Amazon Fine Food Reviews Analysis

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

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
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

Loading the data from Sqlite file

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

# General Packages
import os
import sqlite3
import pandas as pd
import numpy as np
import string
import re
import nltk

# Plotting Packages
import matplotlib.pyplot as plt
import seaborn as sns

# Packages for Tfidf
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

# Packages for BOW (Bag of words)
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc

# Packages for Text Preprocessing
from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer

#Packages for Word2vec, Average Word2vec & Tf-Idf Weighted Word2Vec
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

#Packages for plotting Tsne plot
from sklearn.manifold import TSNE
```

In [2]:
```
#Setting Parent Directory
os.chdir('/users/sujis/Downloads/Applied AI/')#C:\Users\sujit.venka
ta\Downloads\Dev & Imp works\Applied AI'

# using the SQLite Table to read data.
con = sqlite3.connect('/users/sujis/Downloads/Applied AI/amazon-fin
e-food-reviews/database.sqlite')
```

In [3]:
```
# Filtering for the reviews those with Score= 3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE S
core != 3 """, con)

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

# Aliasing the Score to String Format (Positive for Score > 3 & Neg
ative for Score  < 3)

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

In [4]:
```
# Size and Shape of the Data set & printing 5 records
print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

Out[4]:

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

Exploratory Data Analysis

Data Cleaning: Deduplication

In [5]:
```
# Checking for the Duplicate records

display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="ABXLMWJIXXAIN"
ORDER BY ProductID
""", con)
display.head()
```

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	H
0	320691	B000CQ26E0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	0	0
1	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
2	468954	B004DMGQKE	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	0	0

Observation:- As per the result set of the query for userId='ABXLMWJIXXAIN', the same user has multiple reviews. So removing the duplicates are removed ensuring that there is only one review for each product by each user.

In [6]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascendin
g=True, inplace=False, kind='quicksort', na_position='last')
```

In [7]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","T
ime","Text"}, keep='first', inplace=False)
final.shape
```

Out[7]: (364173, 10)

In [8]:
```
# Percentage of data still left after Deduplication
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[8]: 69.25890143662969

In [9]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[9]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

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 [10]:
```
# Removing the records who have HelpfulnessNumerator less than Help
fulnessDenominator
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominato
r]
```

In [11]:
```
#Before starting the next phase of preprocessing lets see the numbe
r of entries left
print(final.shape)

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

```
(364171, 10)
```

Out[11]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

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

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

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

In [13]:
```
# 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). A
t this point, I consider myself a connoisseur of children's books
and this is one of the best. Santa Clause put this under the tree.
Since then, we've read it perpetually and he loves it.<br /><br />
First, this book taught him the months of the year.<br /><br />Sec
ond, it's a pleasure to read. Well suited to 1.5 y/o old to 4+.<br
/><br />Very few children's books are worth owning. Most should be
borrowed from the library. This book, however, deserves a permanen
t spot on your shelf. Sendak's best.
```

In [14]:
```
# Defining Functions to clean html tags & Punctuations
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowba
ll stemmer

#function to clean the word of any html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

#function to clean the word of any punctuation or special character
s
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
#print(stop)
```

In [15]:
```
#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 sentenc
es.
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('utf
8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all w
ords used to describe positive reviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all w
ords used to describe negative reviews reviews
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned wo
rds
    final_string.append(str1)
    i+=1
```

In [16]:
```
final['CleanedText']=final_string #adding a column of CleanedText w
hich displays the data after pre-processing of the review
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
```

In [17]:
```
final.head(3) #below the processed review can be seen in the Cleane
dText 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', in
dex=True, index_label=None, chunksize=None, dtype=None)
```

Bag of Words (BoW)

In [18]:
```
# Due to memory constraints taking 1.25k positive & 1.25k negative
reviews
final_dataset=pd.DataFrame()
positive_dataset=final.loc[final['Score'] == 'positive'].head(1250)
Negative_dataset=final.loc[final['Score'] == 'negative'].head(1250)
final_dataset=pd.concat([positive_dataset,Negative_dataset])
```

In [19]:
```
l1 = positive_dataset['Score']
l2 = Negative_dataset['Score']
label=pd.concat([l1,l2])
```

In [20]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
final_counts = count_vect.fit_transform(final_dataset['CleanedText'
].values)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shap
e())
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  (2500, 7937)
the number of unique words  7937
```

In [21]:
```
# Converting Sparse matric to array
final_counts=final_counts.toarray()
```

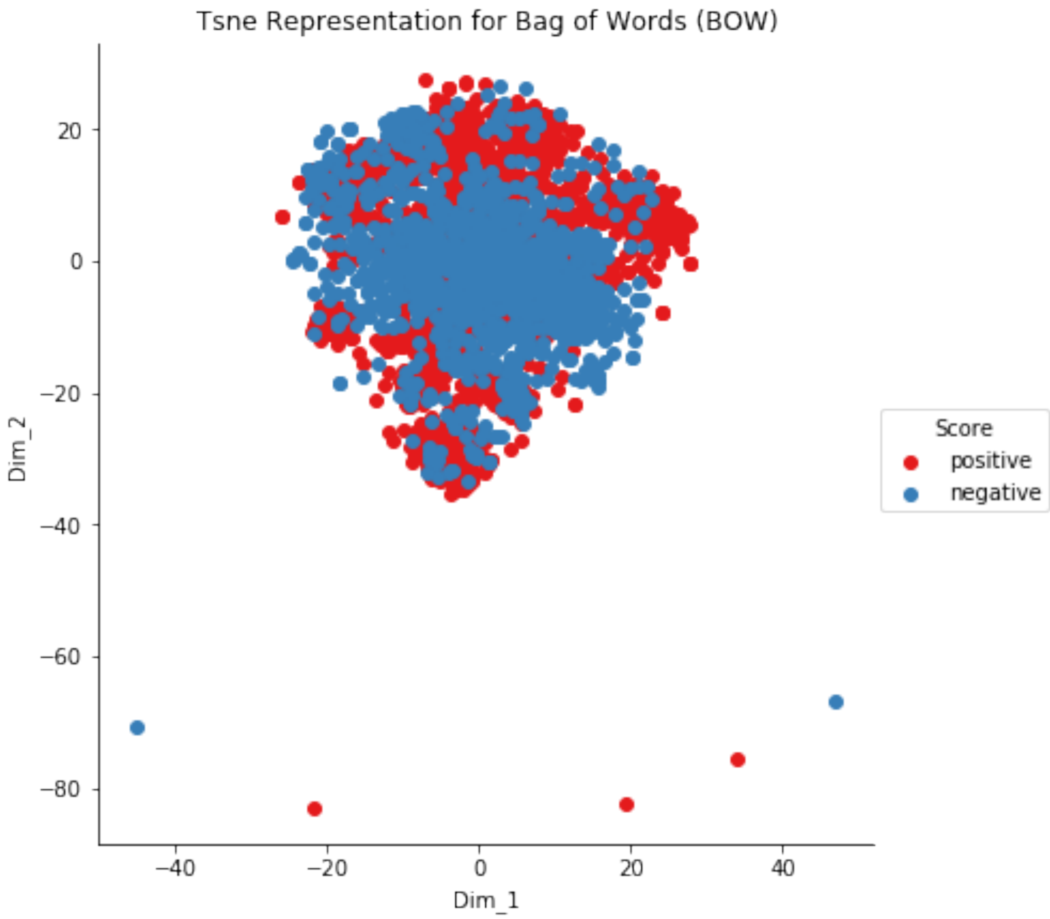
In [22]:
```
#tsne
model = TSNE(n_components=2, random_state=0)
tsne_data = model.fit_transform(final_counts)
```

In [23]:
```
tsne_data.shape
```

Out[23]:
```
(2500, 2)
```

In [24]:
```
tsne_data = np.vstack((tsne_data.T, label)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "
Score"))
```

In [25]:
```
# Scatter plot representing 2 dimensions with the polarity
sns.FacetGrid(tsne_df, hue="Score", size=6,palette="Set1").map(plt.
scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('Tsne Representation for Bag of Words (BOW)')
plt.show()
```



Term Frequency– Inverse Document Frequency (TF-IDF)

Connecting the Sqlite file

con2 = sqlite3.connect('final.sqlite') final= pd.read_sql_query(""" SELECT * FROM Reviews """, con2)

Due to memory constraints taking 1.25k positive & 1.25k negative reviews

In [26]:
```
#final_dataset=pd.DataFrame()
#positive_dataset=final.loc[final['Score'] == 'positive'].head(2500
)
#Negative_dataset=final.loc[final['Score'] == 'negative'].head(2500
)
#final_dataset=pd.concat([positive_dataset,Negative_dataset])
#l1 = positive_dataset['Score']
#l2 = Negative_dataset['Score']
#label=pd.concat([l1,l2])
```

In [27]:
```
# Configuring ngram range from unigram to bigram
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
final_tf_idf = tf_idf_vect.fit_transform(final_dataset['CleanedText
'].values)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_sh
ape())
print("the number of unique words including both unigrams and bigra
ms ", final_tf_idf.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'
>
the shape of out text TFIDF vectorizer  (2500, 89432)
the number of unique words including both unigrams and bigrams  89
432
```

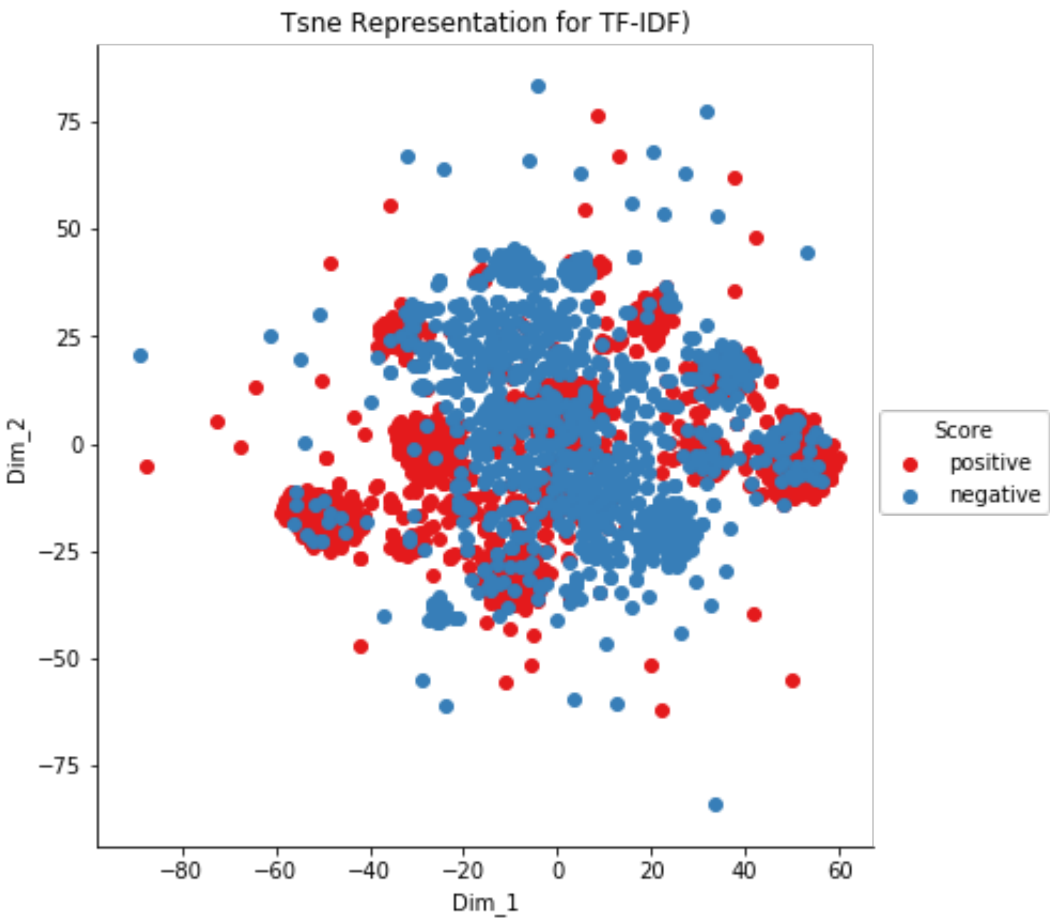
In [28]:
```
# Converting Sparse matric to array
final_tf_idf=final_tf_idf.toarray()
#tsne
model = TSNE(n_components=2, random_state=0)
tsne_data_tfidf = model.fit_transform(final_tf_idf)
```

In [29]:
```
tsne_data_tfidf.shape
```

Out[29]:
```
(2500, 2)
```

In [30]:
```
# Scatter plot representing 2 dimensions with the polarity
tsne_data_tfidf = np.vstack((tsne_data_tfidf.T, label)).T
tsne_tf_idf_df = pd.DataFrame(data=tsne_data_tfidf, columns=("Dim_1
", "Dim_2", "Score"))

sns.FacetGrid(tsne_tf_idf_df, hue="Score", size=6,palette="Set1").m
ap(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('Tsne Representation for TF-IDF)')
plt.show()
```



Average Word2Vec (Avg W2V)

Connecting the Sqlite file

con2 = sqlite3.connect('final.sqlite') final = pd.read_sql_query(""" SELECT * FROM Reviews """, con2)

Due to memory constraints taking 1.25k positive & 1.25k negative reviews

In [31]:
```
#final_dataset=pd.DataFrame()
#positive_dataset=final.loc[final['Score'] == 'positive'].head(2500
)
#Negative_dataset=final.loc[final['Score'] == 'negative'].head(2500
)
#final_dataset=pd.concat([positive_dataset,Negative_dataset])
#l1 = positive_dataset['Score']
#l2 = Negative_dataset['Score']
#label=pd.concat([l1,l2])
```

In [34]:
```
# Word2Vec
#model = KeyedVectors.load_word2vec_format('google_w2v_for_amazon.p
kl', binary=True)
```

In [35]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sent=[]
for sent in final_dataset['CleanedText'].values:
    list_of_sent.append(sent.split())
```

In [36]:
```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [37]:
```
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  2567
sample words  ['littl', 'book', 'make', 'son', 'laugh', 'loud', 'c
ar', 'drive', 'along', 'alway', 'sing', 'hes', 'learn', 'love', 'n
ew', 'word', 'introduc', 'silli', 'classic', 'will', 'still', 'abl
', 'memori', 'grew', 'read', 'sendak', 'watch', 'realli', 'movi',
'howev', 'miss', 'hard', 'cover', 'version', 'seem', 'kind', 'flim
si', 'take', 'two', 'hand', 'keep', 'page', 'open', 'fun', 'way',
'children', 'month', 'year', 'poem', 'throughout']
```

In [38]:
```
# 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 sentenc
e/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))
```

```
2500
```

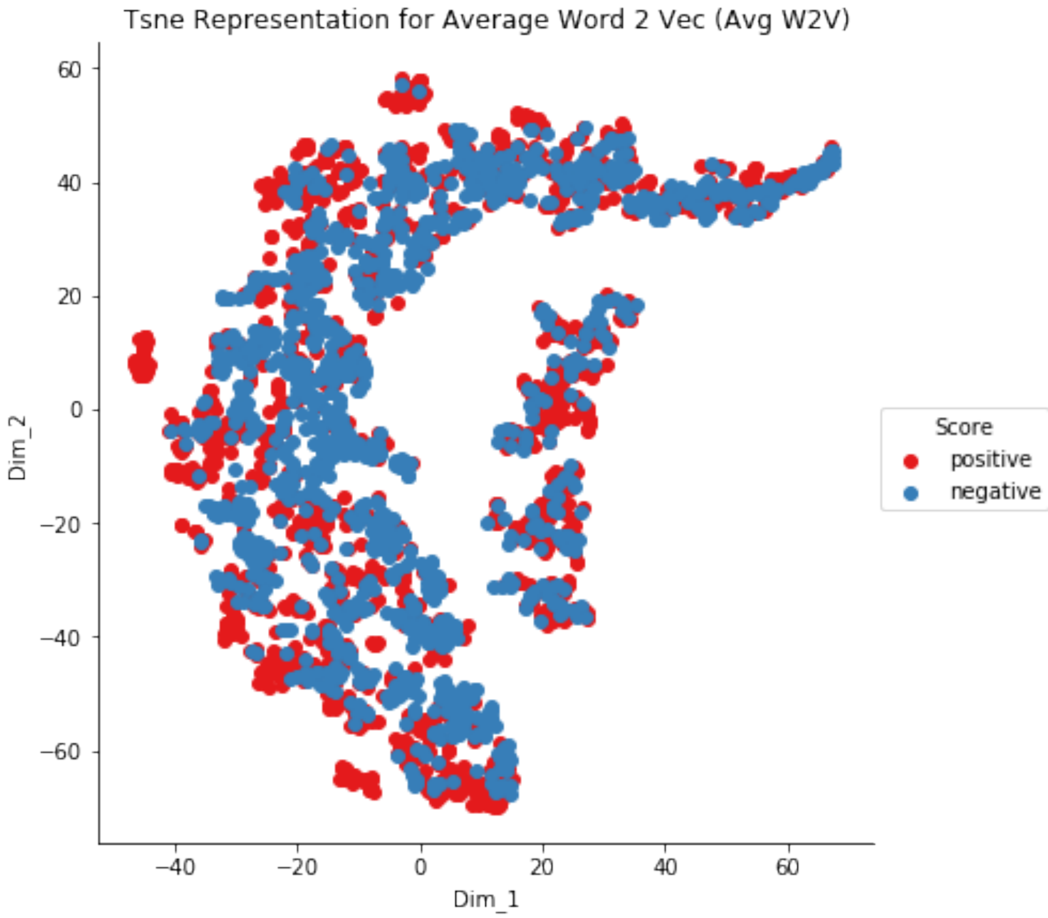
In [39]:
```
#tsne
model = TSNE(n_components=2, random_state=0)
tsne_data_Aw2v = model.fit_transform(sent_vectors)
```

In [40]:
```
tsne_data_Aw2v.shape
```

Out[40]:
```
(2500, 2)
```

In [41]:
```
# Scatter plot representing 2 dimensions with the polarity
tsne_data_Aw2v = np.vstack((tsne_data_Aw2v.T, label)).T
tsne_data_Aw2v_df = pd.DataFrame(data=tsne_data_Aw2v, columns=("Dim
_1", "Dim_2", "Score"))

sns.FacetGrid(tsne_data_Aw2v_df, hue="Score", size=6,palette="Set1"
).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('Tsne Representation for Average Word 2 Vec (Avg W2V)')
plt.show()
```



TF-IDF - W2V

In [42]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-name
s
# final_tf_idf is the sparse matrix with row= sentence, col=word an
d cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review i
s stored in this list
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 senten
ce/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
```

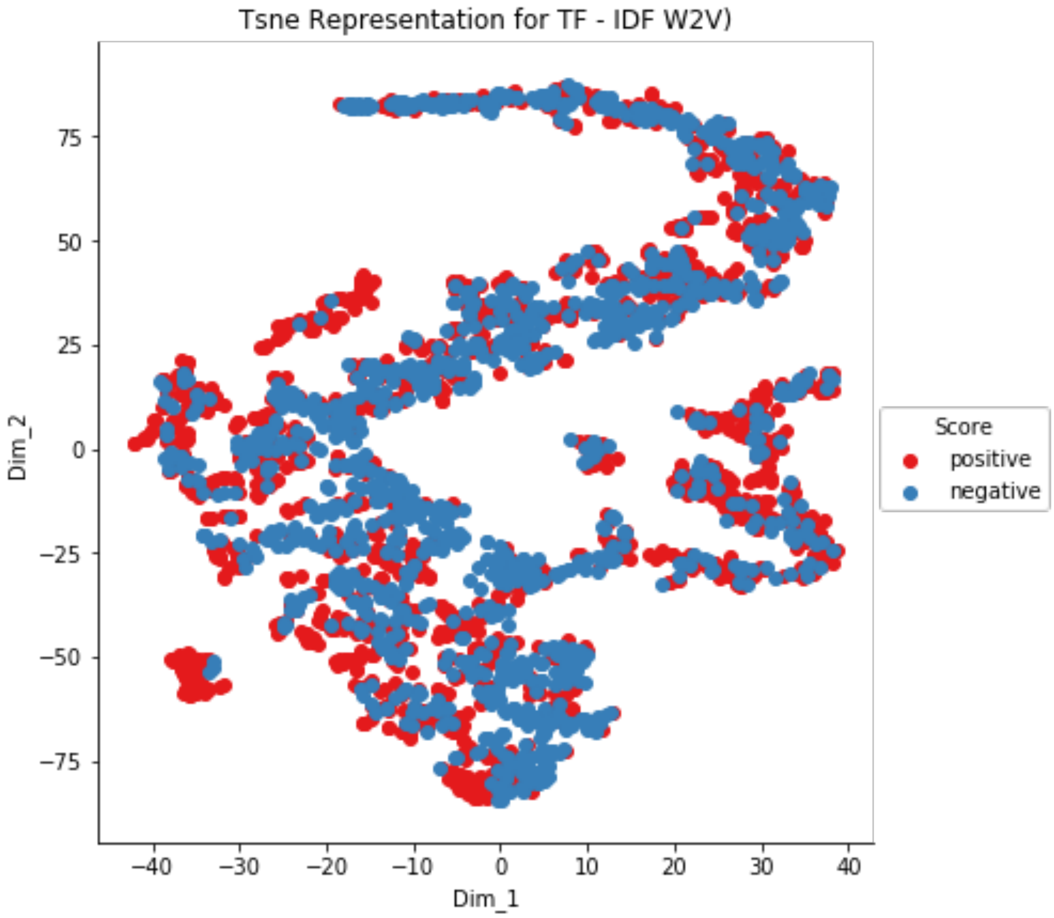
In [43]:
```
#tsne
model = TSNE(n_components=2, random_state=0)
tsne_data_tfidf_Aw2v = model.fit_transform(tfidf_sent_vectors)
```

In [44]:
```
tsne_data_tfidf_Aw2v.shape
```

Out[44]:
```
(2500, 2)
```

In [45]:
```
# Scatter plot representing 2 dimensions with the polarity
tsne_data_tfidf_Aw2v = np.vstack((tsne_data_tfidf_Aw2v.T, label)).T
tsne_data_tfidf_Aw2v_df = pd.DataFrame(data=tsne_data_tfidf_Aw2v, c
olumns=("Dim_1", "Dim_2", "Score"))

sns.FacetGrid(tsne_data_tfidf_Aw2v_df, hue="Score", size=6,palette=
"Set1").map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('Tsne Representation for TF - IDF W2V)')
plt.show()
```



Conclusion
After plotting the Tsne plots for Bag of words, TF-IDF, Average W2v, TF-IDF W2V, came to conclusion that TF_IDF W2V plot is better to differentiate the Positive & Negative Reviews.

Note :- 1.25k Positive & 1.25k Negative data points are used due to memory Constraints