Perfoming T-SNE on Amazon Fine Food Reviews

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 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).

1. Reading Data

1.1. Loading 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 is 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 is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:

```
# Importing Libraries
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [3]:

```
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re

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

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
import warnings
warnings.filterwarnings("ignore")
```

In [4]:

```
# using the SQLite Table to read data.
con1 = sqlite3.connect('database.sqlite')
```

In [5]:

```
# Eliminating neutral reviews i.e. those reviews with Score = 3
filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)
```

In [6]:

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

# Applying polarity function on Score column of filtered_data
filtered_data['Score'] = filtered_data['Score'].map(polarity)
```

In [7]:

```
print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

Out[7]:

	Id	ProductId	UserId	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	

2. Exploratory Data Analysis

2.1. 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 [8]:

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

In [9]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='firs
final.shape
```

Out[9]:

```
(364173, 10)
```

In [10]:

```
#Checking to see how much % of data still remains
((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
```

Out[10]:

```
69.25890143662969
```

In [11]:

```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]
```

In [12]:

```
print(final.shape)
```

```
(364171, 10)
```

In [13]:

```
final[30:50]
```

Out[13]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
138676	150493	0006641040	AMX0PJKV4PPNJ	E. R. Bird "Ramseelbird"	71	
138682	150500	0006641040	A1IJKK6Q1GTEAY	A Customer	2	
138681	150499	0006641040	A3E7R866M94L0C	L. Barker "simienwolf"	2	
476617	515426	141278509X	AB1A5EGHHVA9M	CHelmic	1	
22621	24751	2734888454	A1C298ITT645B6	Hugh G. Pritchard	0	
22620	24750	2734888454	A13ISQV0U9GZIC	Sandikaye	1	
284375	308077	2841233731	A3QD68O22M2XHQ	LABRNTH	0	
157850	171161	7310172001	AFXMWPNS1BLU4	H. Sandler	0	
157849	171160	7310172001	A74C7IARQEM1R	stucker	0	
157833	171144	7310172001	A1V5MY8V9AWUQB	Cheryl Sapper "champagne girl"	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
157832	171143	7310172001	A2SWO60IW01VPX	Sam	0	
157837	171148	7310172001	A3TFTWTG2CC1GA	J. Umphress	0	
157831	171142	7310172001	A2ZO1AYFVQYG44	Cindy Rellie "Rellie"	0	
157830	171141	7310172001	AZ40270J4JBZN	Zhinka Chunmee "gamer from way back in the 70's"	0	
157829	171140	7310172001	ADXXVGRCGQQUO	Richard Pearlstein	0	
157828	171139	7310172001	A13MS1JQG2ADOJ	C. Perrone	0	
157827	171138	7310172001	A13LAE0YTXA11B	Dita Vyslouzilova "dita"	0	
157848	171159	7310172001	A16GY2RCF410DT	LB	0	
157834	171145	7310172001	A1L8DNQYY69L2Z	R. Flores	0	

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

In [14]:

```
final = final[final['ProductId'] != '2841233731']
```

In [15]:

```
final = final[final['ProductId'] != '0006641040']
```

In [16]:

```
final.shape
```

Out[16]:

```
(364136, 10)
```

3. Preprocessing

3.1. Preprocessing Review Text

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 [17]:

```
#set of stopwords in English
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
```

In [18]:

```
words_to_keep = set(('not'))
stop -= words_to_keep
```

In [19]:

```
#initialising the snowball stemmer
sno = nltk.stem.SnowballStemmer('english')
```

In [20]:

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

In [21]:

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

In [22]:

```
#Code for removing HTML tags , punctuations . Code for removing stopwords . Code for checki
# also greater than 2 . Code for stemmimg and also to convert them to lowercase letters
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTML tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describe po
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe ne
                else:
                    continue
            else:
                continue

    str1 = b" ".join(filtered_sentence) #final string of cleaned words


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

In [23]:

```
#adding a column of CleanedText which displays the data after pre-processing of the review
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
#below the processed review can be seen in the CleanedText Column
print('Shape of final',final.shape)
final.head()
```

Shape of final (364136, 11)

Out[23]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
476617	515426	141278509X	AB1A5EGHHVA9M	CHelmic	1	
22621	24751	2734888454	A1C298ITT645B6	Hugh G. Pritchard	0	
22620	24750	2734888454	A13ISQV0U9GZIC	Sandikaye	1	
157850	171161	7310172001	AFXMWPNS1BLU4	H. Sandler	0	
157849	171160	7310172001	A74C7IARQEM1R	stucker	0	

4. Bag of Words (BoW)

In [27]:

```
# Using only 4K (4000) rows for further analysis as my RAM is only 8 GB
my_final = final[0:4000]
```

In [29]:

```
my_final.shape
```

Out[29]:

(4000, 11)

In [34]:

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

Out[34]:

```
positive    3327
negative     673
Name: Score, dtype: int64
```

In [35]:

```
my_final['CleanedText'].values.shape
```

Out[35]:

```
(4000,)
```

In [65]:

```
#BoW
count_vect = CountVectorizer(min_df=10) #in scikit-learn
final_counts = count_vect.fit_transform(my_final['CleanedText'].values)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4000, 2010)
the number of unique words  2010
```

In [66]:

```
# Change sparse matrix to dense matrix
final_counts  = final_counts.toarray()
```

In [67]:

```
final_counts.shape
```

Out[67]:

```
(4000, 2010)
```

In [40]:

```
import warnings
warnings.filterwarnings('ignore')
# Data-preprocessing: Standardizing the data

from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(final_counts)
print(standardized_data.shape)
```

```
(4000, 2010)
```

4.1. t-SNE of Bag Of Words

In [41]:

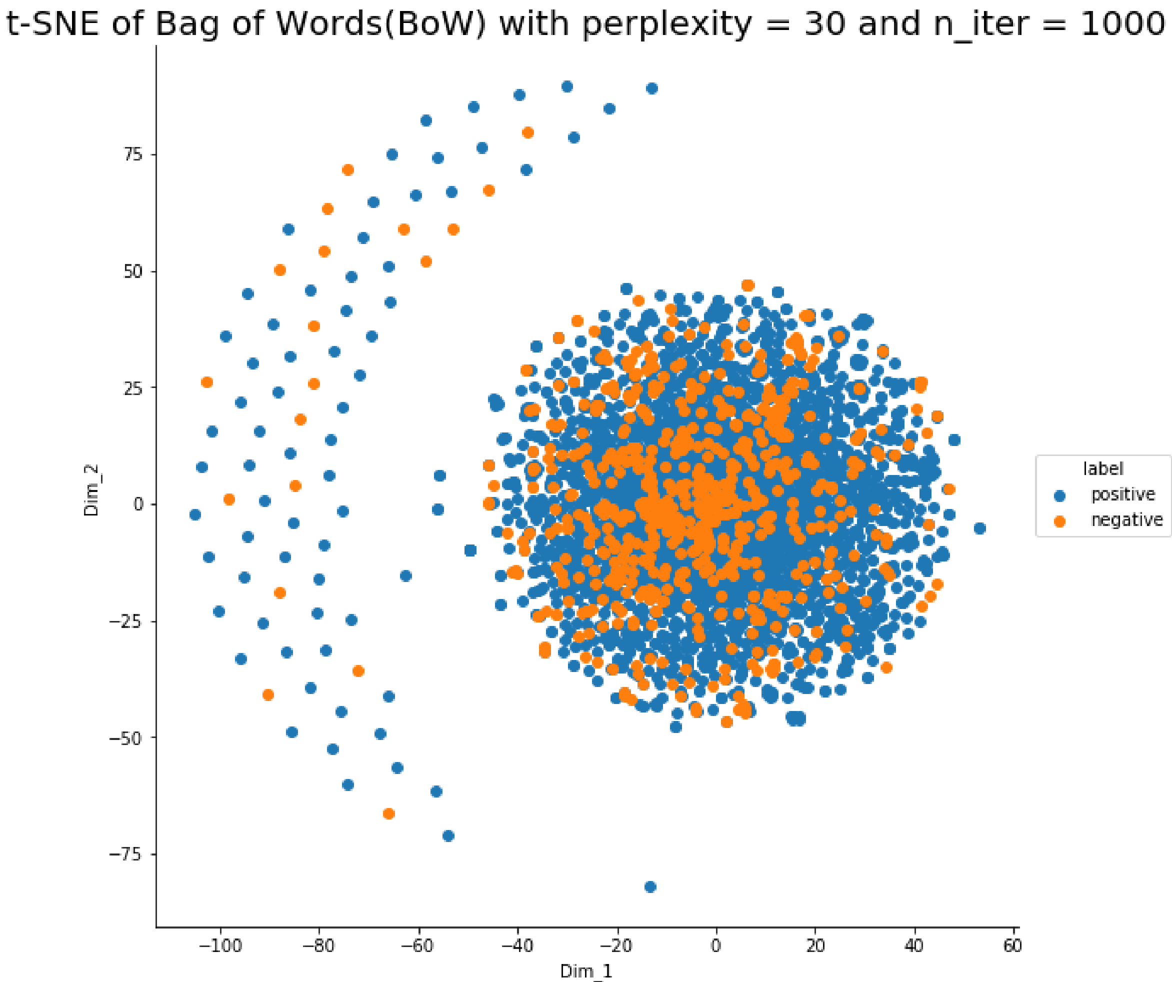
```
my_final['Score'].shape
```

Out[41]:

```
(4000,)
```

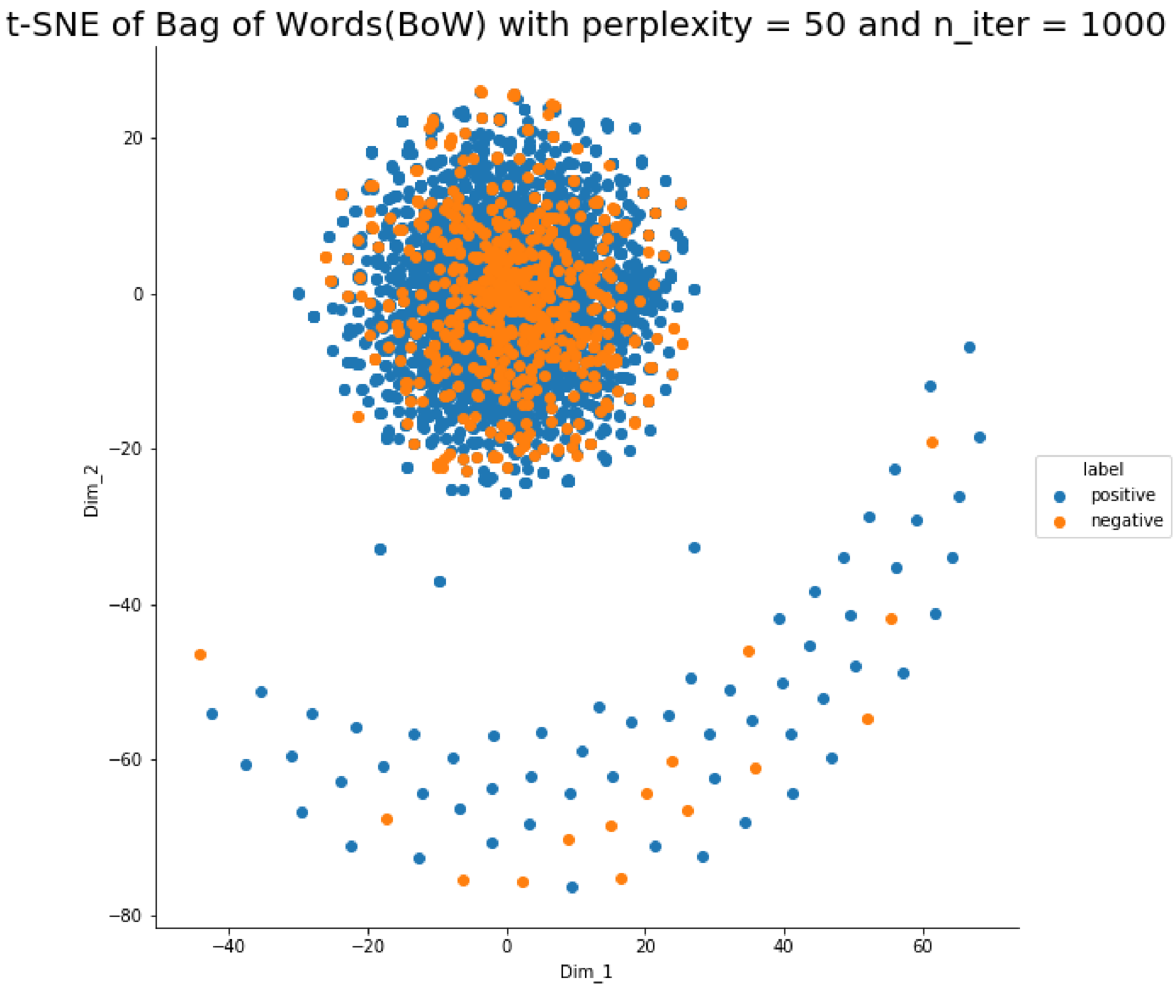
In [42]:

```
# TSNE

from sklearn.manifold import TSNE


model = TSNE(n_components=2, random_state=0)
# configuring the parameteres
# the number of components = 2
# default perplexity = 30
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 30 and n_iter = 1000',size=20)
plt.show()
```



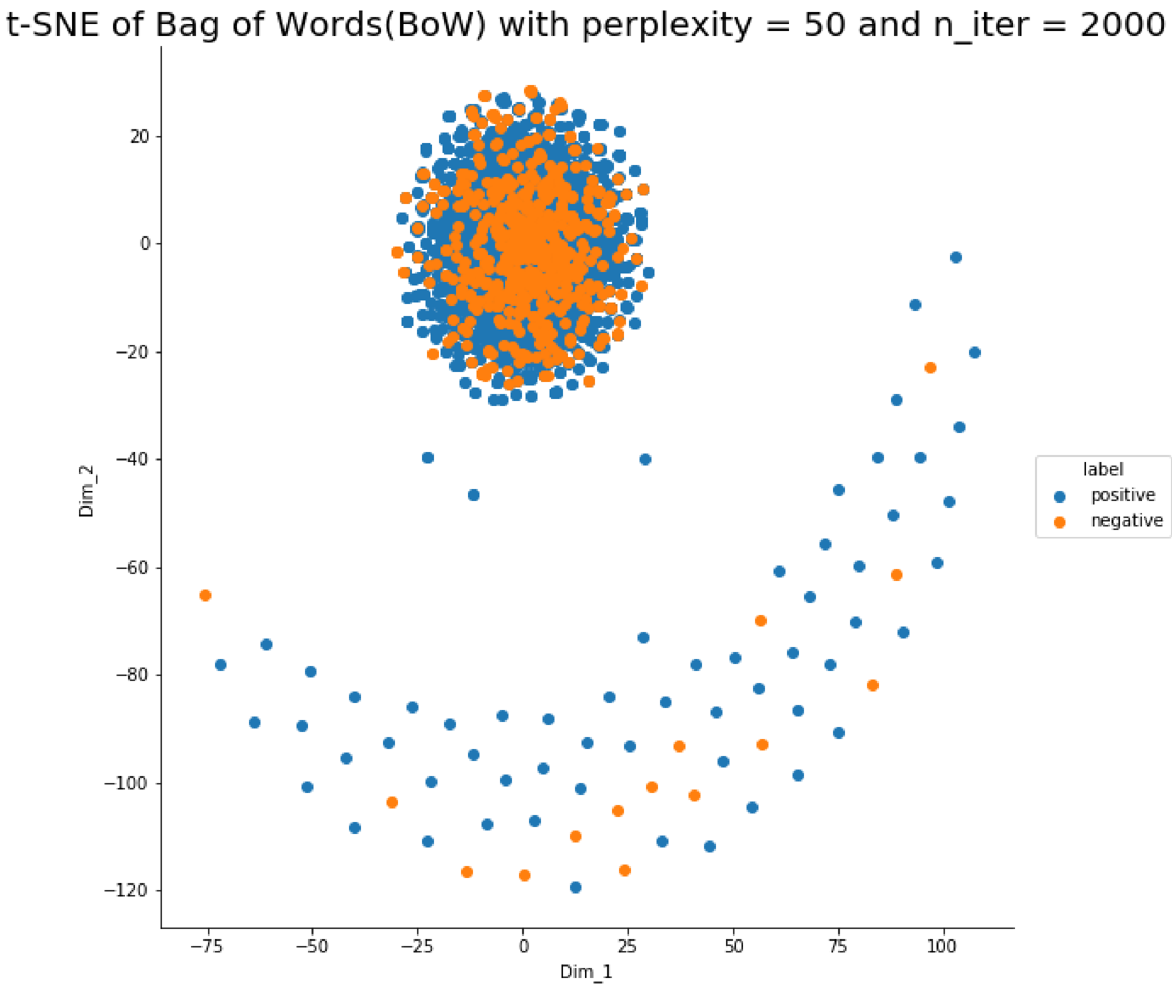
In [43]:

```
# t-SNE with perplexity = 50 and n_iter = 1000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=1000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 1000',size=20)
plt.show()
```



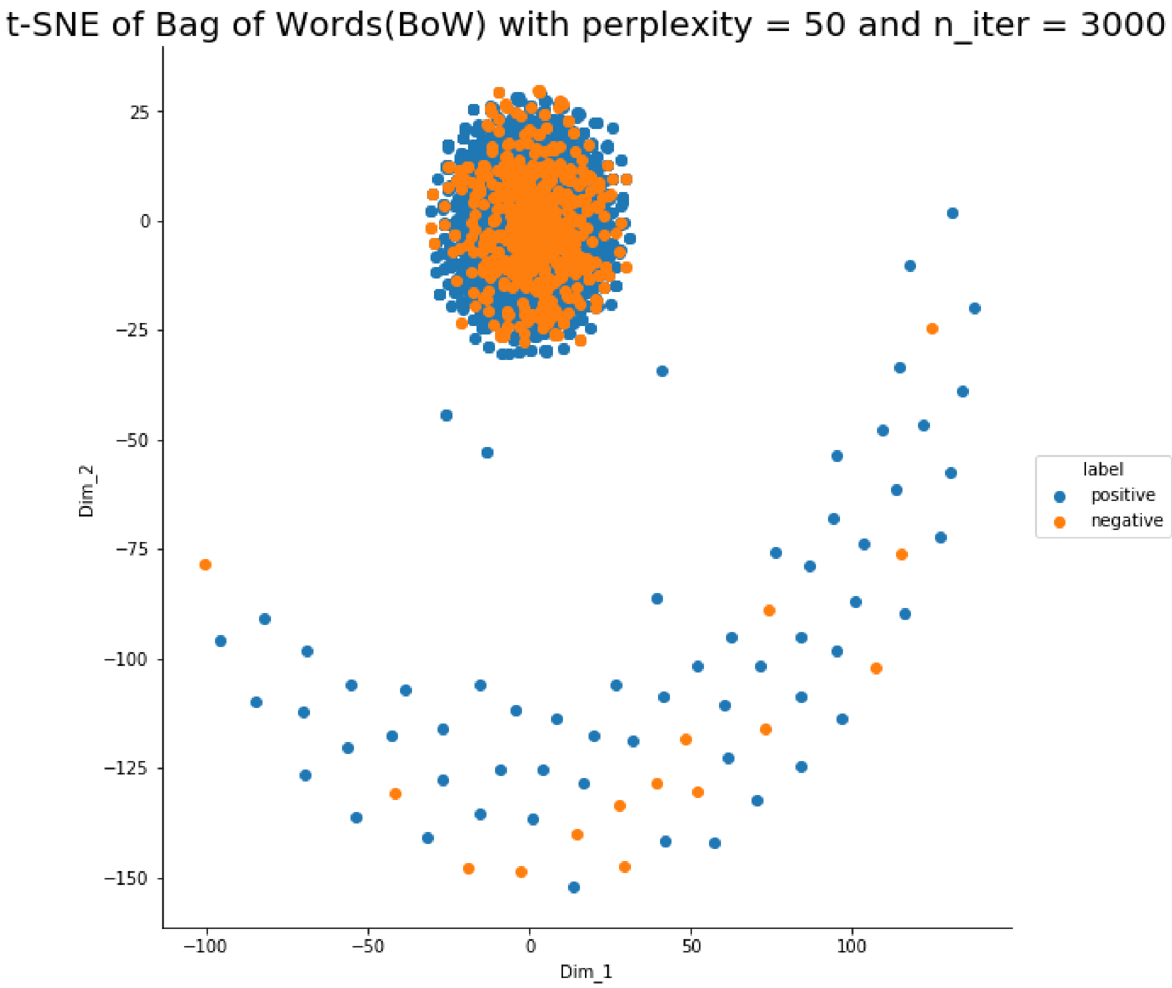
In [44]:

```
# t-SNE with perplexity = 50 and n_iter = 2000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=2000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 2000',size=20)
plt.show()
```



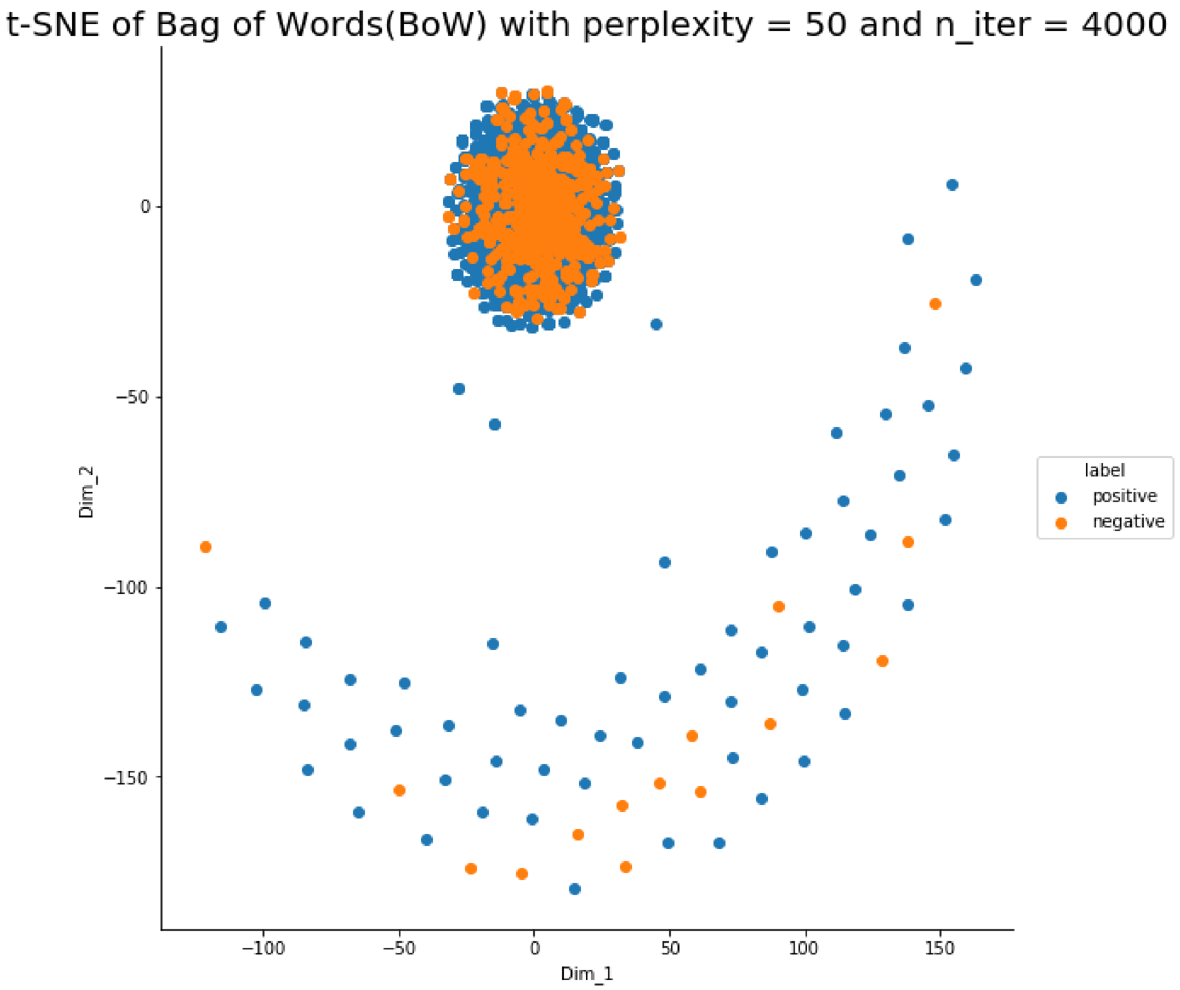
In [45]:

```
# t-SNE with perplexity = 50 and n_iter = 3000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=3000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 3000',size=20)
plt.show()
```



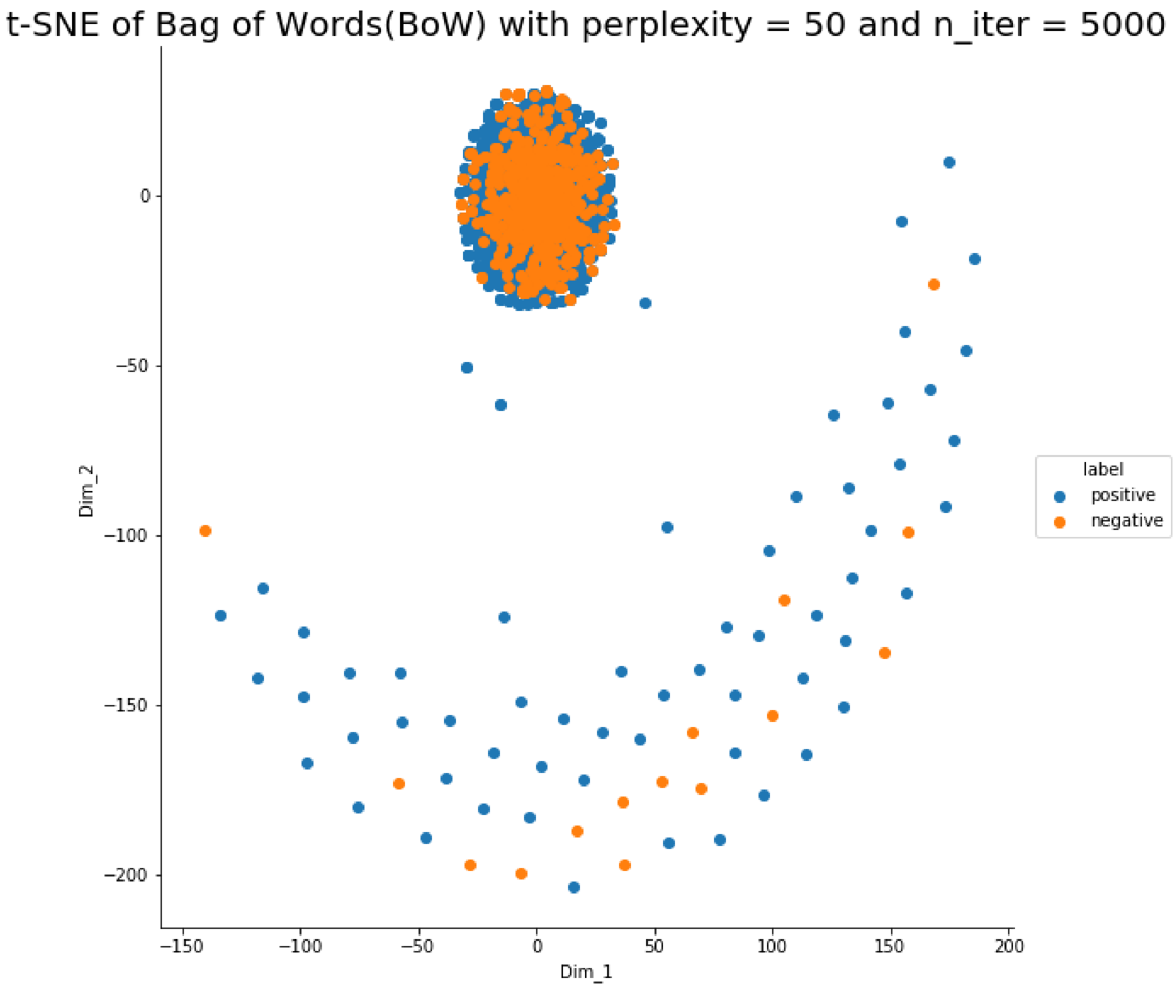
In [46]:

```
# t-SNE with perplexity = 50 and n_iter = 4000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=4000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 4000',size=20)
plt.show()
```



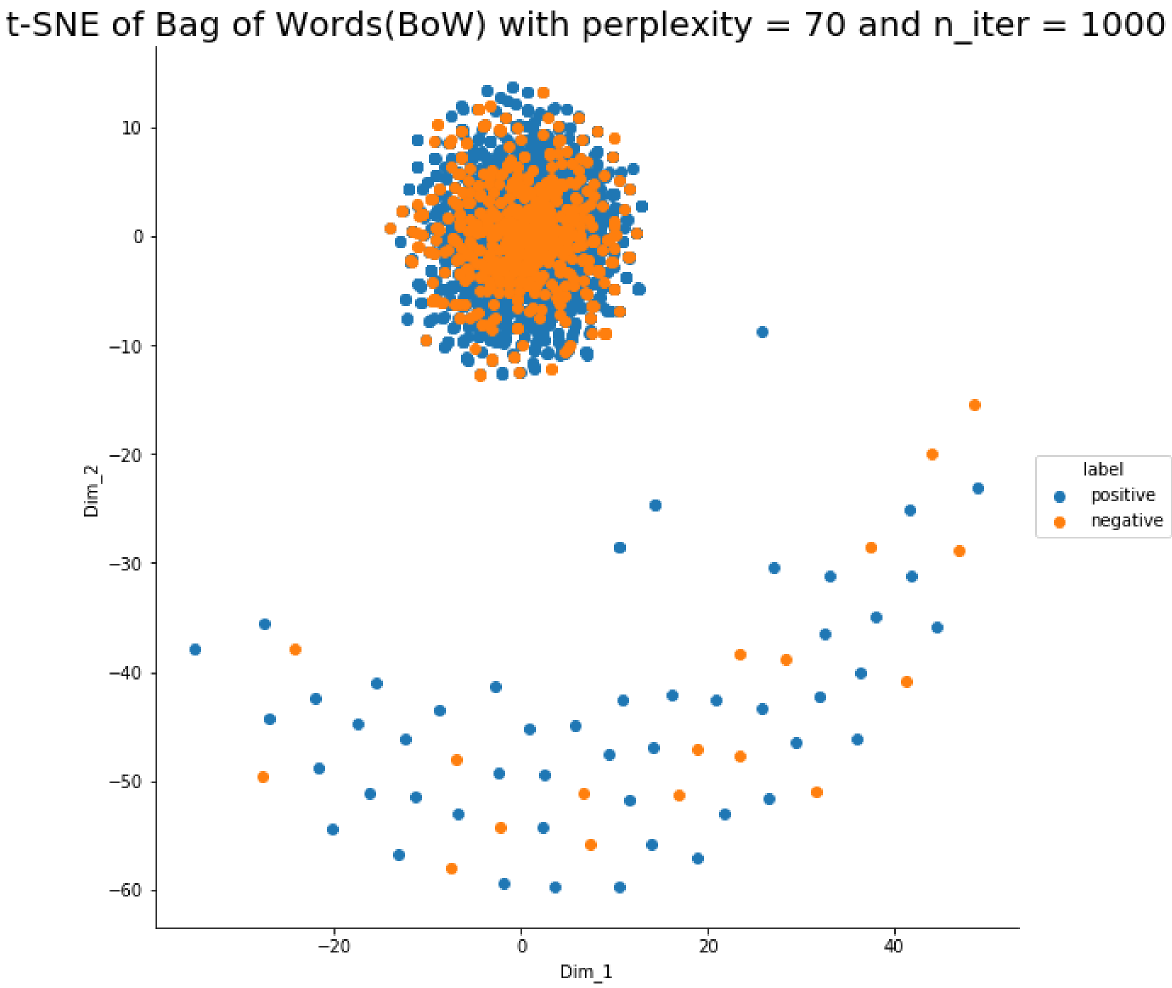
In [47]:

```
# t-SNE with perplexity = 50 and n_iter = 5000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=5000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```



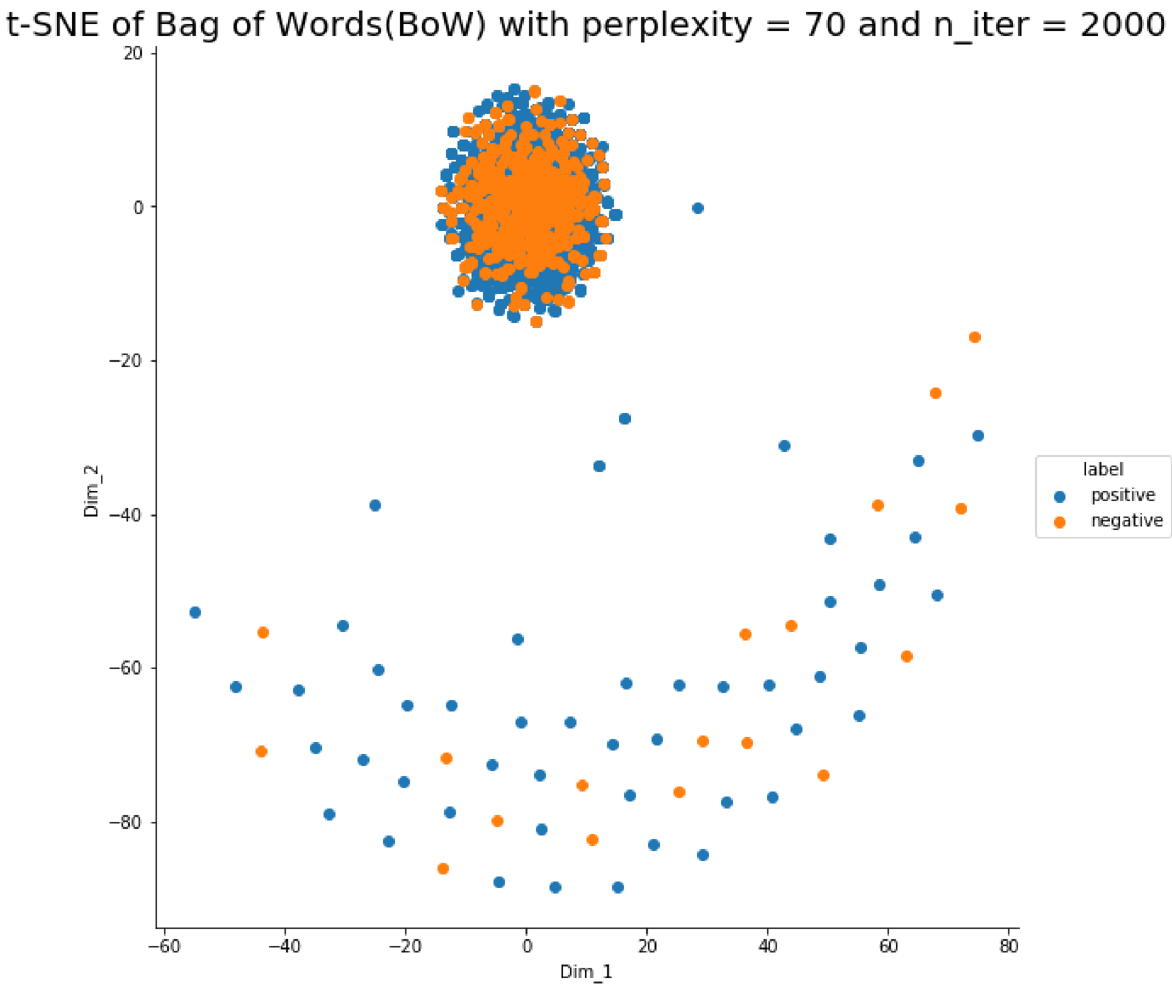
In [48]:

```
# t-SNE with perplexity = 70 and n_iter = 1000
model = TSNE(n_components=2, random_state=0, perplexity=70,  n_iter=1000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 70 and n_iter = 1000',size=20)
plt.show()
```



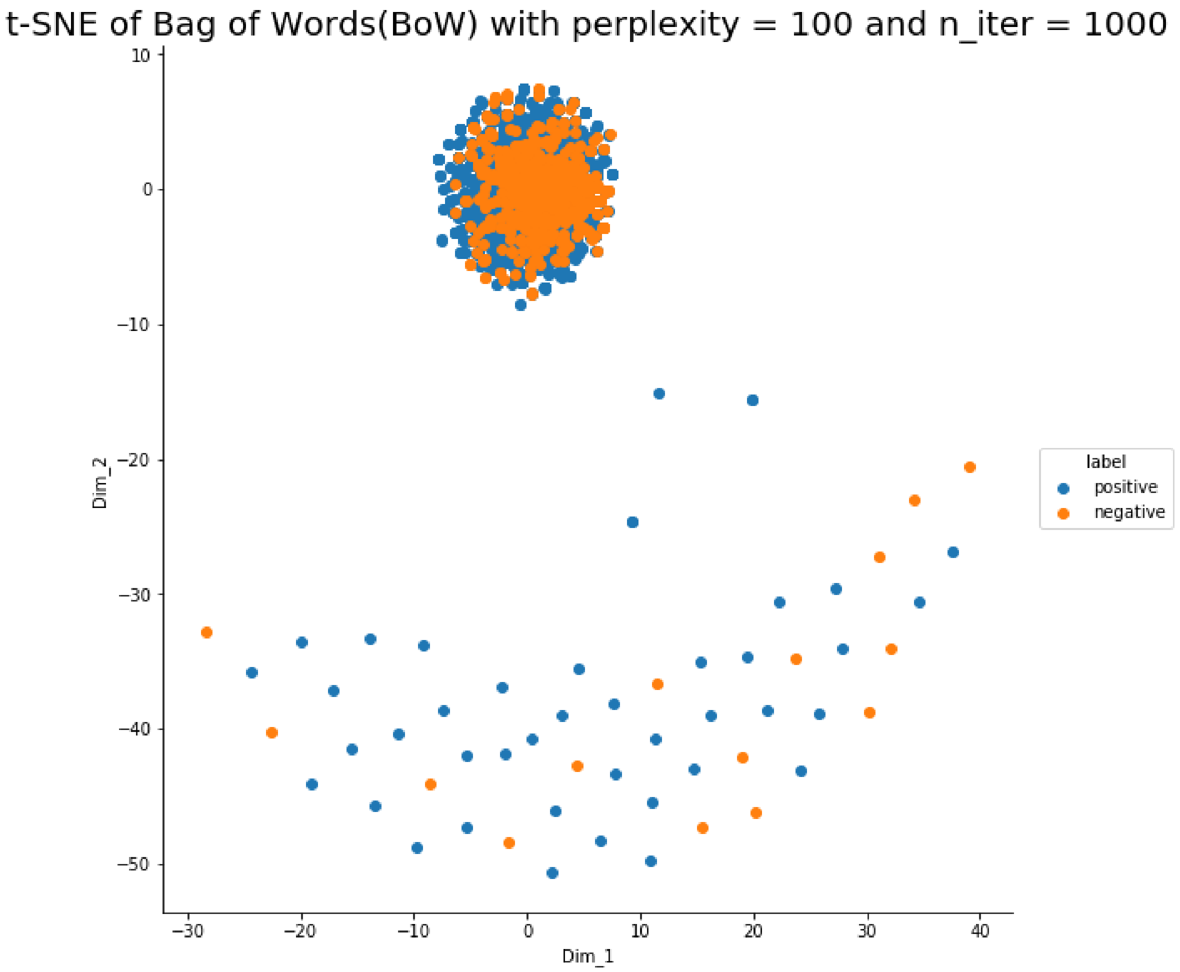
In [49]:

```
# t-SNE with perplexity = 70 and n_iter = 2000
model = TSNE(n_components=2, random_state=0, perplexity=70,  n_iter=2000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 70 and n_iter = 2000',size=20)
plt.show()
```



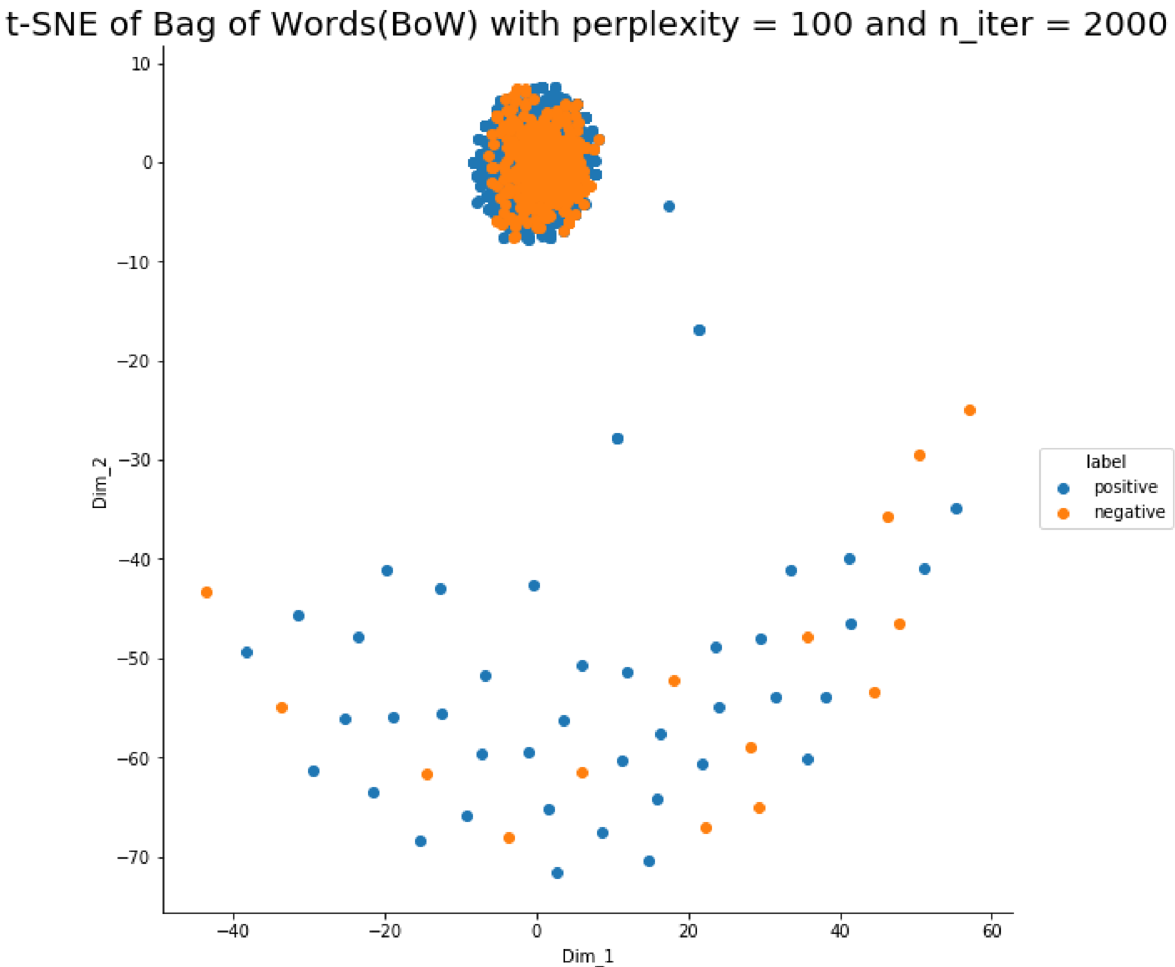
In [50]:

```
# t-SNE with perplexity = 100 and n_iter = 1000
model = TSNE(n_components=2, random_state=0, perplexity=100,  n_iter=1000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 100 and n_iter = 1000',size=20)
plt.show()
```



In [51]:

```
# t-SNE with perplexity = 100 and n_iter = 2000
model = TSNE(n_components=2, random_state=0, perplexity=100,  n_iter=2000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bag of Words(BoW) with perplexity = 100 and n_iter = 2000',size=20)
plt.show()
```



OBSERVATIONS :- After drawing and observing t-SNE plots for different values of perplexity and n_iter . It is good to draw t-SNE plots for further techniques using following hyper-parameters :

(1). perplexity = 50

(2). n_iter = 3000

OBSERVATION FOR ABOVE PLOTS : From above plots it is clear that they are overlapping almost 90%-95% and it is very difficult to draw a line to classify the polarity of the reviews .

5. Bi-Grams

In [63]:

```
#Bi-Gram
count_vect = CountVectorizer(ngram_range=(1,2),min_df=5 ) #in scikit-learn
final_bigram_counts = count_vect.fit_transform(my_final['CleanedText'].values)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_bigram_count
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4000, 6369)
the number of unique words including both unigrams and bigrams  6369
```

In [69]:

```
# Change sparse matrix to dense matrix
final_bigram_counts  = final_bigram_counts.toarray()
```

In [70]:

```
final_bigram_counts.shape
```

Out[70]:

```
(4000, 6369)
```

In [71]:

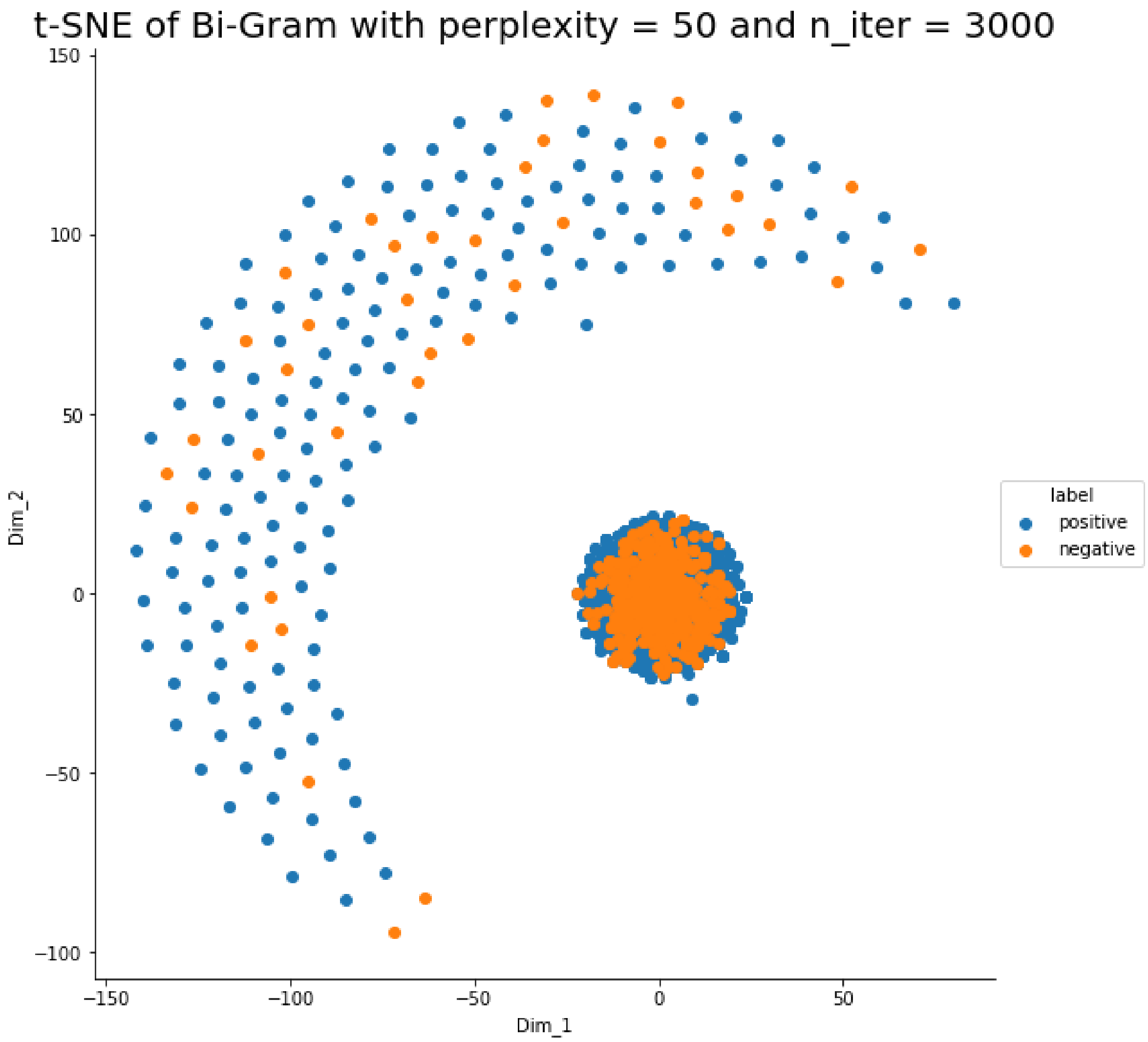
```
import warnings
warnings.filterwarnings('ignore')
# Data-preprocessing: Standardizing the data

from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(final_bigram_counts)
print(standardized_data.shape)
```

```
(4000, 6369)
```

5.1. t-SNE of Bi-Grams

In [72]:

```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 3000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=3000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Bi-Gram with perplexity = 50 and n_iter = 3000',size=20)
plt.show()
```



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 90%-95% and it is very difficult to draw a line to classify the polarity of the reviews .

6. TF-IDF

In [86]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df=5)
final_tf_idf = tf_idf_vect.fit_transform(my_final['CleanedText'].values)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_tf_idf.get_s
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4000, 6369)
the number of unique words including both unigrams and bigrams  6369
```

In [87]:

```
features = tf_idf_vect.get_feature_names()
print("some sample features(unique words in the corpus)",features[1000:1010])
```

```
some sample features(unique words in the corpus) ['coffe use', 'colada', 'co
ld', 'cold water', 'collect', 'colleg', 'colli', 'color', 'color dont', 'col
or ice']
```

In [88]:

```
# Change sparse matrix to dense matrix
final_tf_idf  = final_tf_idf.toarray()
```

In [89]:

```
final_tf_idf.shape
```

Out[89]:

```
(4000, 6369)
```

In [90]:

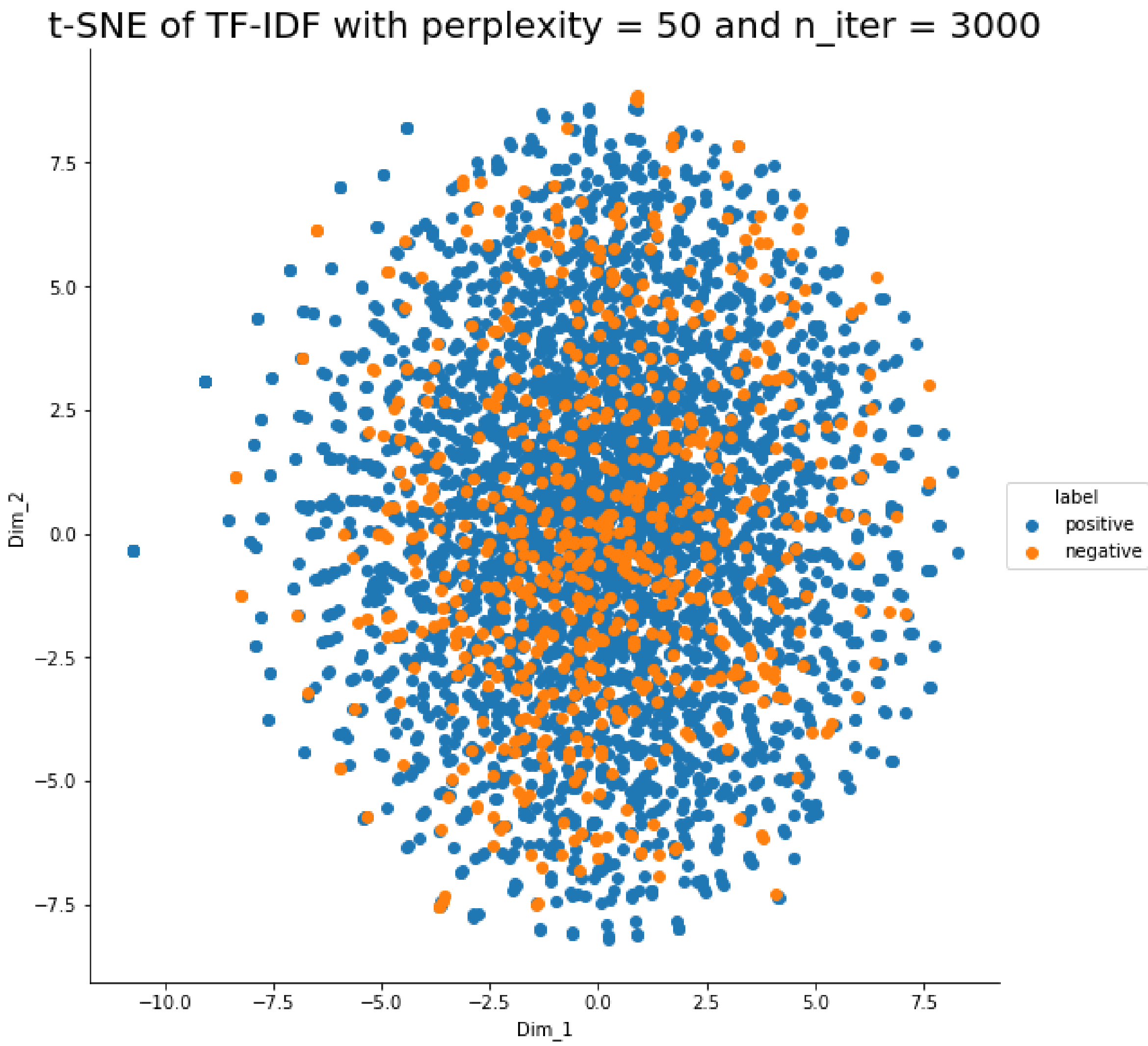
```
import warnings
warnings.filterwarnings('ignore')
# Data-preprocessing: Standardizing the data

from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(final_tf_idf)
print(standardized_data.shape)
```

```
(4000, 6369)
```

6.1. t-SNE of TF-IDF

In [80]:

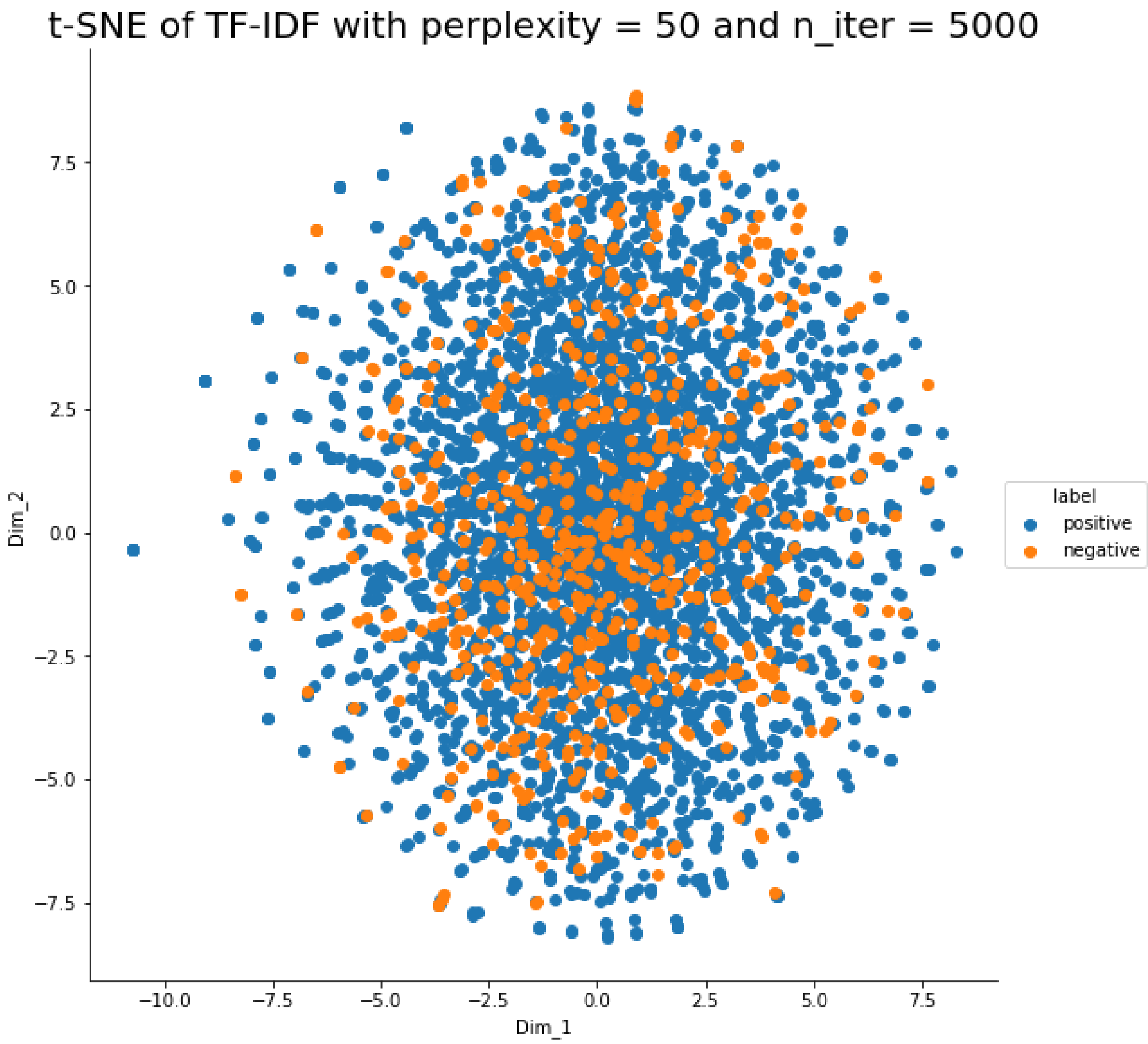
```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 3000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=3000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of TF-IDF with perplexity = 50 and n_iter = 3000',size=20)
plt.show()
```



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 85%-90% and it is very difficult to draw a line to classify the polarity of the reviews .

In [91]:

```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 5000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=5000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of TF-IDF with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 85%-90% and it is very difficult to draw a line to classify the polarity of the reviews .

7. Word2Vec

In [93]:

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

In [94]:

```
print(final['CleanedText'].values[0])
print("*****************************************************************")
print(list_of_sent[0])
```

```
product archer farm best drink mix ever mix flavor packet water bottl contai
n natur sweetner stevia real fruit flavor food color color fruit veget color
pure natur tast great eight packet box contain calori per packet thank arche
r farm
*****************************************************************
['product', 'archer', 'farm', 'best', 'drink', 'mix', 'ever', 'mix', 'flavo
r', 'packet', 'water', 'bottl', 'contain', 'natur', 'sweetner', 'stevia', 'r
eal', 'fruit', 'flavor', 'food', 'color', 'color', 'fruit', 'veget', 'colo
r', 'pure', 'natur', 'tast', 'great', 'eight', 'packet', 'box', 'contain',
'calori', 'per', 'packet', 'thank', 'archer', 'farm']
```

In [95]:

```
# 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 [98]:

```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
number of words that occured minimum 5 times  3253
```

7.1. Avg Word2Vec

In [99]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
4000
50
```

In [101]:

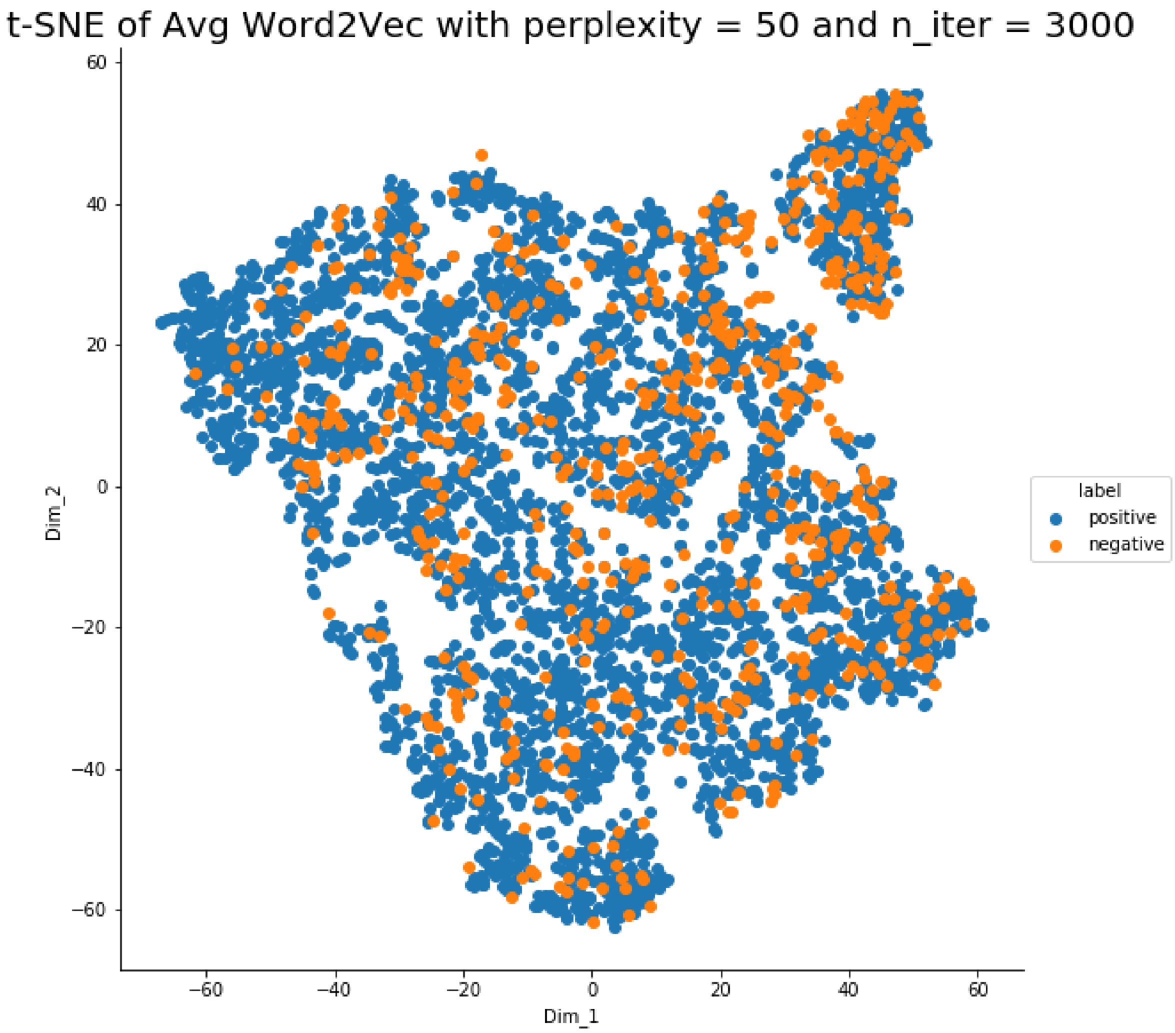
```
import warnings
warnings.filterwarnings('ignore')
# Data-preprocessing: Standardizing the data

from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(sent_vectors)
print(standardized_data.shape)
```

```
(4000, 50)
```

7.1.1. t-SNE of Avg-W2V

In [102]:

```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 3000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=3000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Avg Word2Vec with perplexity = 50 and n_iter = 3000',size=20)
plt.show()
```

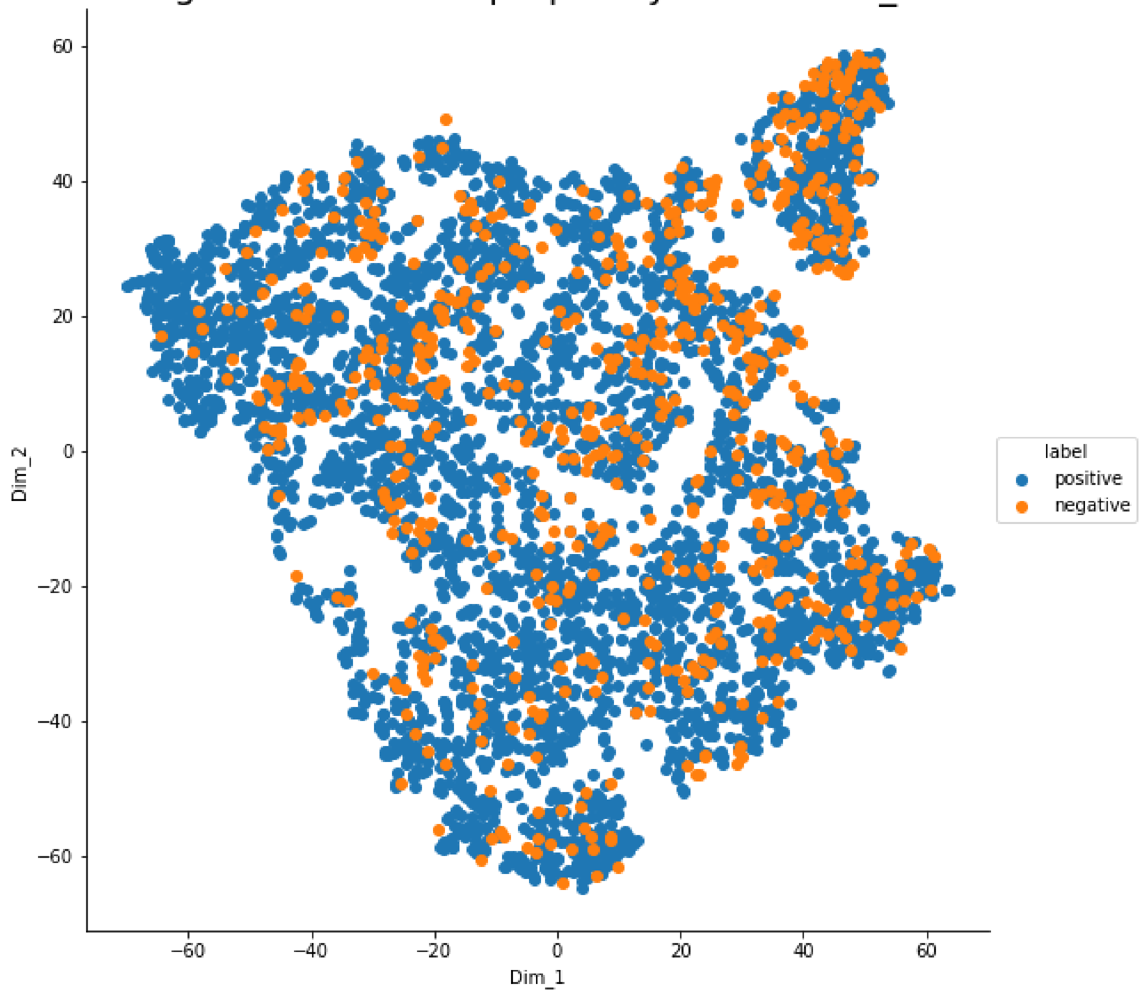


OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 80%-85% and it is very difficult to draw a line to classify the polarity of the reviews . But it is better than above plots .

In [103]:

```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 5000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=5000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of Avg Word2Vec with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```

t-SNE of Avg Word2Vec with perplexity = 50 and n_iter = 5000



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 80%-85% and it is very difficult to draw a line to classify the polarity of the reviews . But it is better than above plots .

7.2. TFIDF-Word2Vec

In [104]:

```
tf_idf_vect = TfidfVectorizer()
final_tf_idf = tf_idf_vect.fit_transform(my_final['CleanedText'].values)
```

In [105]:

```
final_tf_idf.shape
```

Out[105]:

```
(4000, 9454)
```

In [106]:

```
# 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
```

In [107]:

```
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is 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 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
```

In [108]:

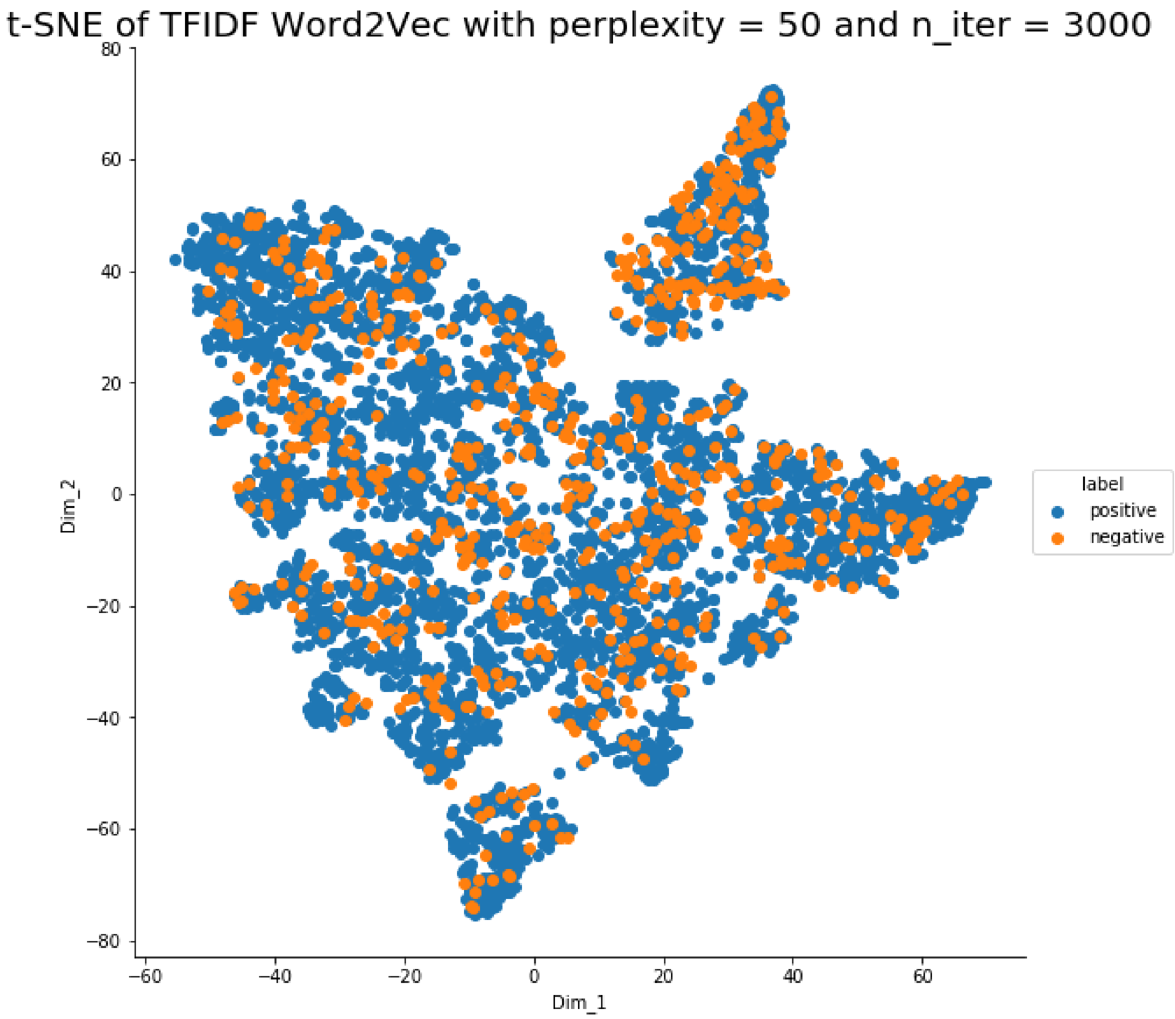
```
import warnings
warnings.filterwarnings('ignore')
# Data-preprocessing: Standardizing the data

from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(tfidf_sent_vectors)
print(standardized_data.shape)
```

```
(4000, 50)
```

7.2.1. t-SNE of TF-IDF W2V

In [109]:

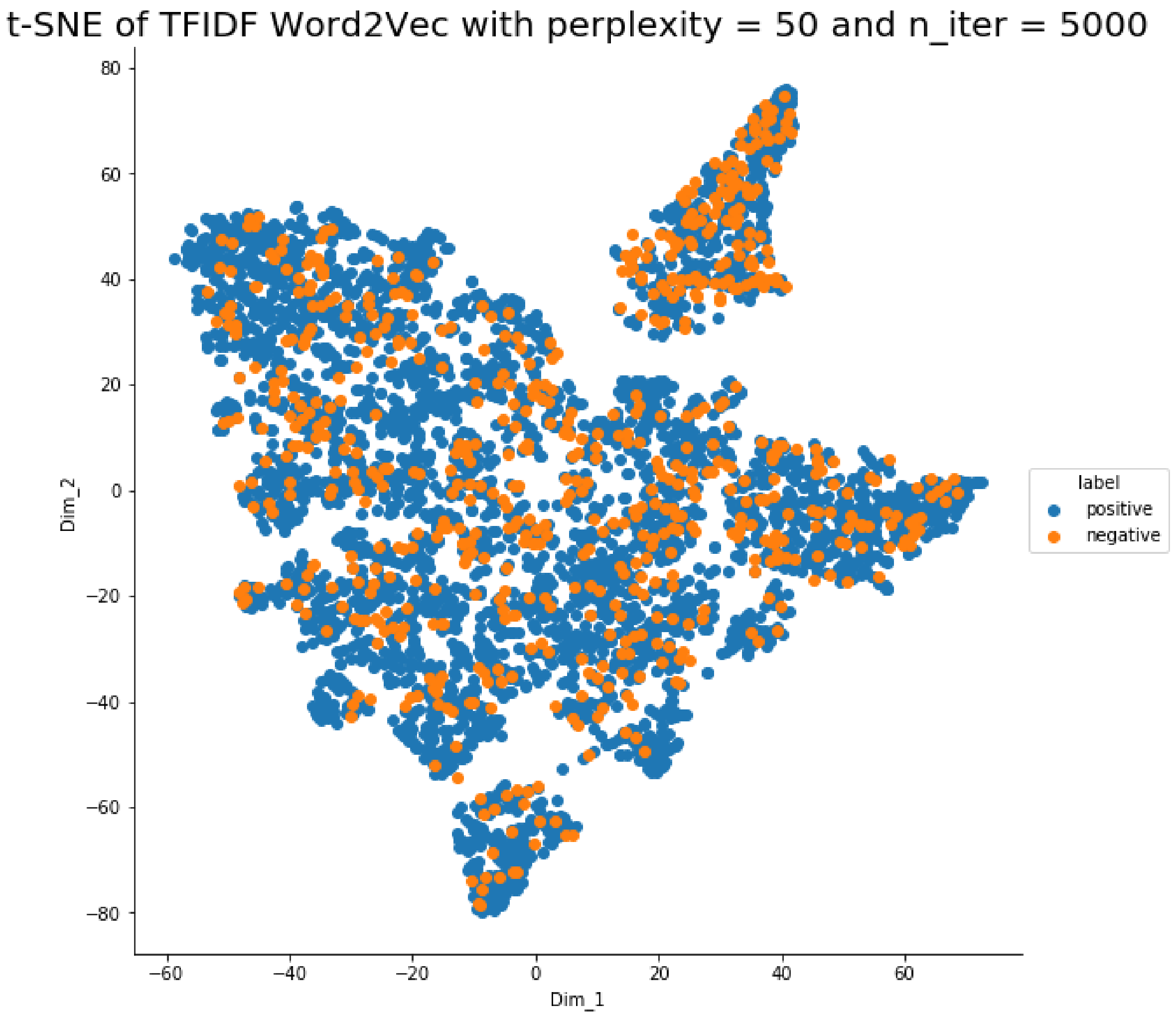
```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 3000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=3000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of TFIDF Word2Vec with perplexity = 50 and n_iter = 3000',size=20)
plt.show()
```



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 70%-80% and it is very difficult to draw a line to classify the polarity of the reviews . But it is better than above plots .

In [110]:

```
# TSNE

from sklearn.manifold import TSNE

# t-SNE with perplexity = 50 and n_iter = 5000
model = TSNE(n_components=2, random_state=0, perplexity=50,  n_iter=5000)

tsne_data = model.fit_transform(standardized_data)


# creating a new data frame which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, my_final['Score'])).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=8).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('t-SNE of TFIDF Word2Vec with perplexity = 50 and n_iter = 5000',size=20)
plt.show()
```



OBSERVATION FOR ABOVE PLOT : From above plot it is clear that they are overlapping almost 70%-80% and it is very difficult to draw a line to classify the polarity of the reviews . But it is much better than above plots .