Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

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

Objective:

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

[Q] How to determine if a review is positive or negative?

[Ans] We could use the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [40]:
```
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

import os
import re
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sb
import pickle
```

```python
from sklearn import metrics
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.metrics import roc_curve,auc

from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.stem import PorterStemmer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors

from sklearn.preprocessing import StandardScaler
#TSNE
from sklearn.manifold import TSNE
from bs4 import BeautifulSoup
```

In [41]:
```python
# Temporarily Suppressing Warnings
def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()
```

[1]. Reading Data

In [42]:
```python
# using the SQLite Table to read data.
# con = sqlite3.connect('./amazon-fine-food-reviews/database.sqlite')

con = sqlite3.connect('C:/Users/Saraswathi/Music/Appliedai/Data/amazon-fine-food-reviews/database.sqlite')
```

```
#filetering only positve and negative reviews
#reviews not taking in to consideration with score = 3

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 5000""", con)

# Give reviews with Score>3 a positive rating, and reviews with a score
<3 a negative rating.
def partition( x ):
    if x > 3:
        return 'Positive'
#           return 1
    else:
        return 'Negative'

#changing reviews with score less than 3 to be positive and vice versa
actual_score = filtered_data['Score']
positivenegative = actual_score.map(partition)
filtered_data['Score']=positivenegative
print('Number of data point in our data',filtered_data.shape)
filtered_data.head(5)
```

```
Number of data point in our data (5000, 10)
```

Out[42]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
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	

Exploratory Data Analysis

[2] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [43]:
```
display = pd.read_sql_query("""
SELECT * FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""",con)
```

In [44]:
```
display.head()
```

Out[44]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
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	

As can be seen above the same user has multiple reviews of the with the same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [45]:
```
#Sorting data according to ProductId in ascending order
sorted_data = filtered_data.sort_values('ProductId',axis=0,ascending= True, inplace=False, kind ='quicksort',na_position='last')
```

In [46]:
```
#Duplication of entries
final = sorted_data.drop_duplicates(subset={'UserId','ProfileName','Time','Text'}, keep = 'first' , inplace= False)
final.shape
```

Out[46]:
```
(4986, 10)
```

In [47]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[47]:
```
99.72
```

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 [48]:
```
display = pd.read_sql_query("""
SELECt *
```

```
FROM Reviews
WHERE Score !=3 AND Id=44737 OR Id=64422
ORDER BY ProductId
""",con)
display.head()
```

Out[48]:

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

In [49]:

```
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominato
r]
```

In [50]:

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

Out[50]:

```
Positive    4178
Negative     808
Name: Score, dtype: int64
```

Text Preprocessing.

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

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. 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)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [51]:
```
def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [52]:
```
stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
```

```
              'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
              'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
              'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
              'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
              'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
              'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
              's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
              've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
              "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
              "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
              'won', "won't", 'wouldn', "wouldn't"])
```

In [53]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+","",sentance)
    sentance = BeautifulSoup(sentance,'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*","",sentance).strip()
    sentance = re.sub('[^A-Za-z]+',' ',sentance)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|████████████████████████████████████████
██████████| 4986/4986 [00:03<00:00, 1301.43it/s]
```

In [54]:
```
preprocessed_reviews[1000]
```

Out[54]:
```
'recently tried flavor brand surprised delicious chips best thing lot b
rown chips bsg favorite bought amazon shared family friends little disa
ppointed not far many brown chips bags flavor still good like better yo
gurt green onion flavor not seem salty onion flavor better not eaten ke
ttle chips recommend try bag buying bulk thicker crunchier lays fresh b
ag'
```

[3.2] Preprocess Summary

In [55]:
```
##preprocessing for review summary also.

# Combining all the above stundents
from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Summary'].values):
    sentance = re.sub(r"http\S+","",sentance)
    sentance = BeautifulSoup(sentance,'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*","",sentance).strip()
    sentance = re.sub('[^A-Za-z]+',' ',sentance)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_summary.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████
████████| 4986/4986 [00:02<00:00, 1997.22it/s]
```

Featurization

BAG OF WORDS, Bi-Grams and n-Grams, TF-IDF, Word2Vec, Converting text into vectors using wAvg W2V, TFIDF-W2V, Avg W2v, TFIDF weighted W2v

I have applied all these codes in the "Applying TSNE" section

Applying TSNE

1. ploted 4 tsne plots with each of these feature set
   A. Review text, preprocessed one converted into vectors using (BOW)
   B. Review text, preprocessed one converted into vectors using (TFIDF)
   C. Review text, preprocessed one converted into vectors using (AVG W2v)
   D. Review text, preprocessed one converted into vectors using (TFIDF W2v)
2. Note 1: The TSNE accepts only dense matrices
3. Note 2: Considered maximun 5k data points

In [56]:

```
#storing label i.e positive and negative in another variable for tsne p
lot
labels = final['Score']
```

BAG OF WORDS

In [57]:

```
#BOW
count_vect = CountVectorizer()
count_vect.fit(preprocessed_reviews)
print('some feature names are',count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words",final_counts.get_shape()[1])
```

```
some feature names are ['aa', 'aahhhs', 'aback', 'abandon', 'abates',
'abbott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

```
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words 12997
```

Applying TNSE on Text BOW vectors

In [58]:

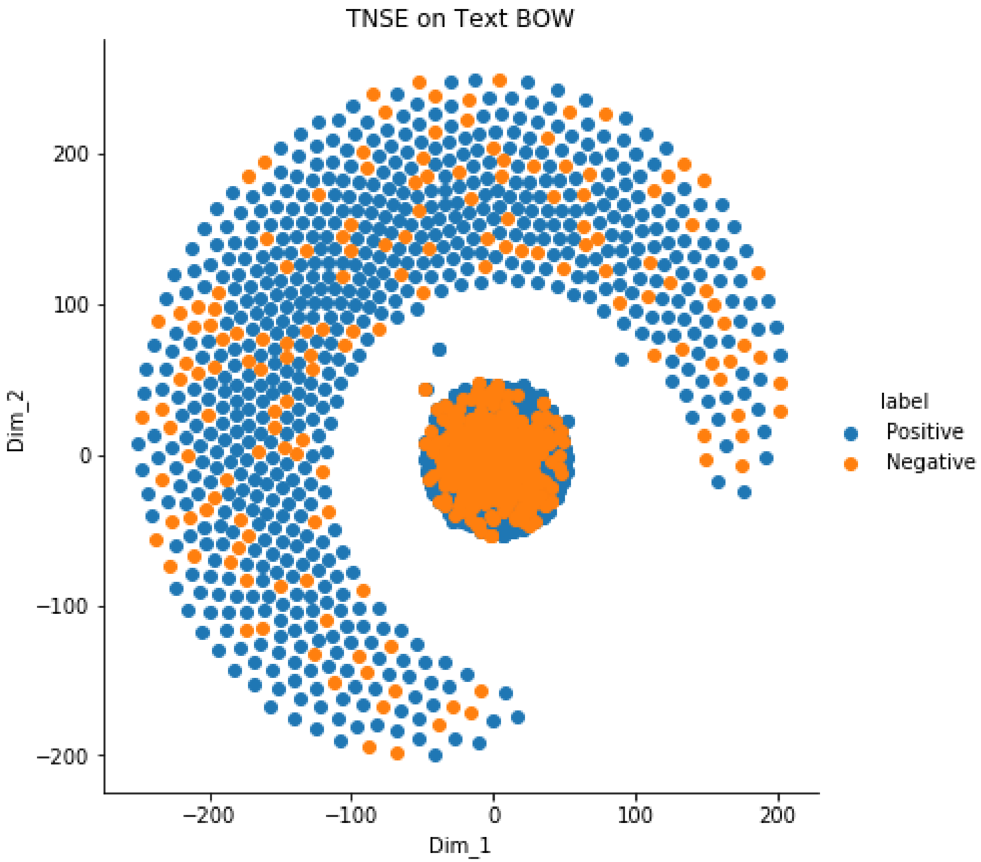
```
# Data-preprocessing: Standardizing the data
BOW_standardized_data = StandardScaler(with_mean = False).fit_transform
(final_counts)
print(type(BOW_standardized_data))

#*************************************************************8
#  Converting sparse matrix to dense matrix
BOW_standardized_data = BOW_standardized_data.todense()
print(type(BOW_standardized_data))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
<class 'numpy.matrix'>
```

In [59]:

```
#Model
model = TSNE(n_components = 2,random_state= 0 , perplexity= 50 ,n_iter=
5000)
#Configure TSNE
#No of componets - 2
#Default perflexity - 30
#Default learning rate - 200
#Maximum no of iteration - 1000
tsne_data = model.fit_transform(BOW_standardized_data)

# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data = tsne_data , columns = ('Dim_1','Dim_2','l
abel'))

# Ploting the result of tsne
sb.FacetGrid(tsne_df,hue = 'label',size = 6).map(plt.scatter, 'Dim_1',
'Dim_2').add_legend()
```

```
plt.title('TNSE on Text BOW')
plt.show()
```



Observation(s):

1. At least 90% of the data is overlapped.
2. we are unable to simply draw a hyperplane and separate pasitive and negative reviews because it overlap each other.

Bi-Grams and n-Grams.

In [60]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
count_vect = CountVectorizer(ngram_range=(1,2),min_df=10,max_features=5
000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer",final_bigram_counts.get_sh
ape())
print("the number of unique words including both unigrams and bigrams",
final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (4986, 3144)
the number of unique words including both unigrams and bigrams 3144
```

TF-IDF

In [61]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df =10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[:10])
print('='*50)
final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape
())
print("the number of unique words including both unigrams and bigrams "
, final_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble find', 'able get', 'absolute', 'absolutely', 'absolutely deliciou
s', 'absolutely love', 'absolutely no', 'according']
```

```
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

Applying TNSE on Text TFIDF vectors

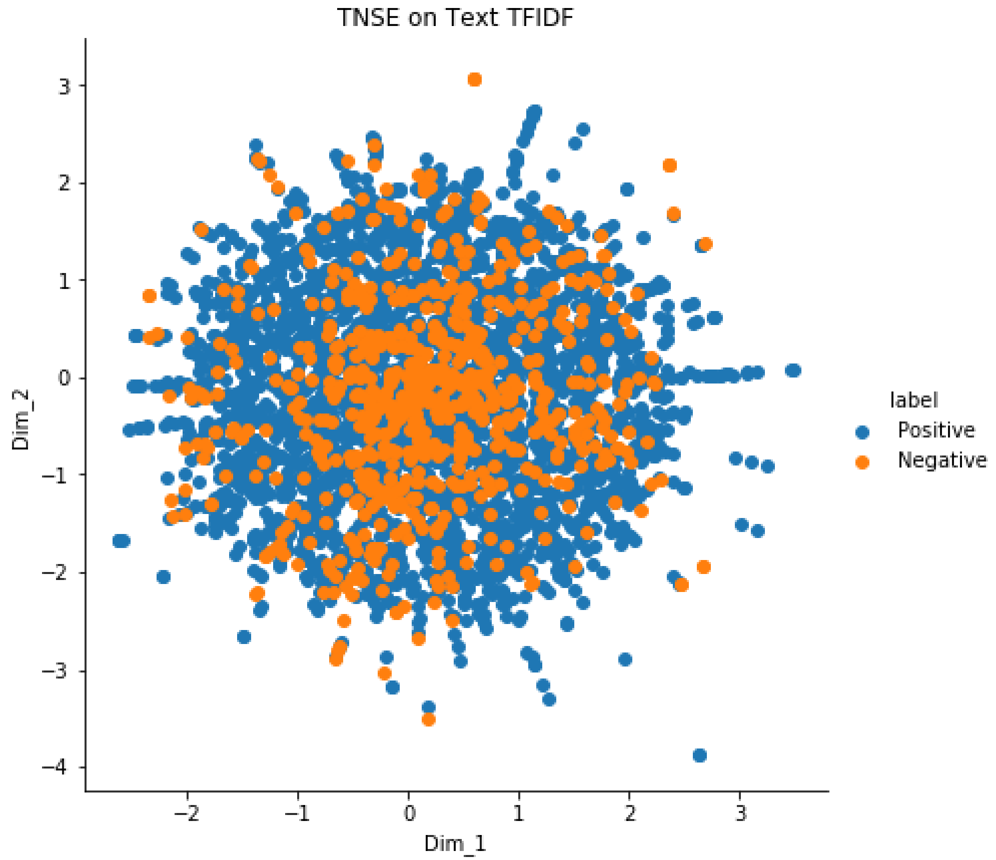
In [62]:

```
# Data-preprocessing: Standardizing the data
# from sklearn.preprocessing import StandardScaler
tf_idf_std_data = StandardScaler(with_mean = False).fit_transform(final
_tf_idf)
print(tf_idf_std_data.shape)
# convert sparse to dense as tsne takes dense vector
tf_idf_std_data = tf_idf_std_data.todense()
print(type(tf_idf_std_data))
```

```
(4986, 3144)
<class 'numpy.matrix'>
```

In [63]:

```
model = TSNE(n_components = 2,random_state= 0 , perplexity= 50 ,n_iter=
5000)
tsne_data = model.fit_transform(tf_idf_std_data)

# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data = tsne_data , columns = ('Dim_1','Dim_2','l
abel'))

# Ploting the result of tsne
sb.FacetGrid(tsne_df,hue = 'label',size = 6).map(plt.scatter, 'Dim_1',
'Dim_2').add_legend()
plt.title('TNSE on Text TFIDF')
plt.show()
```



Observation(s):

1. At least 90% of the data is overlapped.
2. we are unable to simply draw a hyperplane and separate pasitive and negative reviews because it overlap each other.

Word2Vec

In [64]:
```
# Train your own Word2Vec model using your own text corpus
```

```
i = 0
list_of_sentance = []
for sentance in preprocessed_reviews:
#     list_of_sentance.append(sentance)
    list_of_sentance.append(sentance.split())
# print((list_of_sentance))
```

In [65]:
```
# Using Google News Word2Vectors
is_your_ram_gt_16gb = False
want_to_use_google_w2v = True
want_to_train_w2v = True

# print(list_of_sentance)

if want_to_train_w2v:
   # min_count = 5 considers only words that occured atleast 5 times
    w2v_model = Word2Vec(list_of_sentance,min_count = 5 ,size = 50 ,wor
kers = 4)
    print(type(w2v_model))
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))


elif want_to_use_google_w2v and is_your_ram_gt_16gb :
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model = KeyedVectors.load_word2vec_format('GoogleNews-vecto
rs-negative300.bin',binary = True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
<class 'gensim.models.word2vec.Word2Vec'>
[('alternative', 0.9941328763961792), ('snack', 0.9936726093292236),
('regular', 0.9933136105537415), ('excellent', 0.9932251572608948), ('s
atisfying', 0.9922833442687988), ('chewy', 0.9921470284461975), ('espec
ially', 0.9920903444290161), ('earl', 0.9920855760574341), ('absolutel
```

```
y', 0.9920355677604675), ('crisp', 0.9920077919960022)]
==================================================
[('tomatoes', 0.9994714260101318), ('come', 0.9994643330574036), ('simp
ly', 0.9994384050369263), ('gourmet', 0.9994294047355652), ('perhaps',
0.9993866086006165), ('choice', 0.9993788599967957), ('peanuts', 0.9993
764758110046), ('wow', 0.9993703365325928), ('point', 0.99936258792877
2), ('yes', 0.9993584156036377)]
```

In [66]:

```
print(type(w2v_model))
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])
```

```
<class 'gensim.models.word2vec.Word2Vec'>
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'st
inky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'receiv
ed', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'ins
tead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use',
'car', 'windows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fu
n', 'everywhere', 'like', 'tv', 'computer', 'really', 'good', 'idea',
'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'mad
e']
```

Converting text into vectors using wAvg W2V, TFIDF-W2V

Avg W2v

In [67]:

```
#average word2vec
#compute average word2 vec for each review
sent_vectors = [];
for sent in tqdm(list_of_sentance):
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words = 0;
```

```
    for word in sent:
        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]))
```

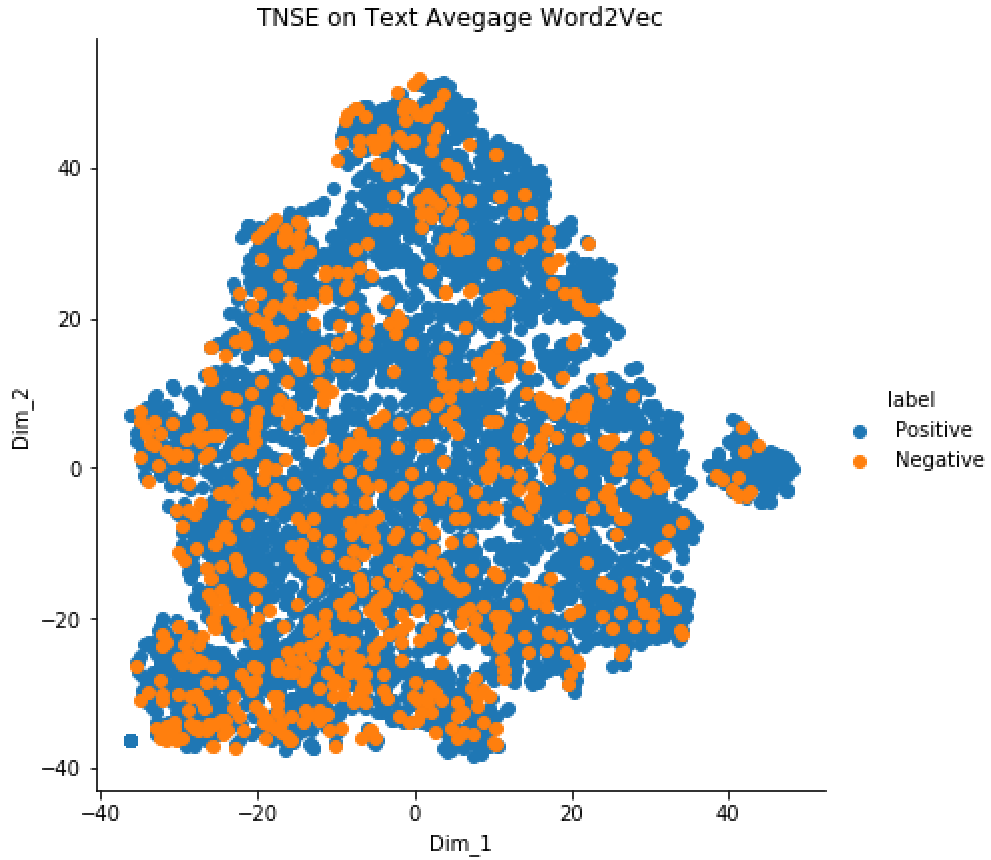
```
100%|██████████████████████████████████████████████████████████████
███████████| 4986/4986 [00:09<00:00, 532.00it/s]
```

```
4986
50
```

Applying TNSE on Text Avg W2V vectors

In [68]:

```
#TSNE
model = TSNE(n_components = 2,random_state= 0 , perplexity= 100 ,n_iter
=10000)
tsne_data = model.fit_transform(sent_vectors)

# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data = tsne_data , columns = ('Dim_1','Dim_2','l
abel'))

# Ploting the result of tsne
sb.FacetGrid(tsne_df,hue = 'label',size = 6).map(plt.scatter, 'Dim_1',
'Dim_2').add_legend()
plt.title('TNSE on Text Avegage Word2Vec')
plt.show()

# print('Completed')
```



Observation(s):

positive and negative reviews are not well seperated this also looks like bow and tfidf vector representations.

TFIDF weighted W2v

In [69]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
model.fit(preprocessed_reviews)
```

```
# 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_)))
```

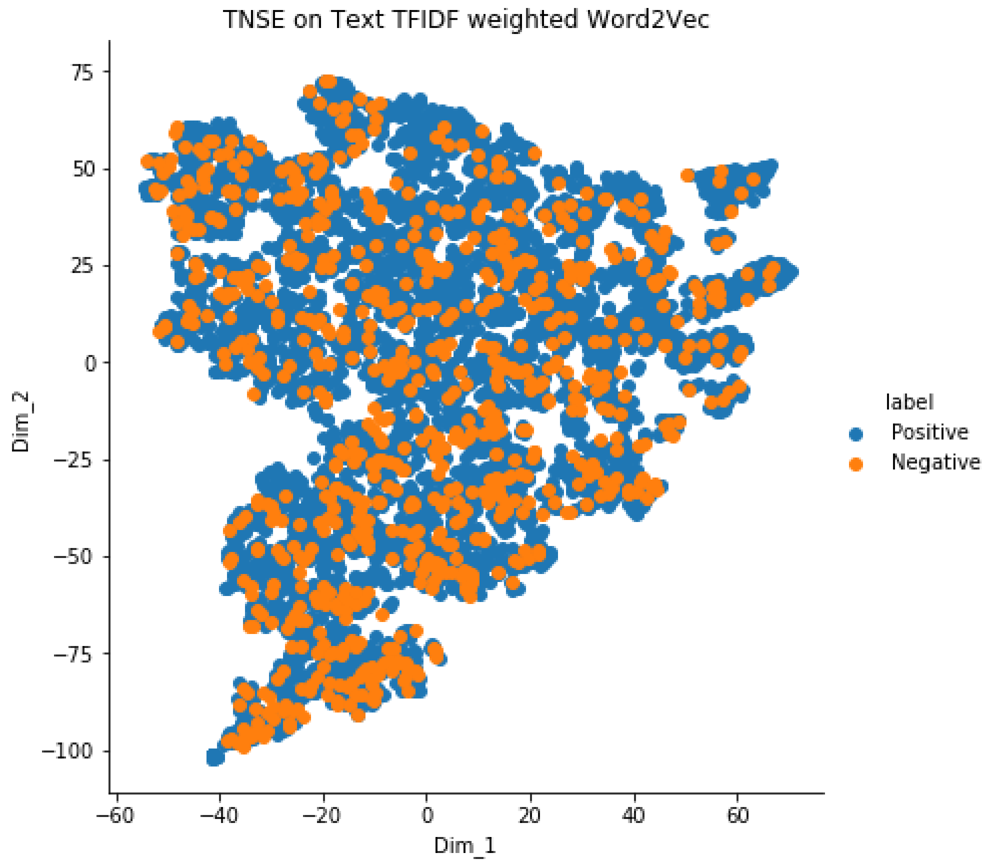
In [70]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names()

# 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
row = 0
for sent in tqdm(list_of_sentance):
    sent_vec = np.zeros(50)
    weight_sum = 0; # as word vectors are of zero length
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            # tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            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
```

```
100%|██████████████████████████████████████████████████| 4986/4986 [00:56<00:00, 88.16it/s]
```

Applying TNSE on Text TFIDF weighted Word2Vec vectors

In [71]:

```
#TSNE

from sklearn.manifold import TSNE

# print(labels)

model = TSNE(n_components = 2,random_state= 0 , perplexity= 50 ,n_iter=
5000)
#Configure TSNE
#No of componets - 2
#Default perflexity - 30
#Default learning rate - 200
#Maximum no of iteration - 1000
tsne_data = model.fit_transform(tfidf_sent_vectors)

# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data = tsne_data , columns = ('Dim_1','Dim_2','l
abel'))

# Ploting the result of tsne
sb.FacetGrid(tsne_df,hue = 'label',size = 6).map(plt.scatter, 'Dim_1',
'Dim_2').add_legend()
plt.title('TNSE on Text TFIDF weighted Word2Vec')
plt.show()

# print('Completed')
```



Observation(s):

positive and negative reviwes are not well seperated they overlapped each other.

Conclusions:

1. By looking at all tsne reprentation, none of these gives well separated positive and negative reviews.
2. As none of TSNE representation gives a well separated both positive and negative reviews.

3. We can not simply draw a plane to separate positive and negative reviews. Although, By looking at only visual representation of data we can not take decision whether to draw a plane or not.
4. We will have some alternative method by that we will look at into this problem like how we can separate positive and negative reviews.