T-SNE_Amazon_Fine_Food_Reviews

November 30, 2018

1 t-SNE: Amazon Find Food Reviews Analysis

- The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful ---> Yes
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not ---> Yes/NO
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

objective:

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

Que:- How to determine if a review is positive or negative?

Ans:-

1. A rating of 4 or 5 could be cosnidered a positive review.
2. A review of 1 or 2 could be considered negative.
3. A review of 3 is nuetral and ignored.

```
In [1]: import warnings
        warnings.filterwarnings('ignore')
```

```
In [2]: %matplotlib inline

        import sqlite3
        import pandas as pd
        import numpy as np
```

```python
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
import nltk
from nltk.stem.porter import PorterStemmer

con = sqlite3.connect('./amazon-fine-food-reviews/database.sqlite')

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

def partition(x):
    if x<3:
        return "negative"
    return "positive"

actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
```

In [3]:
```python
print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

Out[3]:
```
   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...
```

2 Data Cleaning: Deduplication

```
In [4]: display = pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        Order By ProductID
        """, con)
        display.head()
```

```
Out[4]:        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 [5]:
```
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

In [6]:
```
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
final.shape
```

Out[6]:
```
(364173, 10)
```

In [7]:
```
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[7]:
```
69.25890143662969
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [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]:
```
print(final.shape)

final['Score'].value_counts()
```

```
(364171, 10)
```

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

3 Bag of Words (BOW)

```
In [11]: positive_data = final[final["Score"] == "positive"].sample(n = 2000)
         negative_data = final[final["Score"] == "negative"].sample(n = 2000)
         final_4000 = pd.concat([positive_data, negative_data])
```

```
In [12]: score_4000 = final_4000['Score']
```

```
In [13]: score_4000.shape
```

```
Out[13]: (4000,)
```

```
In [14]: final_4000.shape
```

```
Out[14]: (4000, 10)
```

```
In [15]: count_vect = CountVectorizer()
         final_counts = count_vect.fit_transform(final_4000['Text'].values)
```

```
In [16]: type(final_counts)
```

```
Out[16]: scipy.sparse.csr.csr_matrix
```

```
In [17]: final_counts.get_shape()
```

```
Out[17]: (4000, 13752)
```

4 Bi-grams and n-grams

```
In [18]: count_vect = CountVectorizer(ngram_range=(1,2) )
         final_bigram_counts = count_vect.fit_transform(final_4000['Text'].values)
```

```
In [19]: final_bigram_counts.get_shape()
```

```
Out[19]: (4000, 144065)
```

```
In [20]: from sklearn.preprocessing import StandardScaler

         standard_data = StandardScaler(with_mean = False).fit_transform(final_bigram_counts)
         standard_data.shape
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarn
  warnings.warn(msg, DataConversionWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarn
  warnings.warn(msg, DataConversionWarning)
```

```
Out[20]: (4000, 144065)
```

```
In [21]: type(standard_data)
```

Out[21]: scipy.sparse.csr.csr_matrix

In [22]:
```
standard_data = standard_data.todense()
# convert sparse to dense as tsne takes dense vector
```

In [23]:
```
type(standard_data)
```

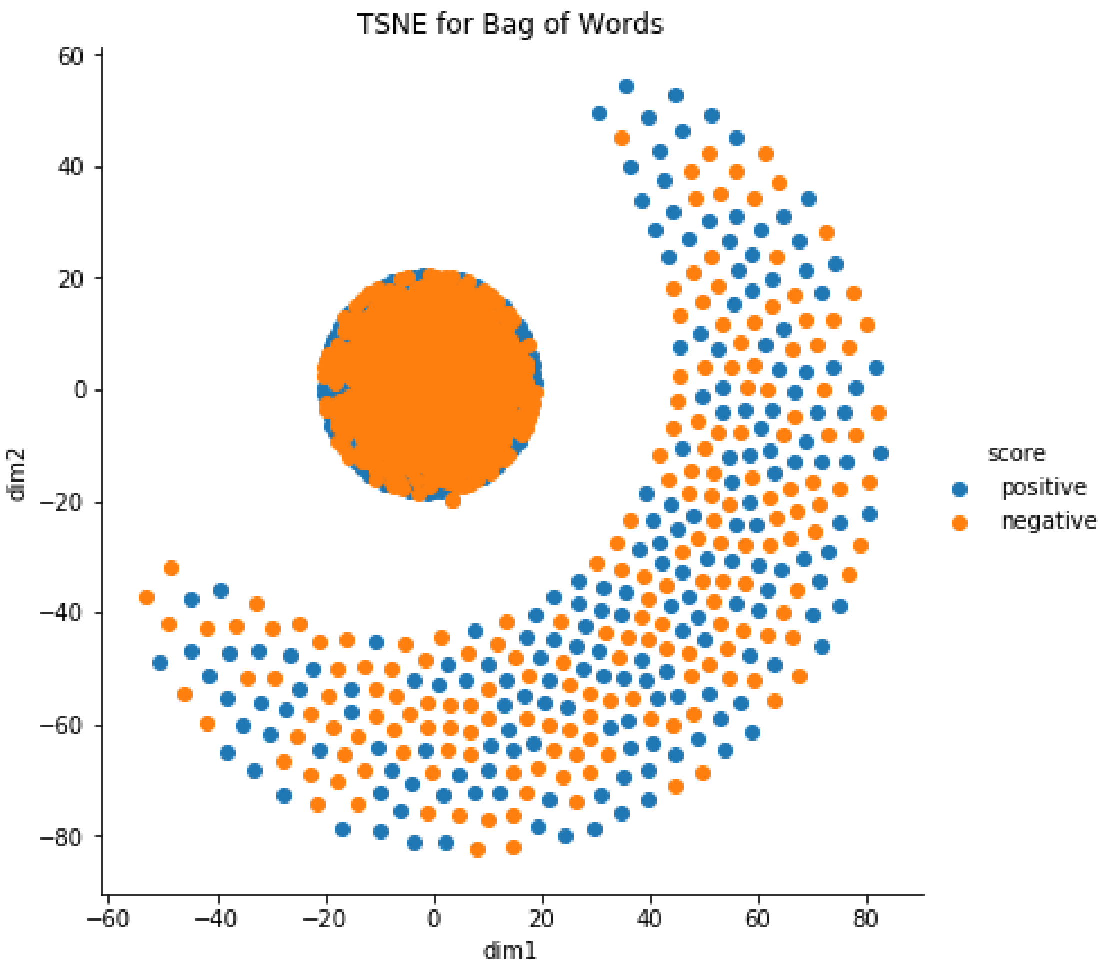
Out[23]: numpy.matrixlib.defmatrix.matrix

In [24]:
```
from sklearn.manifold import TSNE
model = TSNE(n_components=2, random_state=0, perplexity=50)

tsne_data = model.fit_transform(standard_data)

tsne_data = np.vstack((tsne_data.T, score_4000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("dim1", "dim2", "score"))

sns.FacetGrid(tsne_df, hue="score", size=6).map(plt.scatter, 'dim1', 'dim2').add_legen
plt.title("TSNE for Bag of Words")
plt.show()
```



- Obeservation:- Here, we are unable to classify the +ve and -ve points because it overlaps each other.

5 TF-IDF

In [24]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
final_tf_idf = tf_idf_vect.fit_transform(final_4000['Text'].values)
```

In [25]:
```
from sklearn.preprocessing import StandardScaler
std = StandardScaler(with_mean = False)
standard_data = std.fit_transform(final_tf_idf)
```

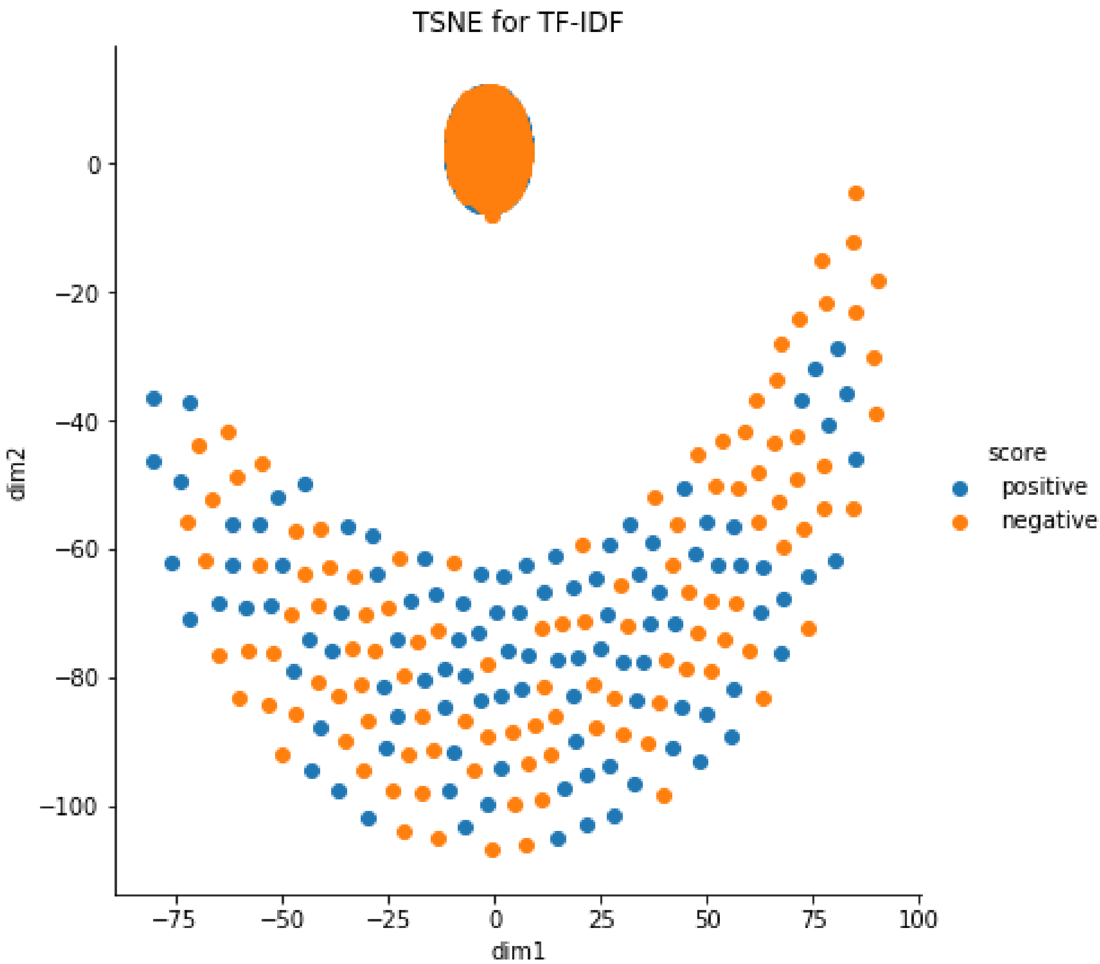
In [26]:
```
standard_data = standard_data.todense()
```

In [27]:
```
standard_data.shape
```

Out[27]:
```
(4000, 144065)
```

In [29]:
```
from sklearn.manifold import TSNE
model = TSNE(n_components = 2, perplexity = 50)
tsne_data = model.fit_transform(standard_data)

tsne_data = np.vstack((tsne_data.T, score_4000)).T
tsne_df = pd.DataFrame(data = tsne_data, columns = ("dim1", "dim2", "score"))
sns.FacetGrid(tsne_df, hue = "score", size = 6).map(plt.scatter, "dim1", "dim2").add_
plt.title("TSNE for TF-IDF")
plt.show()
```



- Observation:- As we saw earlier, it overlaps +ve and -ve points same as Bag of Words.

6 Word2Vec

```
In [28]: import gensim
         from gensim.models import Word2Vec
         from gensim.models import KeyedVectors
         import pickle

         model = KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin.gz', bi

C:\ProgramData\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")


In [29]: model.wv['computer']
```

```
Out[29]: array([ 1.07421875e-01, -2.01171875e-01,  1.23046875e-01,  2.11914062e-01,
               -9.13085938e-02,  2.16796875e-01, -1.31835938e-01,  8.30078125e-02,
                2.02148438e-01,  4.78515625e-02,  3.66210938e-02, -2.45361328e-02,
                2.39257812e-02, -1.60156250e-01, -2.61230469e-02,  9.71679688e-02,
               -6.34765625e-02,  1.84570312e-01,  1.70898438e-01, -1.63085938e-01,
               -1.09375000e-01,  1.49414062e-01, -4.65393066e-04,  9.61914062e-02,
                1.68945312e-01,  2.60925293e-03,  8.93554688e-02,  6.49414062e-02,
                3.56445312e-02, -6.93359375e-02, -1.46484375e-01, -1.21093750e-01,
               -2.27539062e-01,  2.45361328e-02, -1.24511719e-01, -3.18359375e-01,
               -2.20703125e-01,  1.30859375e-01,  3.66210938e-02, -3.63769531e-02,
               -1.13281250e-01,  1.95312500e-01,  9.76562500e-02,  1.26953125e-01,
                6.59179688e-02,  6.93359375e-02,  1.02539062e-02,  1.75781250e-01,
               -1.68945312e-01,  1.21307373e-03, -2.98828125e-01, -1.15234375e-01,
                5.66406250e-02, -1.77734375e-01, -2.08984375e-01,  1.76757812e-01,
                2.38037109e-02, -2.57812500e-01, -4.46777344e-02,  1.88476562e-01,
                5.51757812e-02,  5.02929688e-02, -1.06933594e-01,  1.89453125e-01,
               -1.16210938e-01,  8.49609375e-02, -1.71875000e-01,  2.45117188e-01,
               -1.73828125e-01, -8.30078125e-03,  4.56542969e-02, -1.61132812e-02,
                1.86523438e-01, -6.05468750e-02, -4.17480469e-02,  1.82617188e-01,
                2.20703125e-01, -1.22558594e-01, -2.55126953e-02, -3.08593750e-01,
                9.13085938e-02,  1.60156250e-01,  1.70898438e-01,  1.19628906e-01,
                7.08007812e-02, -2.64892578e-02, -3.08837891e-02,  4.06250000e-01,
               -1.01562500e-01,  5.71289062e-02, -7.26318359e-03, -9.17968750e-02,
               -1.50390625e-01, -2.55859375e-01,  2.16796875e-01, -3.63769531e-02,
                2.24609375e-01,  8.00781250e-02,  1.56250000e-01,  5.27343750e-02,
                1.50390625e-01, -1.14746094e-01, -8.64257812e-02,  1.19140625e-01,
               -7.17773438e-02,  2.73437500e-01, -1.64062500e-01,  7.29370117e-03,
                4.21875000e-01, -1.12792969e-01, -1.35742188e-01, -1.31835938e-01,
               -1.37695312e-01, -7.66601562e-02,  6.25000000e-02,  4.98046875e-02,
               -1.91406250e-01, -6.03027344e-02,  2.27539062e-01,  5.88378906e-02,
               -3.24218750e-01,  5.41992188e-02, -1.35742188e-01,  8.17871094e-03,
               -5.24902344e-02, -1.74713135e-03, -9.81445312e-02, -2.86865234e-02,
                3.61328125e-02,  2.15820312e-01,  5.98144531e-02, -3.08593750e-01,
               -2.27539062e-01,  2.61718750e-01,  9.86328125e-02, -5.07812500e-02,
                1.78222656e-02,  1.31835938e-01, -5.35156250e-01, -1.81640625e-01,
                1.38671875e-01, -3.10546875e-01, -9.71679688e-02,  1.31835938e-01,
               -1.16210938e-01,  7.03125000e-02,  2.85156250e-01,  3.51562500e-02,
               -1.01562500e-01, -3.75976562e-02,  1.41601562e-01,  1.42578125e-01,
               -5.68847656e-02,  2.65625000e-01, -2.09960938e-01,  9.64355469e-03,
               -6.68945312e-02, -4.83398438e-02, -6.10351562e-02,  2.45117188e-01,
               -9.66796875e-02,  1.78222656e-02, -1.27929688e-01, -4.78515625e-02,
               -7.26318359e-03,  1.79687500e-01,  2.78320312e-02, -2.10937500e-01,
               -1.43554688e-01, -1.27929688e-01,  1.73339844e-02, -3.60107422e-03,
               -2.04101562e-01,  3.63159180e-03, -1.19628906e-01, -6.15234375e-02,
                5.93261719e-02, -3.23486328e-03, -1.70898438e-01, -3.14941406e-02,
               -8.88671875e-02, -2.89062500e-01,  3.44238281e-02, -1.87500000e-01,
                2.94921875e-01,  1.58203125e-01, -1.19628906e-01,  7.61718750e-02,
                6.39648438e-02, -4.68750000e-02, -6.83593750e-02,  1.21459961e-02,
```

```
         -1.44531250e-01,  4.54101562e-02,  3.68652344e-02,  3.88671875e-01,
          1.45507812e-01, -2.55859375e-01, -4.46777344e-02, -1.33789062e-01,
         -1.38671875e-01,  6.59179688e-02,  1.37695312e-01,  1.14746094e-01,
          2.03125000e-01, -4.78515625e-02,  1.80664062e-02, -8.54492188e-02,
         -2.48046875e-01, -3.39843750e-01, -2.83203125e-02,  1.05468750e-01,
         -2.14843750e-01, -8.74023438e-02,  7.12890625e-02,  1.87500000e-01,
         -1.12304688e-01,  2.73437500e-01, -3.26171875e-01, -1.77734375e-01,
         -4.24804688e-02, -2.69531250e-01,  6.64062500e-02, -6.88476562e-02,
         -1.99218750e-01, -7.03125000e-02, -2.43164062e-01, -3.66210938e-02,
         -7.37304688e-02, -1.77734375e-01,  9.17968750e-02, -1.25000000e-01,
         -1.65039062e-01, -3.57421875e-01, -2.85156250e-01, -1.66992188e-01,
          1.97265625e-01, -1.53320312e-01,  2.31933594e-02,  2.06054688e-01,
          1.80664062e-01, -2.74658203e-02, -1.92382812e-01, -9.61914062e-02,
         -1.06811523e-02, -4.73632812e-02,  6.54296875e-02, -1.25732422e-02,
          1.78222656e-02, -8.00781250e-02, -2.59765625e-01,  9.37500000e-02,
         -7.81250000e-02,  4.68750000e-02, -2.22167969e-02,  1.86767578e-02,
          3.11279297e-02,  1.04980469e-02, -1.69921875e-01,  2.58789062e-02,
         -3.41796875e-02, -1.44042969e-02, -5.46875000e-02, -8.78906250e-02,
          1.96838379e-03,  2.23632812e-01, -1.36718750e-01,  1.75781250e-01,
         -1.63085938e-01,  1.87500000e-01,  3.44238281e-02, -5.63964844e-02,
         -2.27689743e-05,  4.27246094e-02,  5.81054688e-02, -1.07910156e-01,
         -3.88183594e-02, -2.69531250e-01,  3.34472656e-02,  9.81445312e-02,
          5.63964844e-02,  2.23632812e-01, -5.49316406e-02,  1.46484375e-01,
          5.93261719e-02, -2.19726562e-01,  6.39648438e-02,  1.66015625e-02,
          4.56542969e-02,  3.26171875e-01, -3.80859375e-01,  1.70898438e-01,
          5.66406250e-02, -1.04492188e-01,  1.38671875e-01, -1.57226562e-01,
          3.23486328e-03, -4.80957031e-02, -2.48046875e-01, -6.20117188e-02],
        dtype=float32)
```

In [30]:
```
model.wv.similarity('woman','man')
```

Out[30]:
```
0.7664012230995352
```

In [31]:
```
model.wv.similarity('tasty', 'tast')
```

Out[31]:
```
0.440350541900889
```

In [32]:
```
i=0
list_of_sent=[]
for sent in final['Text'].values:
    list_of_sent.append(sent.split())
```

In [33]:
```
print(final['Text'].values[0])
print("*****************************************************************")
print(list_of_sent[0])
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alon
*****************************************************************
['this', 'witty', 'little', 'book', 'makes', 'my', 'son', 'laugh', 'at', 'loud.', 'i', 'recite
```

```
In [34]: w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

```
In [35]: 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  94472
sample words  ['this', 'witty', 'little', 'book', 'makes', 'my', 'son', 'laugh', 'at', 'loud.'
```

```
In [36]: w2v_model.wv.most_similar('tasty')
```

```
Out[36]: [('tasty,', 0.9057872295379639),
          ('delicious', 0.8898302316665649),
          ('yummy', 0.8788954019546509),
          ('satisfying', 0.8654456734657288),
          ('tastey', 0.844463050365448),
          ('delicious,', 0.812126100063324),
          ('flavorful', 0.8079628944396973),
          ('filling,', 0.7960013151168823),
          ('hearty', 0.7909684181213379),
          ('nutritious', 0.7884812355041504)]
```

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

```
Out[37]: [('like,', 0.7549582719802856),
          ('prefer', 0.6632524728775024),
          ('resemble', 0.6574012041091919),
          ('miss', 0.6534298658370972),
          ('enjoy', 0.6335715055465698),
          ('like.', 0.6291797757148743),
          ('love', 0.614167332649231),
          ('mean', 0.6112775206565857),
          ('dislike', 0.6002678871154785),
          ('like...', 0.5922833681106567)]
```

7 Avg W2V

```
In [38]: 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
                 try:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
```

```
                pass
            sent_vec /= cnt_words
            sent_vectors.append(sent_vec)
        print(len(sent_vectors))
        print(len(sent_vectors[0]))
```

```
364171
50
```

```
In [39]: sent_vectors = sent_vectors[0:4000]
         len(sent_vectors)
```

```
Out[39]: 4000
```

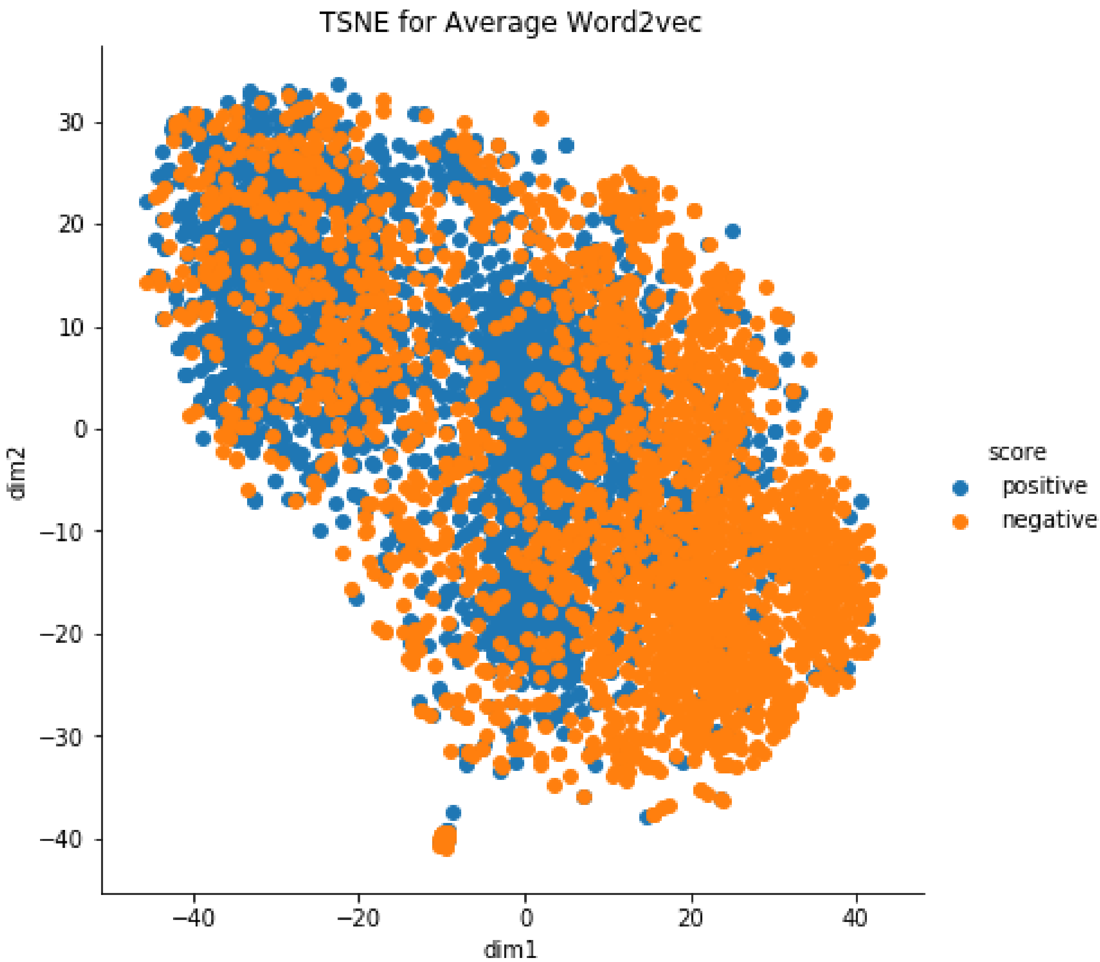
```
In [40]: from sklearn.manifold import TSNE
         model = TSNE(n_components=2, random_state=15, perplexity=50, n_iter=5000)

         tsne_data = model.fit_transform(sent_vectors)

         tsne_data = np.vstack((tsne_data.T, score_4000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("dim1", "dim2", "score"))

         # Ploting the result of tsne
         sns.FacetGrid(tsne_df, hue="score", size=6).map(plt.scatter, 'dim1', 'dim2').add_leger
         plt.title("TSNE for Average Word2vec")
         plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\axisgrid.py:230: UserWarning: The `size` pa
  warnings.warn(msg, UserWarning)
```



Observation:-
We can't classify from the Avg W2V because of all +ve and -ve reviews are not well separated.

8 TFIDF Word2Vec

```
In [41]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
         model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(final['Text'].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 [42]: # 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 l
         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
            try:
                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)]
                tf_idf = dictionary[word]*sent.count(word)
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
            except:
                pass
        sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
```

In [43]:
```
len(tfidf_sent_vectors)
```

Out[43]: 364171

In [44]:
```
tfidf_sent_vectors = tfidf_sent_vectors[0:4000]
len(tfidf_sent_vectors)
```

Out[44]: 4000

In [45]:
```
tfidf_sent_vectors = np.nan_to_num(tfidf_sent_vectors)
```

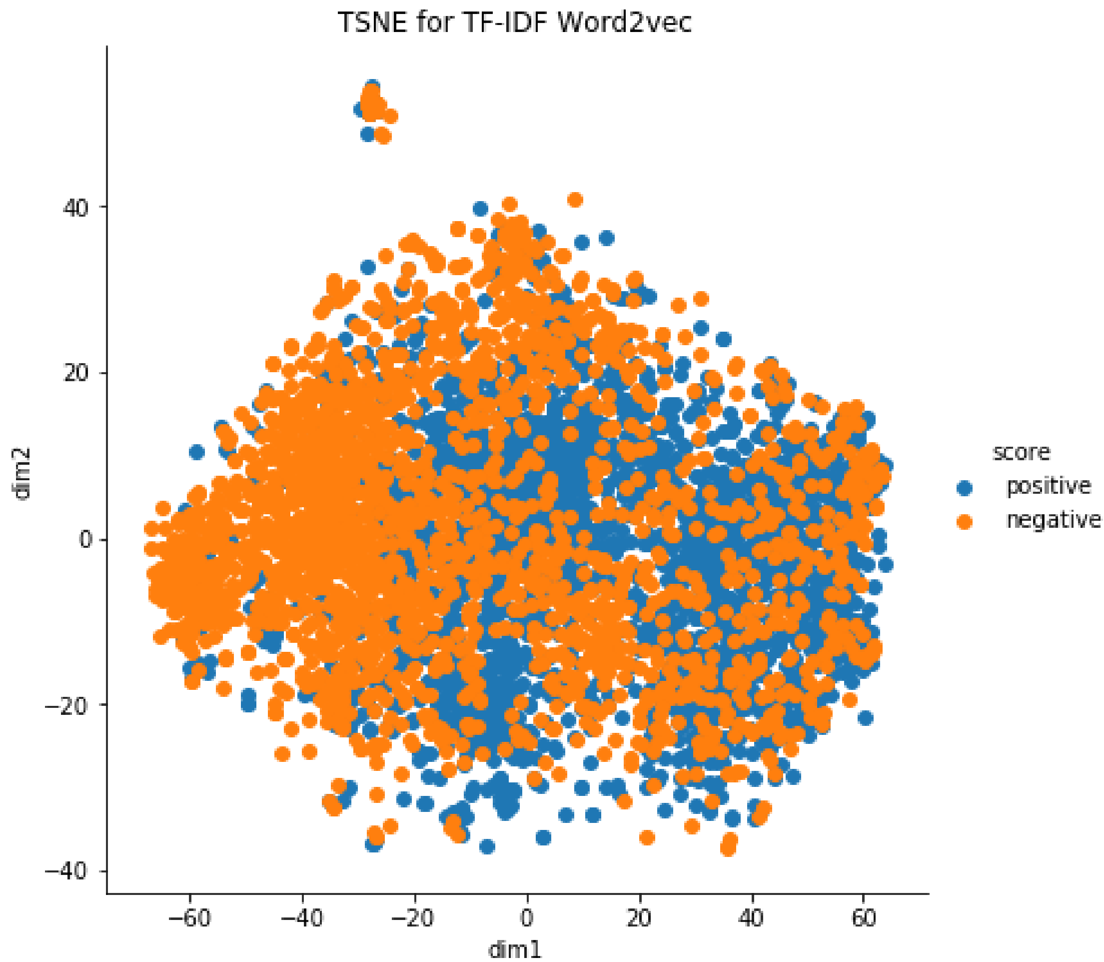
In [46]:
```
from sklearn.manifold import TSNE
model = TSNE(n_components=2, random_state=15, perplexity=50, n_iter=5000)

tsne_data = model.fit_transform(tfidf_sent_vectors)

tsne_data = np.vstack((tsne_data.T, score_4000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("dim1", "dim2", "score"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="score", size=6).map(plt.scatter, 'dim1', 'dim2').add_legen
plt.title("TSNE for TF-IDF Word2vec")
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\axisgrid.py:230: UserWarning: The `size` pa
  warnings.warn(msg, UserWarning)
```



Observation:-

The +ve and -ve reviews are overlapped each other, it looks same as bow, tfidf and avg word2vec.

Conclusion:-

1. As we saw TSNE representation, all the +ve and -ve reviews are overlapped each other.
2. We can not simply draw a plane to separate +ve and -ve reviews.