Amazon Fine Food Reviews using t-SNE

August 13, 2018

1 t-SNE Visualization of Amazon reviews with polarity based color-coding

BY: Subham Sarkar

In [3]:
```
%matplotlib inline

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
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
```

```
# using the SQLite Table to read data.
con = sqlite3.connect('C:/Users/Subham Sarkar/Downloads/database.sqlite')



#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews  WHERE Score != 3 """, con)


# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'

#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


import warnings
warnings.filterwarnings("ignore")
```

In [4]:
```
print(filtered_data.shape) #looking at the number of attributes and size of the data
filtered_data.head()
```

```
(525814, 10)
```

Out[4]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  positive  1303862400
1                     0                       0  negative  1346976000
2                     1                       1  positive  1219017600
3                     3                       3  negative  1307923200
4                     0                       0  positive  1350777600

                 Summary                                              Text
```

```
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...
2  "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...
```

In [5]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[5]:
```
       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 ...
```

In [6]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal
```

In [7]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
final.shape
```

Out[7]: (364173, 10)

In [8]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[8]:
```
      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...
```

In [9]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [10]:
```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
(364171, 10)
```

Out[10]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [11]:
```
# find sentences containing HTML tags
import re
i=0;
for sent in final['Text'].values:
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
    i += 1;
```

```
6
I set aside at least an hour each day to read to my son (3 y/o). At this point, I consider myse
```

In [12]:
```
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to C:\Users\Subham
[nltk_data]     Sarkar\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[12]: True

In [13]:
```
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
print(stop)
print('************************************')
print(sno.stem('tasty'))
```

```
{'nor', 'between', 'am', 'has', 'out', 'by', 'too', 'theirs', 'once', 'only', 'was', 'very', 'i
************************************
tasti
```

In [14]:
```
#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.
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
        #print(filtered_sentence)
        str1 = b" ".join(filtered_sentence) #final string of cleaned words
        #print("***********************************************************************")

        final_string.append(str1)
        i+=1
```

In [15]:
```
print(final_string)
```

```
IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)
```

In [16]:
```
final['CleanedText']=final_string #adding a column of CleanedText which displays the
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
```

In [17]:
```
final.head(3) #below the processed review can be seen in the CleanedText Column


# 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_lal
```

2 Bag of Words

In [18]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
final_counts = count_vect.fit_transform(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  (364171, 71624)
the number of unique words  71624
```

```
In [19]: freq_dist_positive=nltk.FreqDist(all_positive_words)
         freq_dist_negative=nltk.FreqDist(all_negative_words)
         print("Most Common Positive Words : ",freq_dist_positive.most_common(20))
         print("Most Common Negative Words : ",freq_dist_negative.most_common(20))
```

```
Most Common Positive Words :  [(b'like', 139429), (b'tast', 129047), (b'good', 112766), (b'fla
Most Common Negative Words :  [(b'tast', 34585), (b'like', 32330), (b'product', 28218), (b'one
```

3 Observation:-

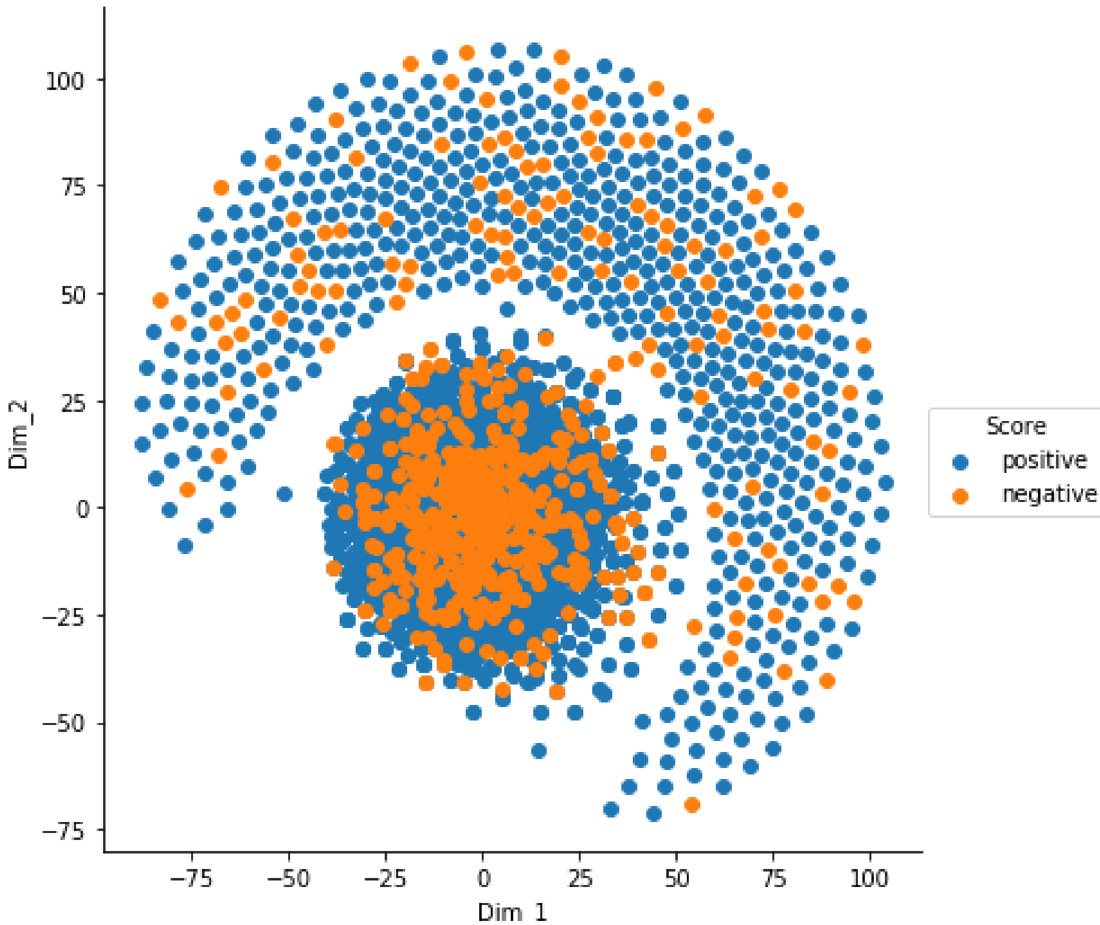
From the above it can be seen that the most common positive and the negative words overlap for eg. 'like' could be used as 'not like' etc. So, it is a good idea to consider pairs of consequent words (bi-grams) or q sequnce of n consecutive words (n-grams)

```
In [20]: import warnings
         warnings.filterwarnings('ignore')
         from sklearn.preprocessing import StandardScaler

         standardized_data=StandardScaler().fit_transform(final_counts[4000].toarray())
         print(standardized_data.shape)
```

```
(1, 71624)
```

4 t-SNE plot for Bag of Words with perplexity = 30

```
In [30]: from sklearn.manifold import TSNE
         label_4000 = final['Score'][0:4000]

         model = TSNE(n_components=2, random_state=0)
         tsne_data = model.fit_transform(standardized_data)
         tsne_data=np.vstack((tsne_data.T,label_4000)).T
         tsne_df=pd.DataFrame(data=tsne_data,columns=('Dim_1','Dim_2','Score'))
         sns.FacetGrid(tsne_df, hue='Score', size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_leg
         plt.show()
```



5 tf-idf (term frequency-inverse document frequency)

```
In [21]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf = tf_idf_vect.fit_transform(final['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  (364171, 2923725)
the number of unique words including both unigrams and bigrams  2923725
```

```
In [22]: features = tf_idf_vect.get_feature_names()
         print("some sample features(unique words in the corpus)",features[100000:100010])
```

```
some sample features(unique words in the corpus) ['antler fair', 'antler fall', 'antler fantas
```

In [28]:
```
print(final_tf_idf[0:100,:].toarray()[0])
```

```
[0. 0. 0. ... 0. 0. 0.]
```

In [29]:
```
def top_tfidf_feats(row, features, top_n=25):
    ''' Get top n tfidf values in row and return them with their corresponding featur
    topn_ids = np.argsort(row)[::-1][:top_n]
    top_feats = [(features[i], row[i]) for i in topn_ids]
    df = pd.DataFrame(top_feats)
    df.columns = ['feature', 'tfidf']
    return df

top_tfidf = top_tfidf_feats(final_tf_idf[1,:].toarray()[0],features,25)
```

In [30]:
```
top_tfidf
```

Out[30]:

	feature	tfidf
0	page open	0.192673
1	read sendak	0.192673
2	movi incorpor	0.192673
3	paperback seem	0.192673
4	version paperback	0.192673
5	flimsi take	0.192673
6	incorpor love	0.192673
7	rosi movi	0.192673
8	keep page	0.192673
9	grew read	0.192673
10	realli rosi	0.186715
11	sendak book	0.186715
12	cover version	0.186715
13	miss hard	0.182488
14	kind flimsi	0.176530
15	hard cover	0.174265
16	watch realli	0.170572
17	book watch	0.170572
18	sendak	0.166345
19	howev miss	0.165169
20	paperback	0.162117
21	hand keep	0.153894
22	two hand	0.150202
23	rosi	0.148291
24	seem kind	0.147253

In [31]:
```
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import StandardScaler

standardize_data=StandardScaler().fit_transform(final_tf_idf[0:100,:].toarray())
print(standardize_data.shape)
```

```
(100, 2923725)
```

6 t-SNE plot of average tf-idf with perplexity = 30

```
In [ ]: from sklearn.manifold import TSNE
        label_4000 = final['Score'][0:4000]

        model = TSNE(n_components=2, random_state=0)
        tsne_data = model.fit_transform(standardize_data)
        tsne_data=np.vstack((tsne_data.T,label_4000)).T
        tsne_df=pd.DataFrame(data=tsne_data,columns=('Dim_1','Dim_2','Score'))
        sns.FacetGrid(tsne_df, hue='Score', size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
        plt.show()
```

7 Word2Vec

```
In [33]: i=0
         list_of_sent=[]
         for sent in final['CleanedText'].values:
             list_of_sent.append(sent.split())

In [34]: print(final['CleanedText'].values[0])
         print("*****************************************************************")
         print(list_of_sent[0])

witti littl book make son laugh loud recit car drive along alway sing refrain hes learn whale i
*****************************************************************
['witti', 'littl', 'book', 'make', 'son', 'laugh', 'loud', 'recit', 'car', 'drive', 'along', 'a


In [35]: w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)

In [36]: 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  21938
sample words  ['witti', 'littl', 'book', 'make', 'son', 'laugh', 'loud', 'recit', 'car', 'drive


In [37]: w2v_model.wv.most_similar('tasti')

Out[37]: [('delici', 0.8079195618629456),
          ('yummi', 0.7775864601135254),
          ('tastey', 0.722675621509552),
          ('good', 0.6968026161193848),
          ('nice', 0.6770238876342773),
```

```
 ('hearti', 0.6712539196014404),
 ('satisfi', 0.6701481938362122),
 ('nutriti', 0.644965648651123),
 ('great', 0.6448278427124023),
 ('terrif', 0.6447775363922119)]
```

```
In [38]: w2v_model.wv.most_similar('like')
```

```
Out[38]: [('weird', 0.7477270364761353),
 ('dislik', 0.7056392431259155),
 ('funki', 0.6866582632064819),
 ('yucki', 0.6820259690284729),
 ('okay', 0.6809946894645691),
 ('prefer', 0.6613717079162598),
 ('gross', 0.6539754271507263),
 ('fake', 0.6539649963378906),
 ('resembl', 0.6470655202865601),
 ('appeal', 0.6464338898658752)]
```

```
In [39]: count_vect_feat = count_vect.get_feature_names() # list of words in the BoW
         print(count_vect_feat[count_vect_feat.index('like')])
```

```
like
```

8 TF-IDF weighted Word2Vec

```
In [ ]: # 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 = tfidf

        tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this li
        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]
                    # obtain the tf_idfidf of a word in a sentence/review
                    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
```

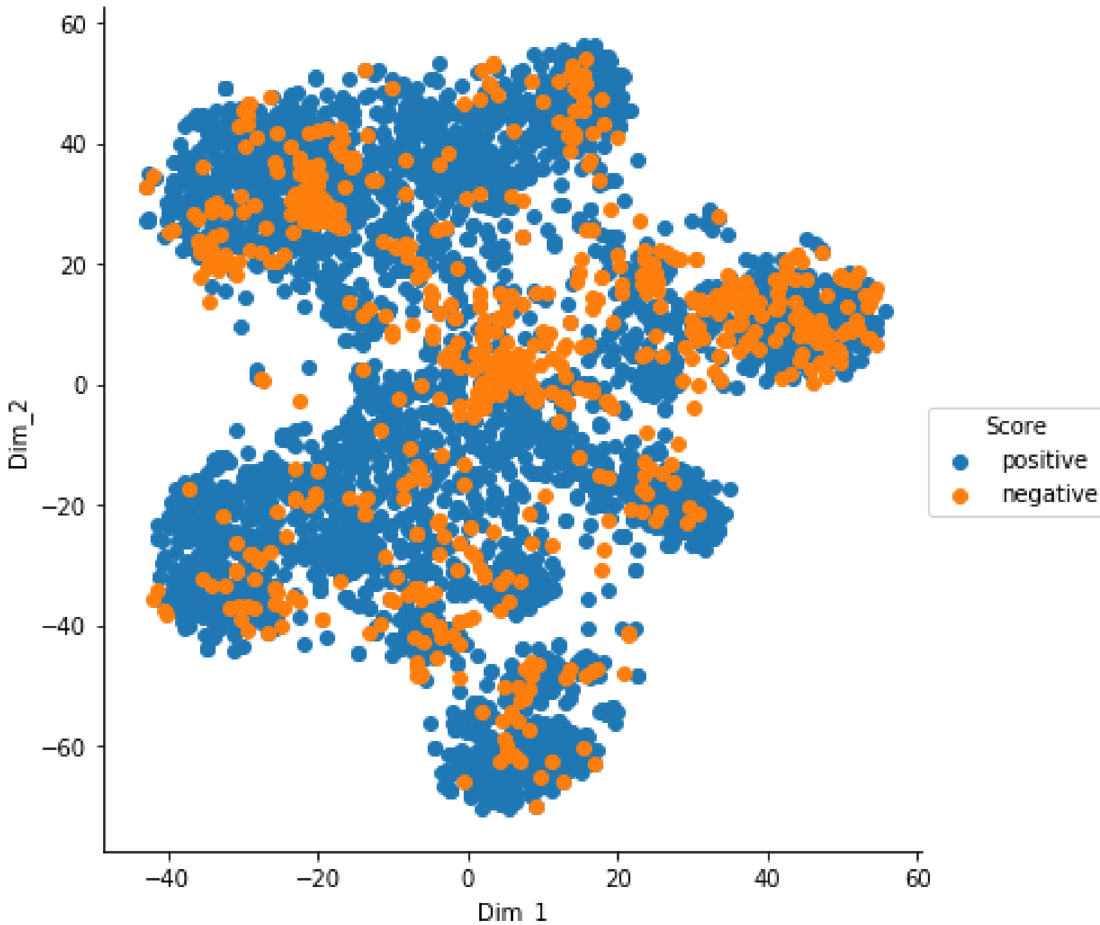
9 average Word2Vec

```
In [49]: # 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]))
```

```
364171
50
```

10 t-SNE plot of average Word2Vec with perplexity = 30

```
In [54]: from sklearn.manifold import TSNE
         label_4000_avg = final['Score'][0:4000]

         model = TSNE(n_components=2, random_state=0)
         tsne_data = model.fit_transform(sent_vectors[0:4000])
         tsne_data=np.vstack((tsne_data.T,label_4000_avg)).T
         tsne_df=pd.DataFrame(data=tsne_data,columns=('Dim_1','Dim_2','Score'))
         sns.FacetGrid(tsne_df, hue='Score', size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_leg
         plt.show()
```


Dim_2
Dim_1
Score
positive
negative
60
40
20
0
−20
−40
−60
−40
−20
0
20
40
60