Amazon Fine Food Reviews Preprocessing

This IPython notebook consists code for preprocessing of text, conversion of text into vectors and saving that information for further use.

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

Public Information -

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

5. Number of Attributes/Columns in data: 10

Attribute Information -

- 1. Id
- 2. ProductId unique identifier for the product
- 3. Userld ungiue identifier for the user
- 4. ProfileName
- 5. HelpfulnessNumerator number of users who found the review helpful
- 6. HelpfulnessDenominator number of users who indicated whether they found the review helpful or not
- 7. Score rating between 1 and 5
- 8. Time timestamp for the review
- 9. Summary brief summary of the review
- 10. Text text of the review

Current Objective -

Go through the reviews and perform preprocessing, convert them into vectors and save them for future use.

Let's start with mounting paths and importing necessary libraries

```
#mounting the dataset from drive
from google.colab import drive
drive.mount('/content/gdrive')
```

Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code (https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code)

```
Enter your authorization code:
.....
Mounted at /content/gdrive
```

```
#importing necessary libraries
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

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

```
#connecting to sqlite db
con = sqlite3.connect('/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/d
#filtering only positive and negative reviews
data = pd.read_sql_query("SELECT * FROM Reviews WHERE Score != 3", con)
print("Shape of data:", data.shape)

#scores < 3 are considered to be negative reviews and > 3 are considered to be positive rev
data.head()
```

Shape of data: (525814, 10)

Out[4]:

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	

Missing values? Yeah, it happens...

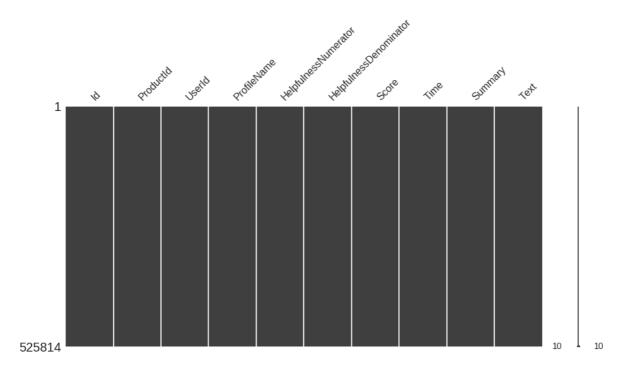
```
#let's just check, just in case if any
print("Missing values? Ans -", data.isnull().values.any())

#visualizing it
msno.matrix(data, figsize=(15,7))
```

Missing values? Ans - False

Out[6]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f35bf4505f8>



One can write more than one review for the same product!

```
df = data.copy()
df['ProdUser'] = df['ProductId'] + df['UserId']
df[df['ProdUser'].duplicated(keep=False)]. \
    sort_values('ProdUser', axis=0, ascending=True, inplace=False, kind='quicksort', na_pos
```

Out[7]:

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominat
157863	171174	7310172001	AE9ZBY7WW3LIQ	W. K. Ota	0	
157871	171183	7310172001	AE9ZBY7WW3LIQ	W. K. Ota	5	
157912	171228	7310172001	AJD41FBJD9010	N. Ferguson "Two, Daisy, Hannah, and Kitten"	5	
157841	171152	7310172001	AJD41FBJD9010	N. Ferguson "Two, Daisy, Hannah, and Kitten"	0	
4						•

Obeservations

- 1. There are some instances where a user has written more than one review for the same product.
- 2. We can remove the one which has less Helpfulness but lets keep all and treat it as review from a different user.
- 3. Will definitely have to remove same reviews because it is just redundant data.

In [0]:

```
#Sorting data according to ProductId in ascending order data = data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort
```

In [0]:

```
#Deduplication of entries
data=data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inpl
data.shape
```

Out[9]:

(364173, 10)

Same reviews on multiple products with different timestamps!!

```
data[data['Text'].duplicated(keep=False)]. \
    sort_values('Text', axis=0, ascending=True, inplace=False, kind='quicksort', na_positic
Out[11]:
                    ProductId
            ld
                                          Userld
                                                    ProfileName
                                                                HelpfulnessNumerator HelpfulnessDenoi
  67574
         73444
                  B0046IISFG
                               A3OXHLG6DIBRW8
                                                  C. F. Hill "CFH"
                                                                                  1
 287090 311004
                 B001EO6FPU
                               A3OXHLG6DIBRW8
                                                  C. F. Hill "CFH"
                                                                                  9
                                                     Rebecca of
                                                    Amazon "The
 302818 327982
                 B0000CEQ6H
                                 A281NPSIMI1C2R
                                                                                  3
                                                       Rebecca
```

```
#removing duplicate reviews
data=data.drop_duplicates(subset={"Text"}, keep='first', inplace=False)
data.shape
Out[12]:
(363836, 10)
```

Observations

- 1. There are reviews which are same on similar products (mostly different flavors).
- 2. These reviews were posted with different timestamps by the same person (weird).
- 3. Since we are interested in a review being positive or negative, having redundant reviews makes no sense, so removing them.

In [0]:

```
#also removing those reviews where HelpfulnessNumerator is greater than HelpfulnessDenomina data=data[data['HelpfulnessNumerator']<=data['HelpfulnessDenominator']] data.shape
```

```
Out[13]:
(363834, 10)
```

In [0]:

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

In [0]:

```
actualScore = data['Score']
positiveNegative = actualScore.map(partition)
data['Score'] = positiveNegative
print("Negatives shape:", data[data['Score']=='negative'].shape)
print("Positives shape:", data[data['Score']=='positive'].shape)
```

Positives shape: (306764, 10)

Now, it's time for some Text Preprocessing

We will be doing the following in order.

Negatives shape: (57070, 10)

- 1. Text cleaning includes removal of special characters which are not required.
- 2. Check if the word is actually an English word.
- 3. 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)
- Convert the word to lower case.
- 5. Remove stop words but let's keep words like 'not' which makes the sentence negative.

6. POS Tagging and WordNet Lemmatizing the word.

In [0]:

```
from nltk.stem.wordnet import WordNetLemmatizer
import re
from nltk.corpus import stopwords
```

In [0]:

```
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 characte
    cleaned = re.sub(r'[?!!\'|"#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return cleaned
```

```
!python -m nltk.downloader stopwords
```

```
/usr/lib/python3.6/runpy.py:125: RuntimeWarning: 'nltk.downloader' found in
sys.modules after import of package 'nltk', but prior to execution of 'nltk.
downloader'; this may result in unpredictable behaviour
  warn(RuntimeWarning(msg))
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Unzipping corpora/stopwords.zip.
```

["it's", 'more', 'just', 'couldn', 'and', 'our', "hasn't", 'this', 've', 'of f', 'needn', 'themselves', 'on', 'now', 'own', 'before', 'yourself', 'i', 'd id', 'didn', 'from', "weren't", 'out', "that'll", 'during', "hadn't", 'thes e', 'but', 'nor', 'don', 'his', 'are', 'an', 'hadn', 'because', 'very', "wou ldn't", "needn't", 'as', 'where', 'too', 'shan', 'them', 'she', 'was', 'th e', 'can', 'who', 'y', 'weren', 're', "haven't", 'whom', 'been', "won't", 'y ou', 'down', 'until', 't', 'd', 'my', 'won', 'through', 'that', "you'll", 'd oes', 'both', "couldn't", 'himself', 'ours', 'being', 'what', 'for', 'when', 'once', 'were', "doesn't", 'again', 'am', 'then', 'so', "mightn't", "sha n't" 'than' 'bow' 'any' 'your' 'doing' 'bone' 'ourselves' 'between' n't", 'than', 'how', 'any', 'your', 'doing', 'here', 'ourselves', 'between', "you're", "should've", 'there', 'myself', "you've", 'hers', 'which', 'unde r', 'same', 'against', 'will', "shouldn't", 'not', 'each', "wasn't", 'over', 'why', 'those', 'further', 'about', 'me', 'yours', 'should', "you'd", 'shouldn', 'other', "she's", 'herself', "don't", "aren't", 'up', 'wouldn', 'in', 's', 'it', 'be', 'have', 'ma', 'has', 'is', 'her', 'few', 'all', 'such', 'ha ven', 'we', 'theirs', 'having', 'only', 'do', "mustn't", 'had', 'yourselve s', 'after', 'hy', 'mightn', 'm', 'its', 'some', 'helow', 'most', 'o', 'he' s', 'after', 'by', 'mightn', 'm', 'its', 'some', 'below', 'most', 'o', 'he', 'above', 'a', 'their', 'wasn', 'isn', 'itself', 'if', 'or', 'no', 'while', 'at', 'into', "didn't", 'll', 'with', 'to', "isn't", 'ain', 'of', 'doesn', 'him', 'hasn', 'aren', 'they', 'mustn'] Final stopwords: ['more', 'just', 'couldn', 'and', 'havent', 'our', 've', 't his', 'off', 'themselves', 'on', 'now', 'own', 'before', 'yourself', 'did', 'i', 'from', 'out', 'during', 'these', 'but', 'nor', 'don', 'his', 'mightn' t', 'are', 'an', 'because', 'very', 'youd', 'isnt', 'where', 'as', 'arent', 'too', 'shan', 'them', 'she', 'was', 'the', 'can', 'shouldve', 'who', 'y', 're', 'youve', 'whom', 'been', 'you', 'down', 'until', 't', 'd', 'my', 'wo n', 'through', 'that', 'does', 'both', 'himself', 'ours', 'being', 'what', 'through', 'th 'wouldnt', 'for', 'when', 'once', 'wont', 'were', 'again', 'am', 'then', 's o', 'than', 'how', 'any', 'your', 'doing', 'here', 'ourselves', 'between', 'there', 'myself', 'hers', 'which', 'under', 'same', 'against', 'will', 'each', 'over', 'why', 'those', 'further', 'about', 'me', 'yours', 'should', 'ot her', 'herself', 'up', 'in', 's', 'youre', 'it', 'shes', 'be', 'have', 'ma', 'has', 'is', 'her', 'few', 'all', 'such', 'haven', 'we', 'theirs', 'having', 'only', 'do', 'youll', 'had', 'yourselves', 'after', 'by', 'mightn', 'm', 'i ts', 'some', 'below', 'most', 'o', 'he', 'above', 'a', 'their', 'isn', 'itse lf', 'if', 'or', 'no', 'while', 'at', 'hasnt', 'into', 'll', 'with', 'to', 'ain', 'of', 'him', 'thatll', 'hasn', 'aren', 'they']

```
from nltk import pos_tag, word_tokenize
wnl = WordNetLemmatizer()
```

```
!python -m nltk.downloader punkt averaged_perceptron_tagger wordnet
```

```
/usr/lib/python3.6/runpy.py:125: RuntimeWarning: 'nltk.downloader' found in
sys.modules after import of package 'nltk', but prior to execution of 'nltk.
downloader'; this may result in unpredictable behaviour
   warn(RuntimeWarning(msg))
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data] /root/nltk_data...
[nltk_data] Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Unzipping corpora/wordnet.zip.
```

```
#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.
scores = data['Score'].values
for sent in data['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTML tags
    tokens = pos_tag(word_tokenize(sent))
    for w in tokens:
        for cleaned_words in cleanpunc(w[0]).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    #s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    # Lemmatization works better with POS tagging
                    tag = w[1][0].lower()
                    tag = tag if tag in ['a', 'n', 'v'] else None
                    if not tag:
                        s = cleaned_words.lower().encode('utf8')
                    else:
                        s = wnl.lemmatize(cleaned_words.lower(), tag).lower().encode("utf8"
                    filtered_sentence.append(s)
                    if scores[i] == "positive":
                        all_positive_words.append(s) #list of all words used to describe pd
                    if scores[i] == "negative":
                        all_negative_words.append(s) #list of all words used to describe ne
                else:
                    continue
            else:
                continue
    #print(filtered sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("****
    final string.append(str1)
    i+=1
print("Done!")
```

Done!

In [0]:

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

```
# store final table into an SQLLite table for future.
conn = sqlite3.connect('/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/
c=conn.cursor()
conn.text_factory = str
data.to_sql('Reviews', conn, schema=None, if_exists='replace', index=True, index_label=Nor
```

TSNE Assignment

Objective

Apply TSNE on Bow, TFIDF, W2V, TFIDF W2v

```
In [0]:
```

```
con = sqlite3.connect('/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/f
data = pd.read_sql_query(""" SELECT * FROM Reviews """, con)
del data['index']
data.shape
```

Out[4]:

(363834, 11)

In [0]:

data.head()

Out[5]:

	ld	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDen
0	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
1	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
2	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	
3	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	
4	150509	0006641040	A3CMRKGE0P909G	Teresa	3	

```
In [0]:
```

```
# positive reviews
pos_df = data[data['Score'] == 'positive'].copy()
pos_df['Time'] = pos_df['Time'].astype('int')
# sorting it based on time so that we can split based on time
pos_df.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na_posi
pos_df.shape
Out[6]:
(306764, 11)
In [0]:
#negative reviews
neg_df = data[data['Score'] == 'negative'].copy()
neg_df['Time'] = neg_df['Time'].astype('int')
neg_df.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na_posi
neg_df.shape
Out[7]:
(57070, 11)
In [0]:
```

```
pos_50k = pos_df.head(50000).copy()
neg_50k = neg_df.head(50000).copy()
```

```
# training data 60%
pos_train = pos_50k.head(30000).copy()
neg_train = neg_50k.head(30000).copy()

# cross validation data 20%
pos_cv = pos_50k[30000:40000].copy()
neg_cv = neg_50k[30000:40000].copy()

# test data 20%
pos_test = pos_50k[40000:].copy()
neg_test = neg_50k[40000:].copy()
```

In [0]:

```
train_df = pos_train.append(neg_train, ignore_index=True).copy()
cv_df = pos_cv.append(neg_cv, ignore_index=True).copy()
test_df = pos_test.append(neg_test, ignore_index=True).copy()
```

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
```

```
#BoW
count_vect = CountVectorizer() #in scikit-learn
train_final_counts = count_vect.fit_transform(train_df['CleanedText'].values)
cv_final_counts = count_vect.transform(cv_df['CleanedText'].values)
test_final_counts = count_vect.transform(test_df['CleanedText'].values)
print("the type of count vectorizer ",type(train_final_counts))
print("the shape of out text BOW vectorizer ",train_final_counts.get_shape())
print("the number of unique words ", train_final_counts.get_shape()[1])
```

the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'> the shape of out text BOW vectorizer (60000, 40286) the number of unique words 40286

In [0]:

```
import nltk
```

In [0]:

```
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', 137224), (b'taste', 122045), (b'goo d', 111390), (b'love', 104938), (b'great', 103358), (b'use', 101467), (b'mak e', 100401), (b'flavor', 99414), (b'one', 96800), (b'get', 93100), (b'produc t', 90812), (b'try', 86221), (b'tea', 82860), (b'coffee', 78957), (b'find', 78423), (b'buy', 75962), (b'food', 64946), (b'would', 59996), (b'eat', 5743 8), (b'time', 54081)]

Most Common Negative Words: [(b'taste', 33523), (b'like', 31734), (b'produ ct', 28122), (b'buy', 20800), (b'one', 20593), (b'would', 20028), (b'get', 20000), (b'flavor', 18123), (b'try', 17575), (b'make', 16240), (b'use', 1491 5), (b'good', 14894), (b'coffee', 14764), (b'order', 12792), (b'food', 1275 6), (b'think', 11931), (b'tea', 11633), (b'eat', 11013), (b'even', 10947), (b'box', 10812)]
```

```
import pickle
```

```
#saving BoW unigrams
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_vec_t
    pickle.dump(train_final_counts, bow)
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/train_lab.pkl
    pickle.dump(train_df['Score'].values, bow)

with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_vec_c
    pickle.dump(cv_final_counts, bow)
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/cv_lab.pkl",
    pickle.dump(cv_df['Score'].values, bow)

with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_vec_t
    pickle.dump(test_final_counts, bow)
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/test_lab.pkl"
    pickle.dump(test_df['Score'].values, bow)
```

In [0]:

```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
count_vect = CountVectorizer(ngram_range=(1,2)) #in scikit-learn
train_bigram_counts = count_vect.fit_transform(train_df['CleanedText'].values)
cv_bigram_counts = count_vect.transform(cv_df['CleanedText'].values)
test_bigram_counts = count_vect.transform(test_df['CleanedText'].values)
print("the type of count vectorizer ",type(train_bigram_counts))
print("the shape of out text BOW vectorizer ",train_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", train_bigram_count
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (60000, 977013)
```

the number of unique words including both unigrams and bigrams 977013

In [0]:

```
#saving BoW bigrams
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_tr
    pickle.dump(train_bigram_counts, bow)
# with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_
# pickle.dump(train_df['Score'].values, bow)

with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_cv
    pickle.dump(cv_bigram_counts, bow)

# with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_
# pickle.dump(cv_df['Score'].values, bow)

with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_te
    pickle.dump(test_bigram_counts, bow)

# with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_te
    pickle.dump(test_df['Score'].values, bow)
```

```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
#tf-idf
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
train_tf_idf = tf_idf_vect.fit_transform(train_df['CleanedText'].values)
cv tfidf = tf idf vect.transform(cv df['CleanedText'].values)
test_tfidf = tf_idf_vect.transform(test_df['CleanedText'].values)
print("the type of count vectorizer ",type(train_tf_idf))
print("the shape of out text TFIDF vectorizer ",train_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", train_tf_idf.get_s
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer (60000, 977013)
the number of unique words including both unigrams and bigrams 977013
In [0]:
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) ['bpa originally', 'bpa pac
kaging', 'bpa person', 'bpa personally', 'bpa plastic', 'bpa prove', 'bpa re
ally', 'bpa recently', 'bpa rest', 'bpa safe']
In [0]:
def top_tfidf_feats(row, features, top_n=25):
    ''' Get top n tfidf values in row and return them with their corresponding feature name
    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(train_tf_idf[1,:].toarray()[0],features,25)

top_tfidf

Out[47]:

	feature	tfidf
0	paperback seem	0.182072
1	rosie movie	0.182072
2	incorporate love	0.182072
3	version paperback	0.182072
4	cover version	0.182072
5	page open	0.182072
6	keep page	0.182072
7	read sendak	0.182072
8	movie incorporate	0.182072
9	hard cover	0.175544
10	miss hard	0.175544
11	sendak book	0.175544
12	grow read	0.175544
13	kind flimsy	0.175544
14	really rosie	0.175544
15	watch really	0.175544
16	flimsy take	0.175544
17	however miss	0.175544
18	book watch	0.175544
19	two hand	0.175544
20	love son	0.167320
21	rosie	0.164385
22	paperback	0.164385
23	seem kind	0.161903
24	hand keep	0.157857

In [0]:

from gensim.models import Word2Vec

In [0]:

```
list_of_sent=[]
for sent in train_df['CleanedText'].values:
    list_of_sent.append(sent.split())
```

In [0]:

```
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=7)
```

In [0]:

```
#saving w2v model
w2v_model.save("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/amzn_w2v
```

In [0]:

```
#Loading model
w2v_model = Word2Vec.load("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_revie
```

```
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 12979 sample words ['witty', 'little', 'book', 'make', 'son', 'laugh', 'loud', 'r ecite', 'car', 'drive', 'along', 'always', 'sing', 'refrain', 'learn', 'whal e', 'india', 'droop', 'rose', 'love', 'new', 'word', 'classic', 'willing', 'bet', 'still', 'able', 'memory', 'college', 'grow', 'read', 'sendak', 'watch', 'really', 'rosie', 'movie', 'incorporate', 'however', 'miss', 'hard', 'c over', 'version', 'paperback', 'seem', 'kind', 'flimsy', 'take', 'two', 'hand', 'keep']
```

```
# average Word2Vec
# compute average word2vec for each review.
def avg_w2vec(list_of_sent):
    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]))
    return sent_vectors
```

In [0]:

```
avg_w2v_train = avg_w2vec([sent.split() for sent in train_df['CleanedText'].values])
avg_w2v_cv = avg_w2vec([sent.split() for sent in cv_df['CleanedText'].values])
avg_w2v_test = avg_w2vec([sent.split() for sent in test_df['CleanedText'].values])
```

50

In [0]:

```
#saving word2vec
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/avg_w2v_train
    pickle.dump(avg_w2v_train, w2v_pickle)
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/avg_w2v_cv.pk
    pickle.dump(avg_w2v_cv, w2v_pickle)
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/avg_w2v_test.
    pickle.dump(avg_w2v_test, w2v_pickle)
```

In [0]:

```
from concurrent.futures import ThreadPoolExecutor, ProcessPoolExecutor
from concurrent import futures
```

```
!pip install numba
```

```
Requirement already satisfied: numba in /usr/local/lib/python3.6/dist-packag es (0.40.1)

Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packag es (from numba) (1.14.6)

Requirement already satisfied: llvmlite>=0.25.0dev0 in /usr/local/lib/python 3.6/dist-packages (from numba) (0.26.0)
```

```
from numba import jit
```

In [0]:

```
def helper(list of sent, final tf idf):
    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this lis
    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
        print(row, end=" ")
    return tfidf_sent_vectors
```

```
helper_numba = jit()(helper)
```

```
# 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 list
#for sent in list_of_sent: # for each review/sentence
#this was taking a lot of time
# with ThreadPoolExecutor(max workers=10000) as executor:
#
      result_futures = [executor.submit(helper_numba, sent=x, row=y) for y, x in enumerate(
#
      for f in futures.as_completed(result_futures):
#
          i = f.result()
          print(i)
#
# print("Threading done!")
# for y, x in enumerate(list_of_sent):
     i = helper_numba(sent=x, row=y)
#
      print(i)
list_of_sent = [sent.split() for sent in train_df['CleanedText'].values]
train_tfidf_w2v = helper(list_of_sent, train_tf_idf)
print("Done!")
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 2
9
                                          Traceback (most recent call last)
KeyboardInterrupt
```

```
<ipython-input-67-e5652b938fbd> in <module>()
              print(i)
     19 list_of_sent = [sent.split() for sent in train_df['CleanedText'].val
ues]
---> 20 train_tfidf_w2v = helper(list_of_sent, train_tf_idf)
     21
     22 print("Done!")
<ipython-input-64-410d0381b5e3> in helper(list of sent, final tf idf)
                        vec = w2v model.wv[word]
     9
     10
                        # obtain the tf_idfidf of a word in a sentence/revie
                        tf_idf = final_tf_idf[row, tfidf_feat.index(word)]
---> 11
                        sent_vec += (vec * tf_idf)
     12
     13
                        weight sum += tf idf
```

KeyboardInterrupt:

```
# TF-IDF weighted Word2Vec was taking a lot of time!! So for TSNE, will run it on 2k data p
#saving tfidf weighted w2v
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_weighte
    pickle.dump(train_tfidf_w2v, tfidf_w2v_pickle)
print("Done!")
```

```
In [0]:
```

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import pandas as pd
from sklearn.manifold import TSNE
```

```
#Loading sparse matrices of BoW
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_vec_tr
    bigram_counts = pickle.load(bow)
#Loading LabeLs
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/train_lab.pkl
    labels = pickle.load(bow)
bigram_counts.shape[0]
```

Out[3]:

60000

In [0]:

```
from scipy.sparse import vstack
```

In [0]:

```
bigram_counts.shape
```

Out[5]:

(60000, 977013)

In [0]:

```
final = bigram_counts[0:1000,:]
final.shape
```

Out[6]:

(1000, 977013)

In [0]:

```
#picking 1k positive and 1k negative review vectors
final = bigram_counts[0:1000,:]
final = vstack((final, bigram_counts[30000:31000,:]))
final_labels = labels[:1000].tolist()
final_labels.extend(labels[30000:31000].tolist())
print(final.shape, len(final_labels))
```

(2000, 977013) 2000

BoW

```
# tried with above dimensions - BoW unique word dict is based on 60k reviews, was getting "
# hence will create BOW using 2000 reviews

pos_1k = pos_df.sort_values('HelpfulnessNumerator', axis=0, ascending=False, inplace=False,
neg_1k = neg_df.sort_values('HelpfulnessNumerator', axis=0, ascending=False, inplace=False,
pos_1k.head(5)
```

In [0]:

```
reviews = pos_1k.append(neg_1k, ignore_index=True)
```

In [0]:

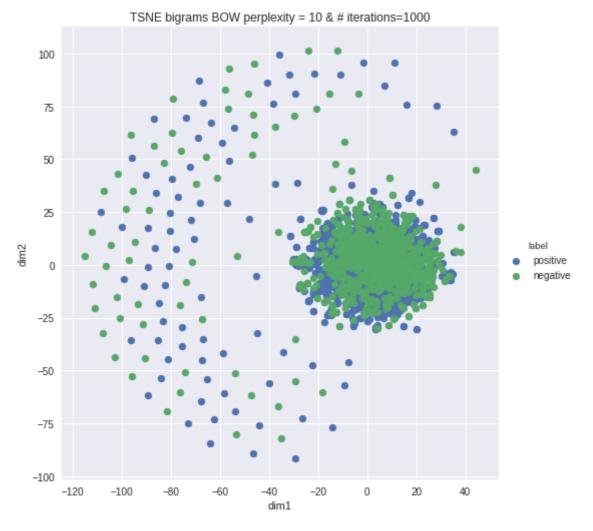
```
reviews.shape
```

Out[9]:

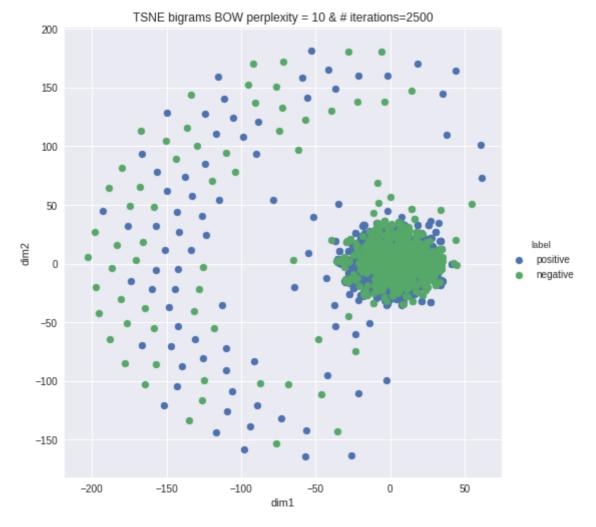
(2000, 11)

```
count_vect = CountVectorizer(ngram_range=(1,2) ) #in scikit-learn
final = count_vect.fit_transform(reviews['CleanedText'].values)
final_labels = reviews['Score'].values
```

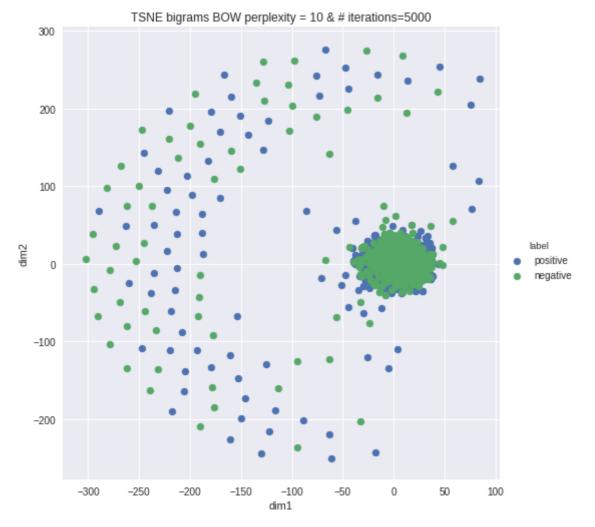
```
#TSNE for bi-grams BOW
#perplexity=10 and #iterations=1000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=10, n_iter=1000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 10 & # iterations=1000')
plt.show()
```



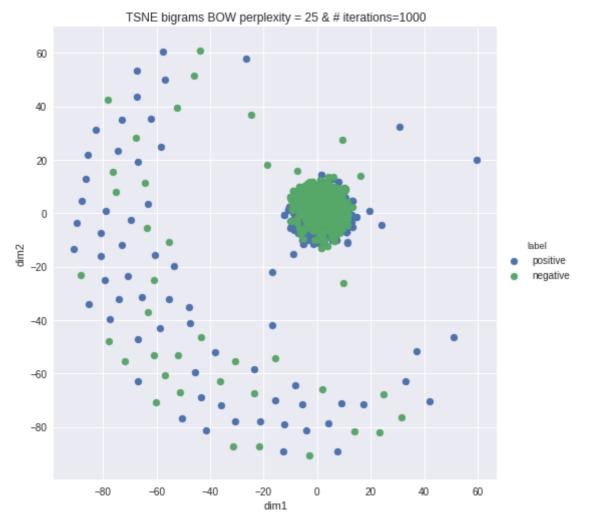
```
#TSNE for bi-grams BOW
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=10, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 10 & # iterations=2500')
plt.show()
```



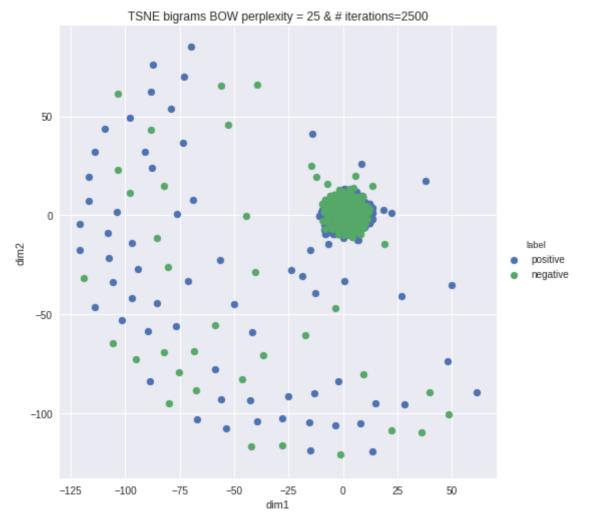
```
#TSNE for bi-grams BOW
#perplexity=10 and #iterations=5000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=10, n_iter=5000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 10 & # iterations=5000')
plt.show()
```



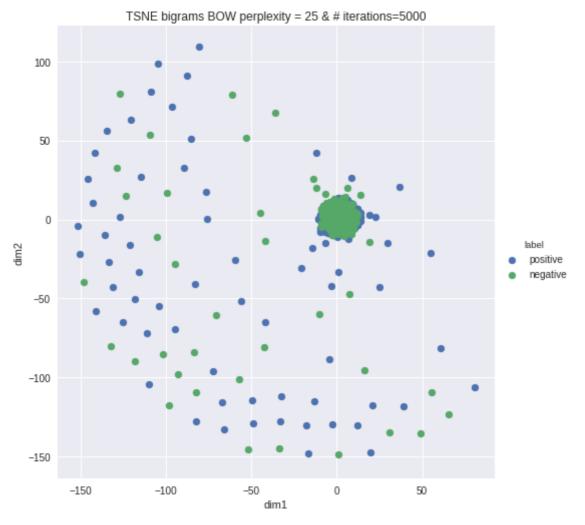
```
#TSNE for bi-grams BOW
#perplexity=25 and #iterations=1000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=25, n_iter=1000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 25 & # iterations=1000')
plt.show()
```



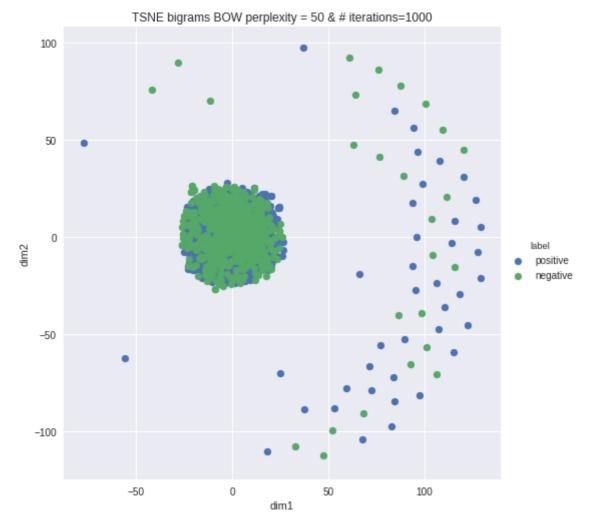
```
#TSNE for bi-grams BOW
#perplexity=25 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=25, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 25 & # iterations=2500')
plt.show()
```



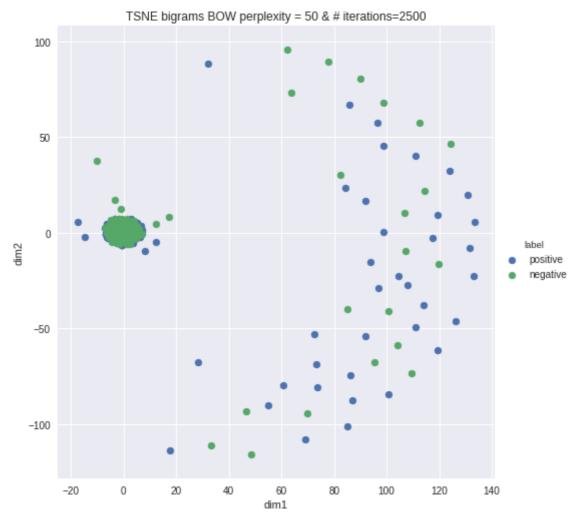
```
#TSNE for bi-grams BOW
#perplexity=25 and #iterations=5000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=25, n_iter=5000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 25 & # iterations=5000')
plt.show()
```



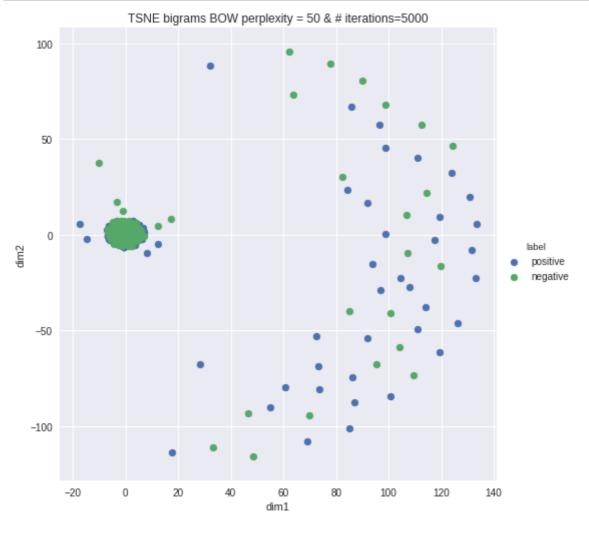
```
#TSNE for bi-grams BOW
#perplexity=50 and #iterations=1000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=1000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 50 & # iterations=1000')
plt.show()
```



```
#TSNE for bi-grams BOW
#perplexity=50 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 50 & # iterations=2500')
plt.show()
```



```
#TSNE for bi-grams BOW
#perplexity=50 and #iterations=5000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 50 & # iterations=5000')
plt.show()
```



```
pos_1k = pos_df. \
    sort_values('Time', axis=0, ascending=False, inplace=False, kind='quicksort', na_positi
neg_1k = neg_df. \
    sort_values('Time', axis=0, ascending=False, inplace=False, kind='quicksort', na_positi
pos_1k.head(5)
```

Out[15]:

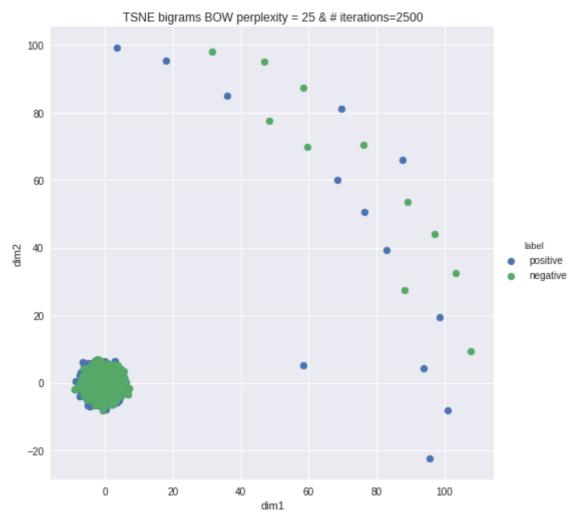
	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	Helpfulr
261071	227839	B0033HPPIO	A2U3RRCA2URS56	ashley	0	
117303	300676	B000RQMQAO	A3KFOZ5D1KQLIU	Phyllis Brown	0	
343811	194172	B005UGSR72	A382RNG86OC7N0	Jennifer	0	
304007	276219	B004AA2MUM	A1YZ4FP8H9AV6I	Marburg	0	
362720	320388	B008JA73RG	AFJFXN42RZ3G2	R. DelParto "Rose2"	0	
4						•

In [0]:

```
reviews = pos_1k.append(neg_1k, ignore_index=True)
```

```
count_vect = CountVectorizer(ngram_range=(1,2) ) #in scikit-learn
final = count_vect.fit_transform(reviews['CleanedText'].values)
final_labels = reviews['Score'].values
```

```
#TSNE for bi-grams BOW
#perplexity=25 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=25, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 25 & # iterations=2500')
plt.show()
```

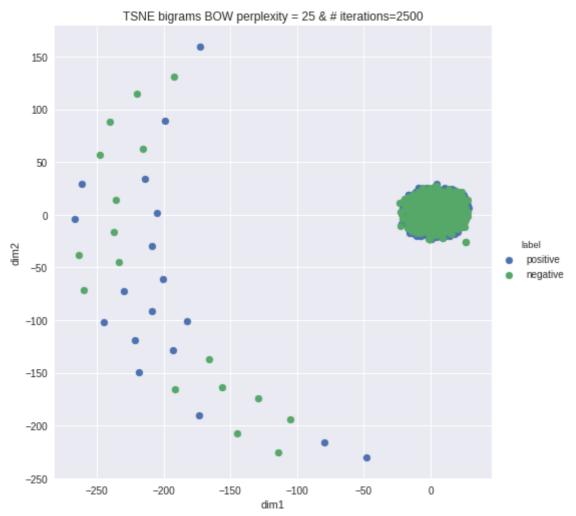


In [0]:

```
pos_1k = pos_df.sample(n=1000).copy()
neg_1k = neg_df.sample(n=1000).copy()
reviews = pos_1k.append(neg_1k, ignore_index=True)
```

```
count_vect = CountVectorizer(ngram_range=(1,2) ) #in scikit-learn
final = count_vect.fit_transform(reviews['CleanedText'].values)
final_labels = reviews['Score'].values
```

```
#TSNE for bi-grams BOW
#perplexity=25 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=25, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE bigrams BOW perplexity = 25 & # iterations=2500')
plt.show()
```



I guess no change in TSNE however data you feed (Sorted based on Helpfulness/Time, Random). Why?

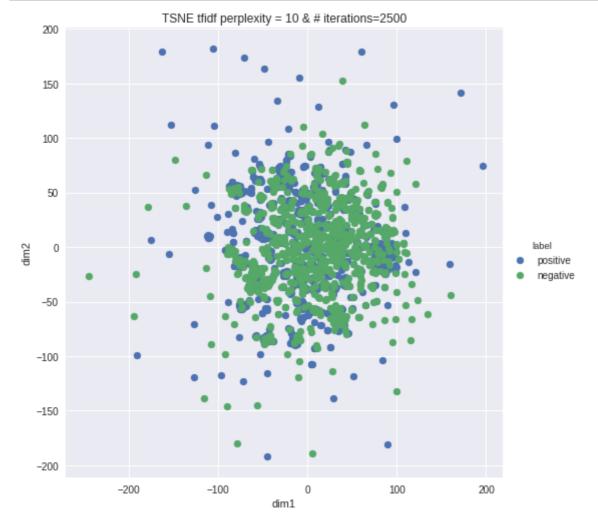
TFIDF

```
# TSNE for TFIDF
pos_1k = pos_df. \
    sort_values('HelpfulnessNumerator', axis=0, ascending=False, inplace=False, kind='quick head(1000).copy()
neg_1k = neg_df. \
    sort_values('HelpfulnessNumerator', axis=0, ascending=False, inplace=False, kind='quick head(1000).copy()
reviews = pos_1k.append(neg_1k, ignore_index=True)
reviews.shape

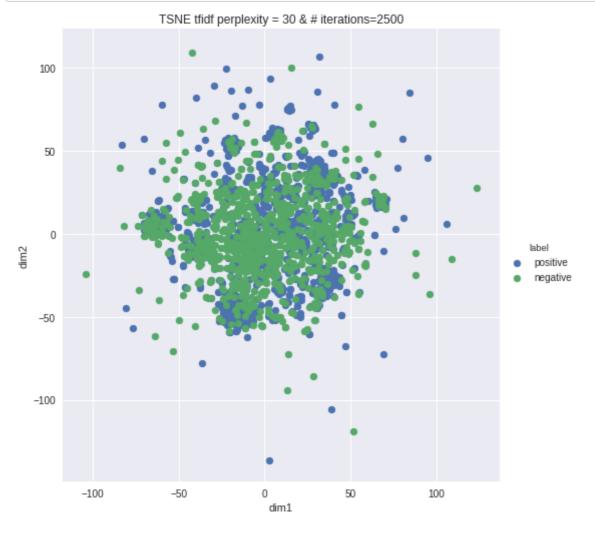
Out[23]:
(2000, 11)
```

```
vect = TfidfVectorizer(ngram_range=(1,2))
final = vect.fit_transform(reviews['CleanedText'].values)
final_labels = reviews['Score'].values
```

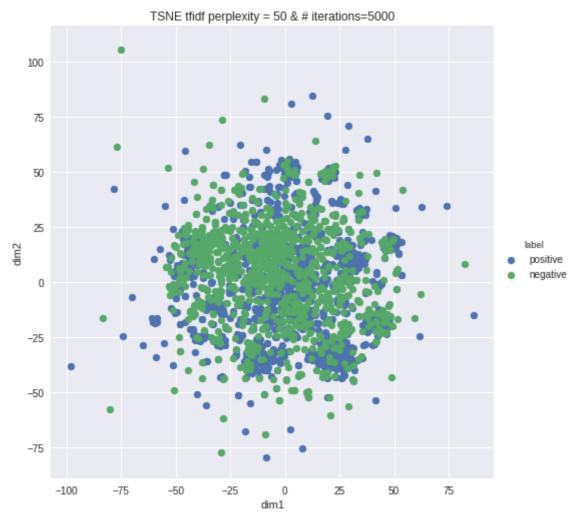
```
#TSNE for tfidf
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=10, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf perplexity = 10 & # iterations=2500')
plt.show()
```



```
#TSNE for tfidf
#perplexity=30 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=30, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf perplexity = 30 & # iterations=2500')
plt.show()
```



```
#TSNE for tfidf
#perplexity=50 and #iterations=5000
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf perplexity = 50 & # iterations=5000')
plt.show()
```

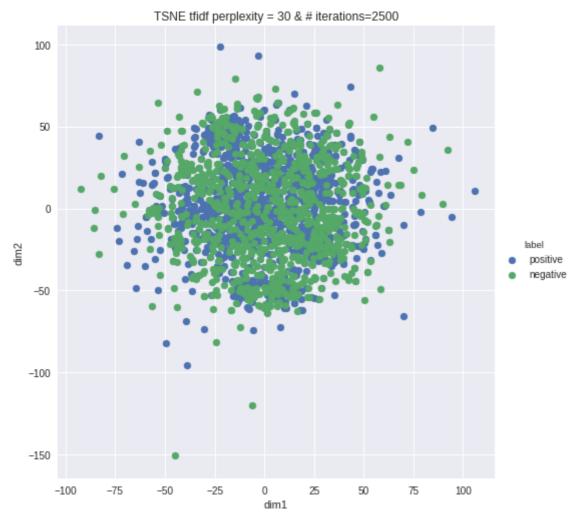


In [0]:

```
pos_1k = pos_df.sample(n=1000).copy()
neg_1k = neg_df.sample(n=1000).copy()
reviews = pos_1k.append(neg_1k, ignore_index=True)
```

```
vect = TfidfVectorizer(ngram_range=(1,2))
final = vect.fit_transform(reviews['CleanedText'].values)
final_labels = reviews['Score'].values
```

```
#TSNE for tfidf
#perplexity=30 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=30, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final.todense())
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf perplexity = 30 & # iterations=2500')
plt.show()
```



W₂V

```
# TSNE for W2V
pos_1k = pos_df. \
    sort_values('HelpfulnessNumerator', axis=0, ascending=False, inplace=False, kind='quick
        head(1000).copy()
neg_1k = neg_df. \
    sort_values('HelpfulnessNumerator', axis=0, ascending=False, inplace=False, kind='quick
        head(1000).copy()
reviews = pos_1k.append(neg_1k, ignore_index=True)
reviews.shape
```

Out[32]:

(2000, 11)

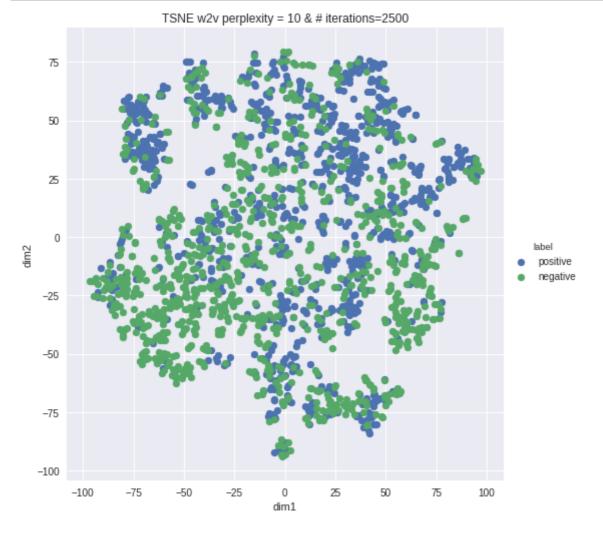
In [0]:

```
final = avg_w2vec([sent.split() for sent in reviews['CleanedText'].values])
final_labels = reviews['Score'].values
```

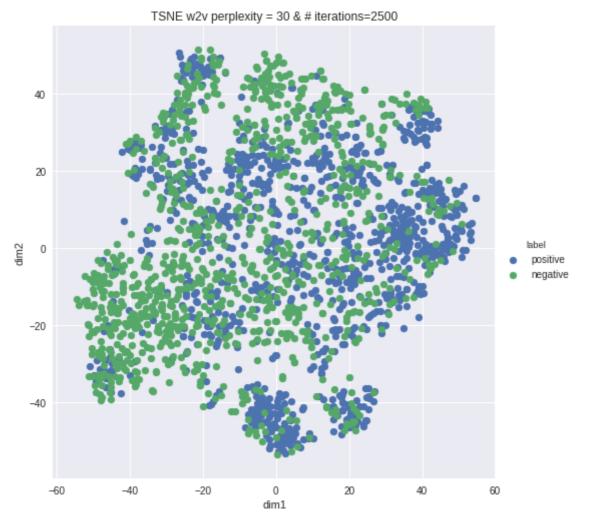
2000

50

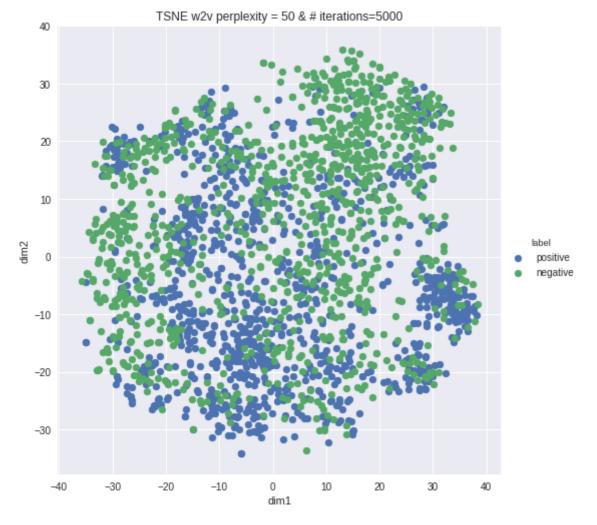
```
#TSNE for W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=10, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE w2v perplexity = 10 & # iterations=2500')
plt.show()
```



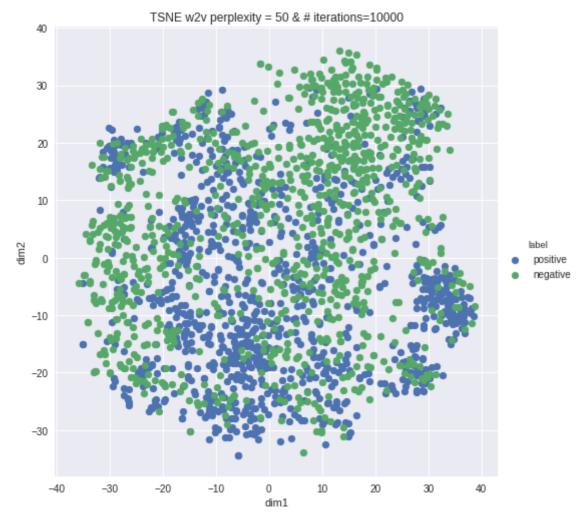
```
#TSNE for W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=30, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE w2v perplexity = 30 & # iterations=2500')
plt.show()
```



```
#TSNE for W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE w2v perplexity = 50 & # iterations=5000')
plt.show()
```



```
#TSNE for W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=10000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE w2v perplexity = 50 & # iterations=10000')
plt.show()
```



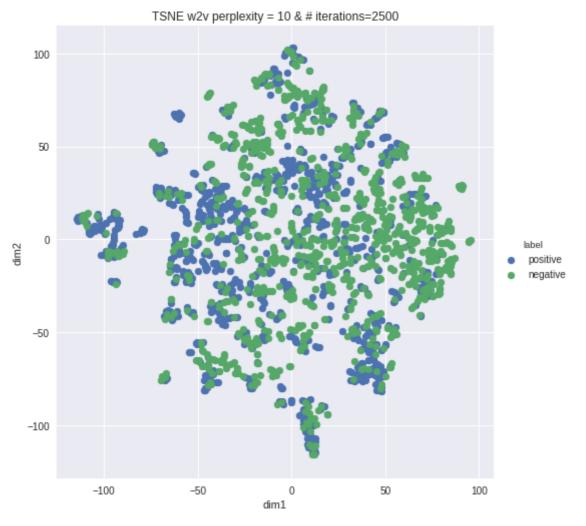
TFIDF W2V

```
vect = TfidfVectorizer(ngram_range=(1,2))
final_tfidf = vect.fit_transform(reviews['CleanedText'].values)
final_labels = reviews['Score'].values
```

```
tfidf_feat = vect.get_feature_names()
# def top_tfidf_feats(row, features, top_n=25):
# ''' Get top n tfidf values in row and return them with their corresponding feature na
# 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_tfidf[1,:].toarray()[0],features,25)
```

```
list_of_sent = [sent.split() for sent in reviews['CleanedText'].values]
final = helper(list_of_sent, final_tfidf)
```

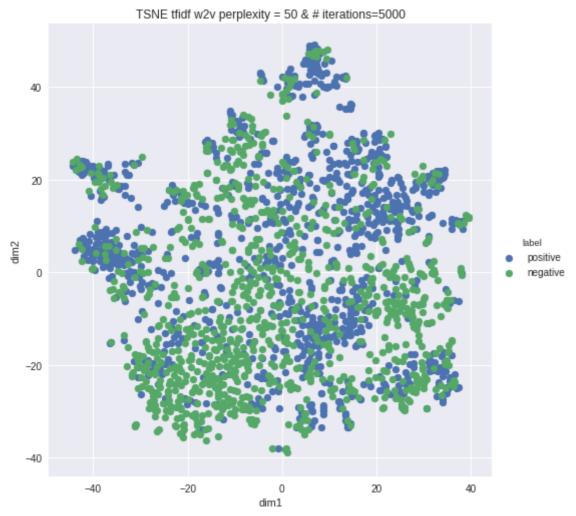
```
#TSNE for tfidf W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=10, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf w2v perplexity = 10 & # iterations=2500')
plt.show()
```



```
#TSNE for tfidf W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=25, n_iter=2500)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf w2v perplexity = 25 & # iterations=2500')
plt.show()
```



```
#TSNE for tfidf W2V
#perplexity=10 and #iterations=2500
tsne_model = TSNE(n_components=2, random_state=0, perplexity=50, n_iter=5000)
#converting sparse to dense matrix
data = tsne_model.fit_transform(final)
tsne = np.vstack((data.T, final_labels)).T
df = pd.DataFrame(data=tsne, columns=("dim1", "dim2", "label"))
sns.FacetGrid(df, hue="label", size=7).map(plt.scatter, 'dim1', 'dim2').add_legend()
plt.title('TSNE tfidf w2v perplexity = 50 & # iterations=5000')
plt.show()
```



Observations and Questions

- 1. TSNE indicates that positive and negative reviews overlap a lot in 2D.
- 2. The patterns between BoW TSNE and TFIDF/W2V TSNE are completely different. Would like to know what causes this.
- 3. Does TSNE works better with large data sets? I understand algorithms require large data, but internally what actually happens with algorithms when we feed large data?