
In [70]: final_bigram_counts.shape
Out[70]: (4000, 6369)
In [71]: import warnings
         warnings.filterwarnings('ignore')
         # Data-preprocessing: Standardizing the data
         from sklearn.preprocessing import StandardScaler
         standardized_data = StandardScaler().fit_transform(final_bigram_counts)
         print(standardized_data.shape)
(4000, 6369)
In [72]: # TSNE
         from sklearn.manifold import TSNE
         # t-SNE with perplexity = 50 and n_iter = 3000
         model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=3000)
         tsne_data = model.fit_transform(standardized_data)
         # creating a new data frame which help us in ploting the result data
         tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
         # Ploting the result of tsne
         sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_le
         plt.title('t-SNE of Bi-Gram with perplexity = 50 and n_iter = 3000',size=20)
         plt.show()
```

the number of unique words including both unigrams and bigrams 6369



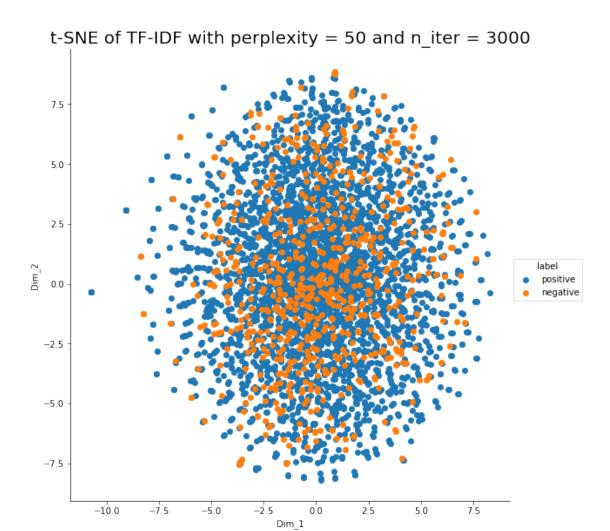
OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 90%-95% and it is very difficult to draw a line to classify the polarity of the reviews .

7 (2). TF-IDF

the shape of out text TFIDF vectorizer (4000, 6369)

the number of unique words including both unigrams and bigrams 6369

```
In [87]: features = tf_idf_vect.get_feature_names()
         print("some sample features(unique words in the corpus)",features[1000:1010])
some sample features (unique words in the corpus) ['coffe use', 'colada', 'cold', 'cold water',
In [88]: # Change sparse matrix to dense matrix
         final tf idf = final tf idf.toarray()
In [89]: final_tf_idf.shape
Out[89]: (4000, 6369)
In [90]: import warnings
         warnings.filterwarnings('ignore')
         # Data-preprocessing: Standardizing the data
         from sklearn.preprocessing import StandardScaler
         standardized_data = StandardScaler().fit_transform(final_tf_idf)
         print(standardized_data.shape)
(4000, 6369)
In [80]: # TSNE
         from sklearn.manifold import TSNE
         # t-SNE with perplexity = 50 and n_iter = 3000
         model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=3000)
         tsne_data = model.fit_transform(standardized_data)
         # creating a new data frame which help us in ploting the result data
         tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
         # Ploting the result of tsne
         sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_lepton
         plt.title('t-SNE of TF-IDF with perplexity = 50 and n_iter = 3000', size=20)
         plt.show()
```



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 85%-90% and it is very difficult to draw a line to classify the polarity of the reviews .

```
In [91]: # TSNE
```

```
from sklearn.manifold import TSNE

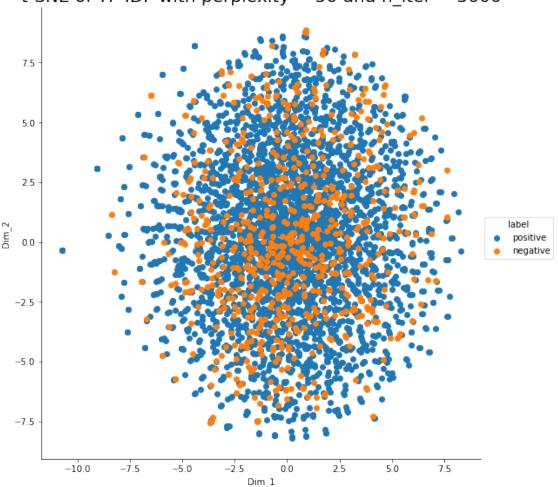
# t-SNE with perplexity = 50 and n_iter = 5000
model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)

tsne_data = model.fit_transform(standardized_data)

# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
```

```
# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_leg
plt.title('t-SNE of TF-IDF with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```

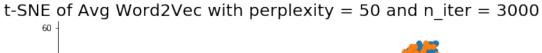


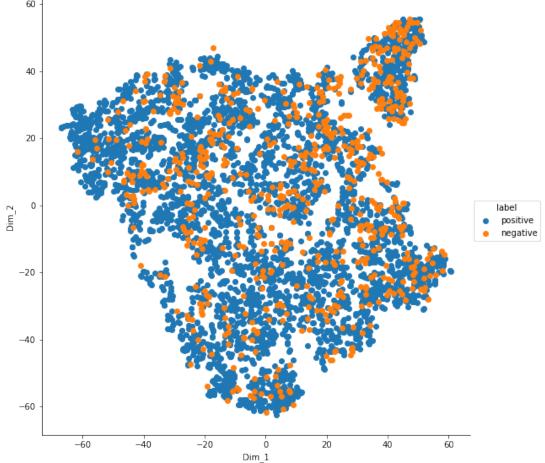


OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 85%-90% and it is very difficult to draw a line to classify the polarity of the reviews .

8 Word2Vec

```
print(list_of_sent[0])
product archer farm best drink mix ever mix flavor packet water bottl contain natur sweetner s
************************
['product', 'archer', 'farm', 'best', 'drink', 'mix', 'ever', 'mix', 'flavor', 'packet', 'wate:
In [95]: # min_count = 5 considers only words that occurred at least 5 times
        w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
In [98]: w2v_words = list(w2v_model.wv.vocab)
        print("number of words that occured minimum 5 times ",len(w2v words))
number of words that occured minimum 5 times 3253
   (3). Avg Word2Vec
In [99]: # average Word2Vec
        # compute average word2vec for each review.
        sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
        for sent in list_of_sent: # for each review/sentence
            sent_vec = np.zeros(50) # as word vectors are of zero length
            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]))
4000
50
```





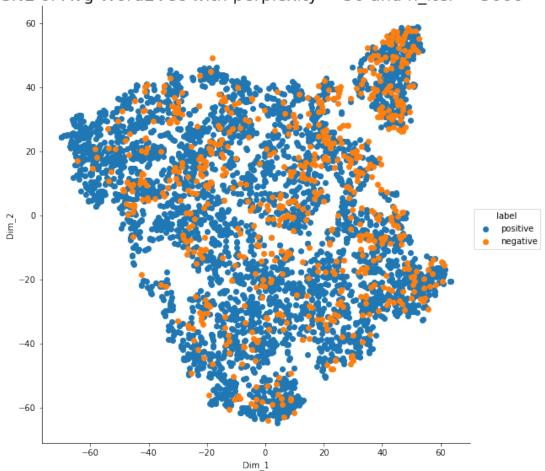
OBSERVATION FOR ABOVE PLOT: From above plot it is clear that they are overlapping almost 80%-85% and it is very difficult to draw a line to classify the polarity of the reviews . But it is better than above plots.

```
In [103]: # TSNE
          from sklearn.manifold import TSNE
          # t-SNE with perplexity = 50 and n_iter = 5000
          model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)
          tsne_data = model.fit_transform(standardized_data)
          # creating a new data frame which help us in ploting the result data
          tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
```

tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

```
# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_1
plt.title('t-SNE of Avg Word2Vec with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```



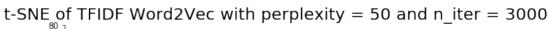


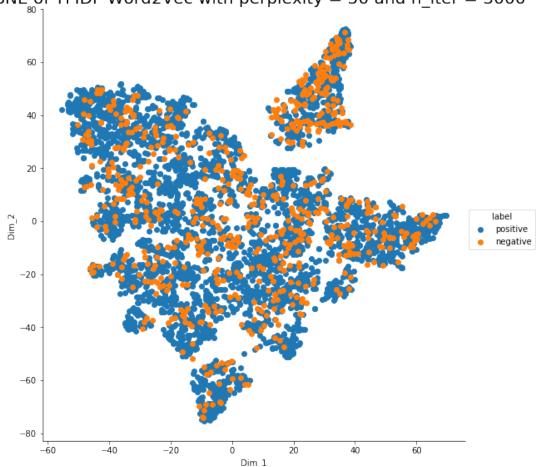
OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 80%-85% and it is very difficult to draw a line to classify the polarity of the reviews . But it is better than above plots .

10 (4). TFIDF-Word2Vec

```
In [106]: # TF-IDF weighted Word2Vec
          tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
          # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfid
In [107]: tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this
          row=0:
          for sent in 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]
                        \begin{tabular}{lll} \# \ obtain \ the \ tf\_idfidf \ of \ a \ word \ in \ a \ sentence/review \\ \end{tabular} 
                       tf_idf = final_tf_idf[row, tfidf_feat.index(word)]
                       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
In [108]: import warnings
          warnings.filterwarnings('ignore')
          # Data-preprocessing: Standardizing the data
          from sklearn.preprocessing import StandardScaler
          standardized_data = StandardScaler().fit_transform(tfidf_sent_vectors)
          print(standardized_data.shape)
(4000, 50)
In [109]: # TSNE
          from sklearn.manifold import TSNE
          # t-SNE with perplexity = 50 and n_iter = 3000
          model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=3000)
          tsne_data = model.fit_transform(standardized_data)
          # creating a new data frame which help us in ploting the result data
          tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
          tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
          # Ploting the result of tsne
          sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_le
```

plt.title('t-SNE of TFIDF Word2Vec with perplexity = 50 and n_iter = 3000',size=20)
plt.show()



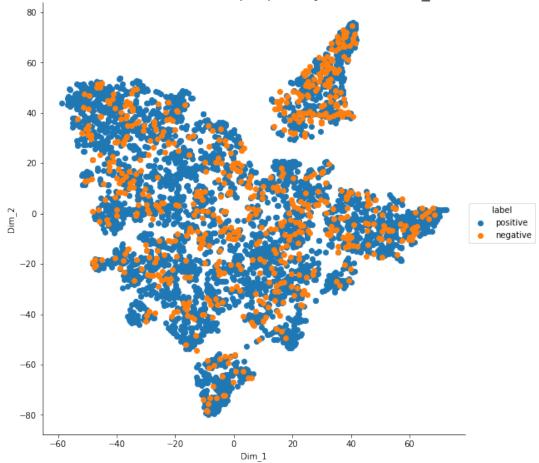


OBSERVATION FOR ABOVE PLOT: From above plot it is clear that they are overlapping almost 70%-80% and it is very difficult to draw a line to classify the polarity of the reviews. But it is better than above plots.

```
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_1
plt.title('t-SNE of TFIDF Word2Vec with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```

t-SNE of TFIDF Word2Vec with perplexity = 50 and n_iter = 5000



OBSERVATION FOR ABOVE PLOT: From above plot it is clear that they are overlapping almost 70%-80% and it is very difficult to draw a line to classify the polarity of the reviews . But it is much better than above plots .