Amazon Fine Food Reviews Assignment

July 22, 2018

1 Amazon Fine Food Reviews Analysis:

=> Predictions:

```
The purpose of this analysis is to make up a prediction model where we will be able to
predict whether a recommendation is positive or negative. In this analysis, we will
not focus on the Score, but only the positive/negative sentiment of the recommendation.
To do so, we will work on Amazon's recommendation dataset, we will build a Term-doc
incidence matrix using term frequency and inverse document frequency ponderation.
When the data is ready, we will load it into predicitve algorithms, mainly naïve Bayesian
and regression.In the end, we hope to find a "best" model for predicting the
recommendation's sentiment.
```

=> Loading the data:

1. In order to load the data, we will use the SQLITE dataset where we will only fetch the Score and the recommendation summary.

2.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 "postive". Otherwise, it will be set to "negative".

```
The data will be split into an training set and a test set with a test set ratio of 0.2
```

=> Attribute information:

```
1.Id
2.Product id
3.User id
4.Profile name
5.Helpful numerator
6.helpful denominator
7.Reviews=Positive (4 or 5) and Negative (1 or 2)
8.Time
9.Summary
10.Text
```

Objective:

We have to find TSNE representation of :

1. Bag of words,
2. tf-idf,
3. Avg w2v,
4. tf-idf w2v

In [2]:
```
# Importing Necesssry Packages

%matplotlib inline
import re
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.manifold import TSNE
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



# Using the  table to read data

df=pd.read_csv('Reviews.csv')
df.head()
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600

```
                  Summary                                                Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

In [3]:
```
# Filtering only positive and negative reviews.
# Not taking into consideration yhose reviews with score=3
```

In [3]:
```
filtered_data=pd.read_csv('Reviews.csv')
filtered_data.head()
```

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

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      5  1303862400
1                     0                       0      1  1346976000
2                     1                       1      4  1219017600
3                     3                       3      2  1307923200
4                     0                       0      5  1350777600

                  Summary                                                Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

In [4]:
```
# Give review with score>3 a positive rating and reviews with a score<3

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

In [5]:
```
# Changing Reviews with score less than 3 to be positive and vice versa

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

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	positive	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	negative	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	positive	1219017600	"Delight" says it all	This is a confection that has been around a fe...
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	negative	1307923200	Cough Medicine	If you are looking for the secret ingredient i...
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	positive	1350777600	Great taffy	Great taffy at a great price. There was a wid...

In [6]:
```
df.duplicated()
df.head()
```

Out[6]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe...
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient i...
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid...

In [7]:
```
# Sorting Data according to ProductId in ascending order

sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True,)
```

```
In [8]: # Deduplication of entries

        final=sorted_data.drop_duplicates(subset={'UserId','ProfileName','Time','Text'}
                                          ,keep='first',inplace=False)
        final.shape
```

```
Out[8]: (393933, 10)
```

```
In [9]: (final["Id"].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

```
Out[9]: 69.29901100176971
```

=> Observation:

```
In [10]: # Always remember that helpfulness num<=helpfulness denominator.

         display=pd.read_csv('Reviews.csv')
         display

         final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [11]: # before starting the next phase of preprocessing
         # let us seee the number of items

         print(final.shape)
```

```
(393931, 10)
```

```
In [12]: # How many positive and negative reviews are present in our dataset.

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

```
Out[12]: positive    336824
         negative     57107
         Name: Score, dtype: int64
```

```
In [13]: final.head()
```

```
Out[13]:             Id   ProductId          UserId  \
         150528  150529  0006641040   A25ACLV5KPB4W
         150506  150507  0006641040  A1S4A3IQ2MU7V4
         150505  150506  0006641040  A2IW4PEEKO2R0U
         150504  150505  0006641040  A2PTSM496CF40Z
         150503  150504  0006641040   AQEYF1AXARWJZ

                                                ProfileName  \
         150528                              Matt Hetling "Matt"
         150506                            sally sue "sally sue"
         150505                                          Tracy
```

```
150504  Jason A. Teeple "Nobody made a greater mistak...
150503                        Les Sinclair "book maven"

        HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
150528                     0                       1  positive  1108425600
150506                     1                       1  positive  1191456000
150505                     1                       1  positive  1194739200
150504                     1                       1  positive  1210809600
150503                     1                       1  positive  1212278400

                                          Summary  \
150528                Nice cadence, catchy rhymes
150506               chicken soup with rice months
150505  Love the book, miss the hard cover version
150504                                   A classic
150503                     Chicken Soup with Rice

                                                     Text
150528  In June<br />I saw a charming group<br />of ro...
150506  This is a fun way for children to learn their ...
150505  I grew up reading these Sendak books, and watc...
150504  Get the movie or sound track and sing along wi...
150503  A very entertaining rhyming story--cleaver and...
```

In [ ]: Text Preprocessing: Stemming, stop-word removal and Lemmatization

In [ ]: => 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)
8. After which we collect the words used to describe positive and negative reviews

In [14]:
```
# find sentences containing HTML tags
i=0;
for sent in final['Text'].values:
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
```

```
                break;
            i += 1;
```

```
0
In June<br />I saw a charming group<br />of roses all begin<br />to droop<br />I pepped them u
```

```
In [15]: import nltk
         from nltk.corpus import stopwords
         nltk.download('stopwords')
         stopwords = stopwords.words('english')
         import re
         import string
         from nltk.corpus import stopwords
         from nltk.stem import PorterStemmer
         from nltk.stem.wordnet import WordNetLemmatizer
         stop = set(stopwords.words('english')) #set of stopwords
         sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer
         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_ch
             cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
             cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
             return cleaned
         print(stop)
         print('************************************')
         print(sno.stem('tasty'))
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Saurabh\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
{'while', 't', 'them', 'own', 'most', "needn't", "shan't", 'yourselves', 'they', 'a', 'herself
**********************************
tasti
```

```
In [16]: #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.
         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 us
                            if(final['Score'].values)[i] == 'negative':
                                all_negative_words.append(s) #list of all words used to descr
                        else:
                            continue
                    else:
                        continue
            #print(filtered_sentence)
            str1 = b" ".join(filtered_sentence) #final string of cleaned words
            #print("*****************************************************************")

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

```
In [17]: final['CleanedText']=final_string  #adding a column of CleanedText which displays the
                                             #data after pre-processing of the review
```

2 An Introduction to Bag Of Words =>

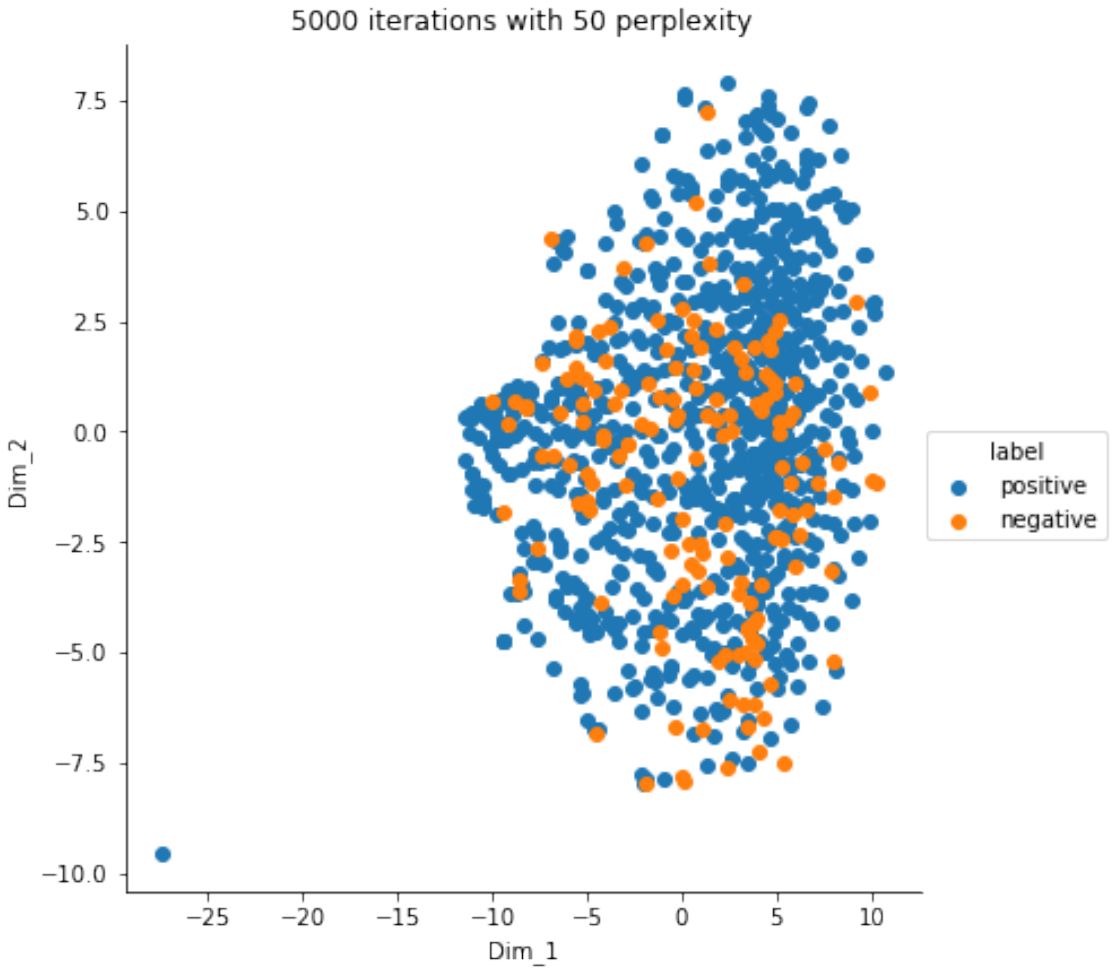
```
In [ ]: We convert text to a numerical representation called a feature vector.
        A feature vector can be as simple as a list of numbers.

        The bag-of-words model is one of the feature extraction algorithms for text.
```

3 Classification Of Bag Of Words Using Tsne

```
In [24]: count_vect = CountVectorizer() #in scikit-learn
         final_counts = count_vect.fit_transform(final['Text'].values)

In [25]: type(final_counts)

Out[25]: scipy.sparse.csr.csr_matrix

In [26]: final_counts.get_shape()

Out[26]: (393931, 120251)

In [27]: print(df.shape)

(568454, 10)
```

```
In [29]: from sklearn.manifold import TSNE
         data_1000 = final_counts[0:1000,:]
         top_1000 = data_1000.toarray()
         labels = final['Score']
         labels_1000 = labels[0:1000]

         model = TSNE(n_components=2,random_state=0,perplexity=50,n_iter=5000)
         tsne_data = model.fit_transform(top_1000)

         # creating a new data frame which help us in ploting the result data

         tsne_data = np.vstack((tsne_data.T, labels_1000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

         print(tsne_df.head())
         print(tsne_df.shape)
         print(tsne_df['label'].unique())

         sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
         .add_legend()
         plt.title("5000 iterations with 50 perplexity")
         plt.show()
```

```
     Dim_1     Dim_2     label
0 -8.48749  -3.44611  positive
1 -2.49999   -5.7627  positive
2  1.72465   4.95329  positive
3  4.23387 -0.756875  positive
4  3.36928   3.15518  positive
(1000, 3)
['positive' 'negative']
```



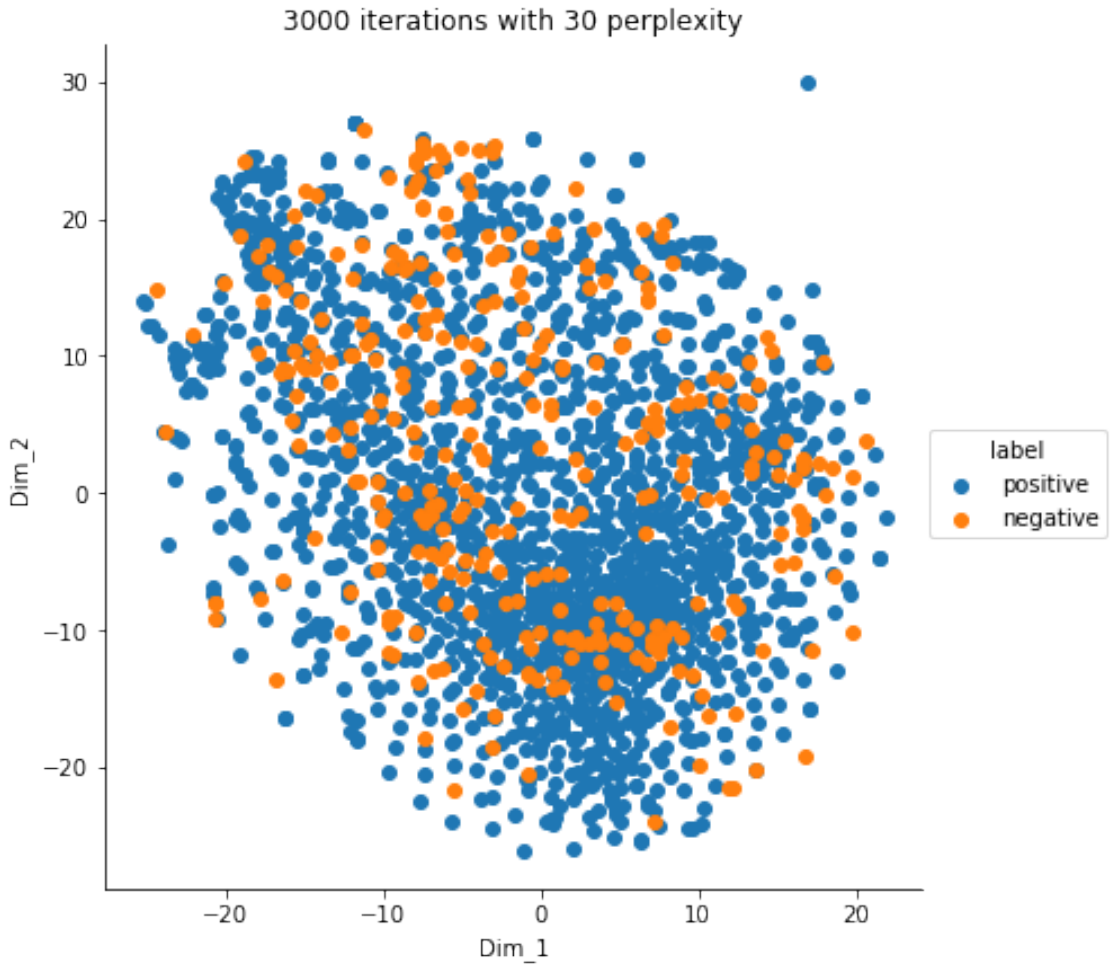
In [ ]: Observation=> when we take 1000 data points,perplexity=50 and iterations=5000

Here,we seen that the all fo the my data points are overlap each other but in some are there no overlaps and we clearly seen that positive data there. But in some parts the data are overlaps are we not distinguish easily that data into positive or negative.

In [30]:
```
from sklearn.manifold import TSNE
data_2000 = final_counts[0:2000,:]
top_2000 = data_2000.toarray()
labels = final['Score']
labels_2000 = labels[0:2000]

model = TSNE(n_components=2,random_state=0,perplexity=30,n_iter=3000)
tsne_data = model.fit_transform(top_2000)

# creating a new data frame which help us in ploting the result data
```

```
        tsne_data = np.vstack((tsne_data.T, labels_2000)).T
        tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

        print(tsne_df.head())
        print(tsne_df.shape)
        print(tsne_df['label'].unique())

        sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
        .add_legend()
        plt.title("3000 iterations with 30 perplexity")
        plt.show()
```

```
     Dim_1    Dim_2     label
0 -9.07576  16.4308  positive
1 -6.34227 -1.47371  positive
2 -11.3146 -2.79909  positive
3  6.76442 -6.39409  positive
4 -7.89755 -12.0329  positive
(2000, 3)
['positive' 'negative']
```



In [ ]: Observation => When we use 2000 data points,perplexity=30 and iterations=3000

Here,we seen that the all fo the my data points are overlap each other but in some are there no overlaps and we clearly seen that positive data there. But in some parts the data are overlaps are we not distinguish easily that data into positive or negative.

4 An introduction to TF-IDF =>

In [ ]: TF-IDF stands for Term Frequenct Inverse Data Frequency.

Term Frequency (tf): gives us the frequency of the word in each document in the corpus It is the ratio of number of times the word appears in a document compared to the total number of words in that document.It increases as the number of occurrences of that word within the document increases. Each document has its own tf.

```
Inverse Data Frequency (idf)=>

Used to calculate the weight of rare words across all documents in the corpus.
The words that occur rarely in the corpus have a high IDF score. It is given by
the equation below.
```

5 Classification of TF-IDF using Tsne

```
In [31]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf = tf_idf_vect.fit_transform(final['Text'].values)

In [32]: final_tf_idf.get_shape()

Out[32]: (393931, 3086788)

In [33]: features = tf_idf_vect.get_feature_names()
         len(features)

Out[33]: 3086788

In [34]: features[100000:100010]

Out[34]: ['agreeable but',
          'agreeable crunch',
          'agreeable due',
          'agreeable enough',
          'agreeable flavor',
          'agreeable food',
          'agreeable for',
          'agreeable from',
          'agreeable had',
          'agreeable if']

In [35]: # covnert a row in saprsematrix to a numpy array

         print(final_tf_idf[3,:].toarray()[0])

[0. 0. 0. ... 0. 0. 0.]


In [36]: def top_tfidf_feats(row, features, top_n=25):
             ''' Get top n tfidf values in row and return them with their corresponding
                 feature names.'''
             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_tf_idf[1,:].toarray()[0],features,25)
```

In [37]: top_tfidf

Out[37]:

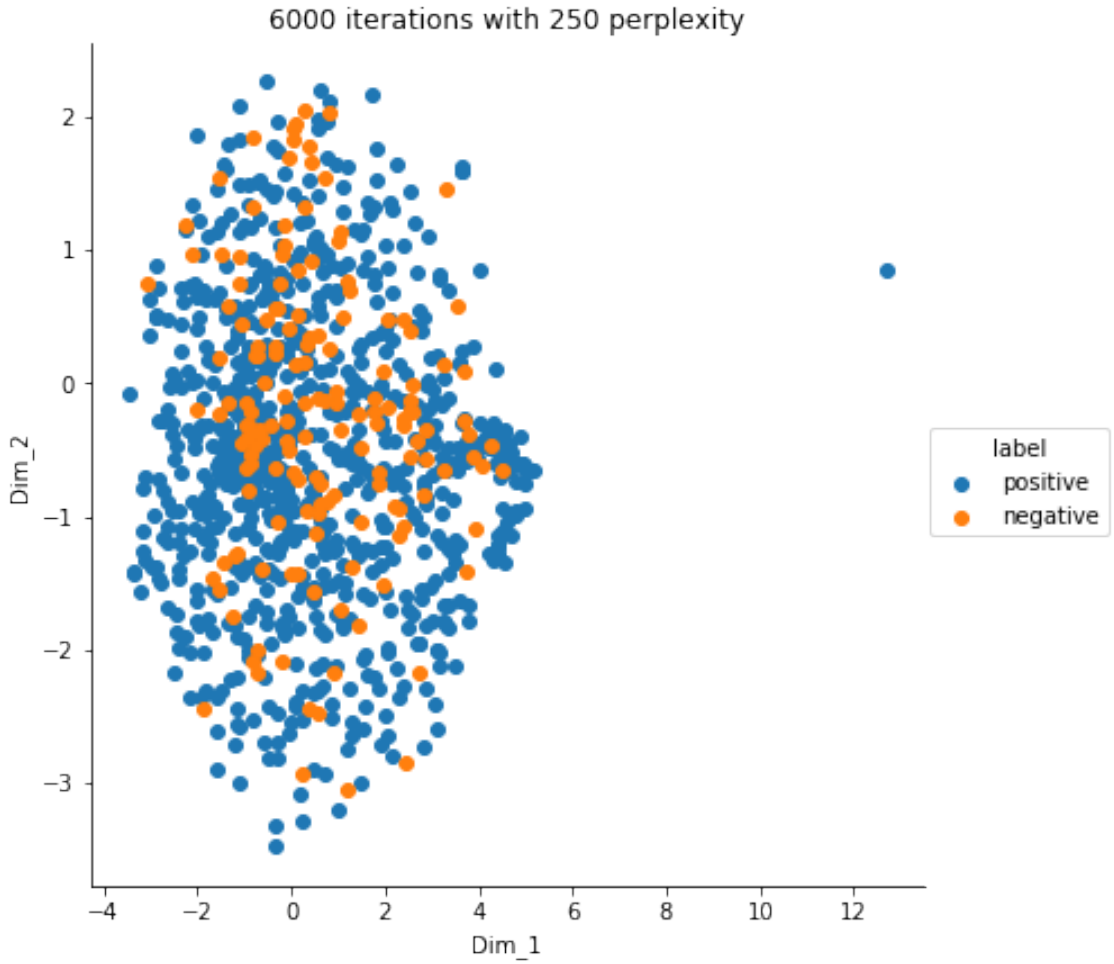
	feature	tfidf
0	learn	0.216779
1	handmotions	0.206926
2	the handmotions	0.206926
3	handmotions which	0.206926
4	invent for	0.206926
5	each poem	0.206926
6	which invent	0.206926
7	poems throughout	0.206926
8	their months	0.200565
9	learn their	0.200565
10	the poems	0.196052
11	poems	0.187273
12	learn all	0.185179
13	poem	0.167304
14	school year	0.166097
15	invent	0.164976
16	will learn	0.162481
17	fun way	0.152805
18	the school	0.147037
19	children to	0.145715
20	year they	0.140966
21	year we	0.139407
22	year	0.135486
23	for children	0.129018
24	is fun	0.128167

In [38]:
```
from sklearn.manifold import TSNE
data_1000 = final_counts[0:1000,:]
top_1000 = data_1000.toarray()
labels = final['Score']
labels_1000 = labels[0:1000]

model = TSNE(n_components=2, learning_rate = 500, random_state=0,n_iter=6000,
             perplexity=250)
tsne_data = model.fit_transform(top_1000)

# creating a new data frame which help us in ploting the result data

tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

print(tsne_df.head())
print(tsne_df.shape)
print(tsne_df['label'].unique())
```

```
        sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
        .add_legend()
        plt.title("6000 iterations with 250 perplexity")
        plt.show()
```

```
C:\Users\Saurabh\Anaconda3\lib\site-packages\sklearn\neighbors\base.py:371: RuntimeWarning: inv
  result = np.sqrt(dist[sample_range, neigh_ind]), neigh_ind
```

```
      Dim_1     Dim_2     label
0   3.33478  0.697132  positive
1  0.531072  -0.96371  positive
2  0.655461  -1.20048  positive
3   -1.0255 -0.552503  positive
4 -0.467639 -0.965703  positive
(1000, 3)
['positive' 'negative']
```

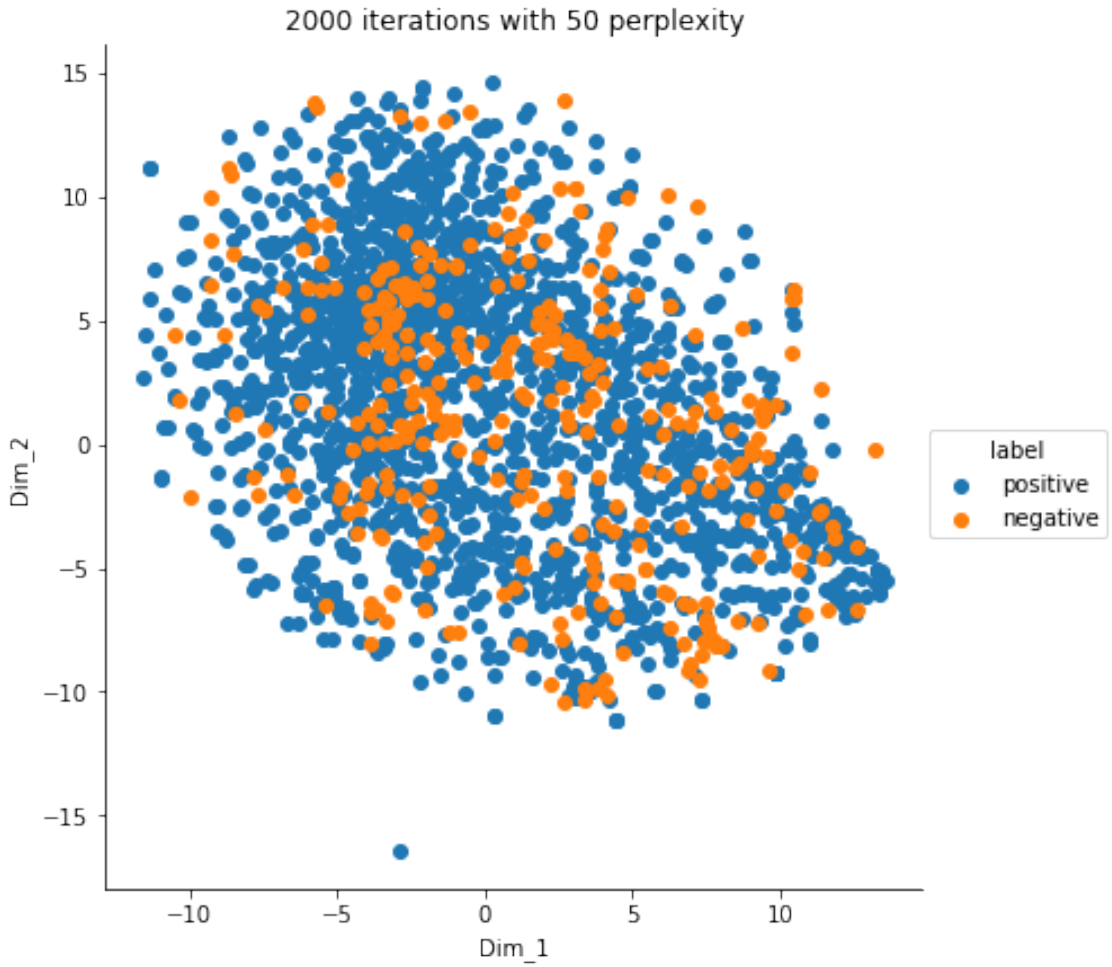


In [ ]: Observation=> When we take 1000 data points,perpexity=250 and iterations=6000

Here we seen that all positive and negative data points are overlapping each other so we cannot easily distinguish the positive and negative data points but here we also seen that a single positive point is shown far from all the points

In [40]:
```
from sklearn.manifold import TSNE
data_2000 = final_counts[0:2000,:]
top_2000 = data_2000.toarray()
labels = final['Score']
labels_2000 = labels[0:2000]

model = TSNE(n_components=2, learning_rate = 500, random_state=0,n_iter=2000
             ,perplexity=50)
tsne_data = model.fit_transform(top_2000)

# creating a new data frame which help us in ploting the result data

tsne_data = np.vstack((tsne_data.T, labels_2000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

print(tsne_df.head())
print(tsne_df.shape)
print(tsne_df['label'].unique())

sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
.add_legend()
plt.title("2000 iterations with 50 perplexity")
plt.show()
```

```
      Dim_1    Dim_2     label
0   3.75879 -9.58516  positive
1   3.58767  3.95223  positive
2    4.7222    2.884  positive
3  -4.51457  4.78176  positive
4 -0.517519  6.14237  positive
(2000, 3)
['positive' 'negative']
```



In [ ]: Observation=> When we take 2000 data pointsperpexity=50 and iterations 2000

Here we seen that all positive and negative data points are overlapping each other so we cannot easily distinguish the positive and negative data points but here we also seen that a single positive point is shown far from all the points

6 Word2vec =>

In [ ]: word2vec is an algorithm for constructing vector representations of words, also known as word embeddings. The vector for each word is a semantic description of how that word is used in context, so two words that are used similarly in text will get similar vector represenations.Once you map words into vector space, you can then use vector math to find words that have similar semantics.

7 Using Google News Word2Vectors

In [42]:
```
import re
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

model = KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin',
                                          binary=True)
```

In [44]:
```
model.wv.similarity('woman', 'man')
```

```
C:\Users\Saurabh\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: DeprecationWarning: Call
  """Entry point for launching an IPython kernel.
C:\Users\Saurabh\Anaconda3\lib\site-packages\gensim\matutils.py:737: FutureWarning: Conversion
  if np.issubdtype(vec.dtype, np.int):
```

Out[44]:
```
0.76640123
```

In [45]:
```
model.wv.most_similar('tasty')
```

```
C:\Users\Saurabh\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: DeprecationWarning: Call
  """Entry point for launching an IPython kernel.
C:\Users\Saurabh\Anaconda3\lib\site-packages\gensim\matutils.py:737: FutureWarning: Conversion
  if np.issubdtype(vec.dtype, np.int):
```

Out[45]:
```
[('delicious', 0.8730390071868896),
 ('scrumptious', 0.8007042407989502),
 ('yummy', 0.7856923937797546),
 ('flavorful', 0.7420163154602051),
 ('delectable', 0.7385421991348267),
 ('juicy_flavorful', 0.7114803791046143),
 ('appetizing', 0.7017217874526978),
 ('crunchy_salty', 0.7012301087379456),
 ('flavourful', 0.6912213563919067),
 ('flavoursome', 0.6857703328132629)]
```

In [46]:
```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent=[]
for sent in final['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
```

```
                        filtered_sentence.append(cleaned_words.lower())
                    else:
                        continue
            list_of_sent.append(filtered_sentence)
```

```
In [47]: print(final['Text'].values[0])
         print("*****************************************************************")
         print(list_of_sent[0])
```

```
In June<br />I saw a charming group<br />of roses all begin<br />to droop<br />I pepped them u
*****************************************************************
['in', 'june', 'i', 'saw', 'a', 'charming', 'group', 'of', 'roses', 'all', 'begin', 'to', 'dro
```

```
In [48]: w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50,
                                          workers=4)
```

```
In [49]: words = list(w2v_model.wv.vocab)
         print(len(words))
```

```
35140
```

```
In [50]: w2v_model.wv.most_similar('tasty')
```

```
C:\Users\Saurabh\Anaconda3\lib\site-packages\gensim\matutils.py:737: FutureWarning: Conversion
  if np.issubdtype(vec.dtype, np.int):
```

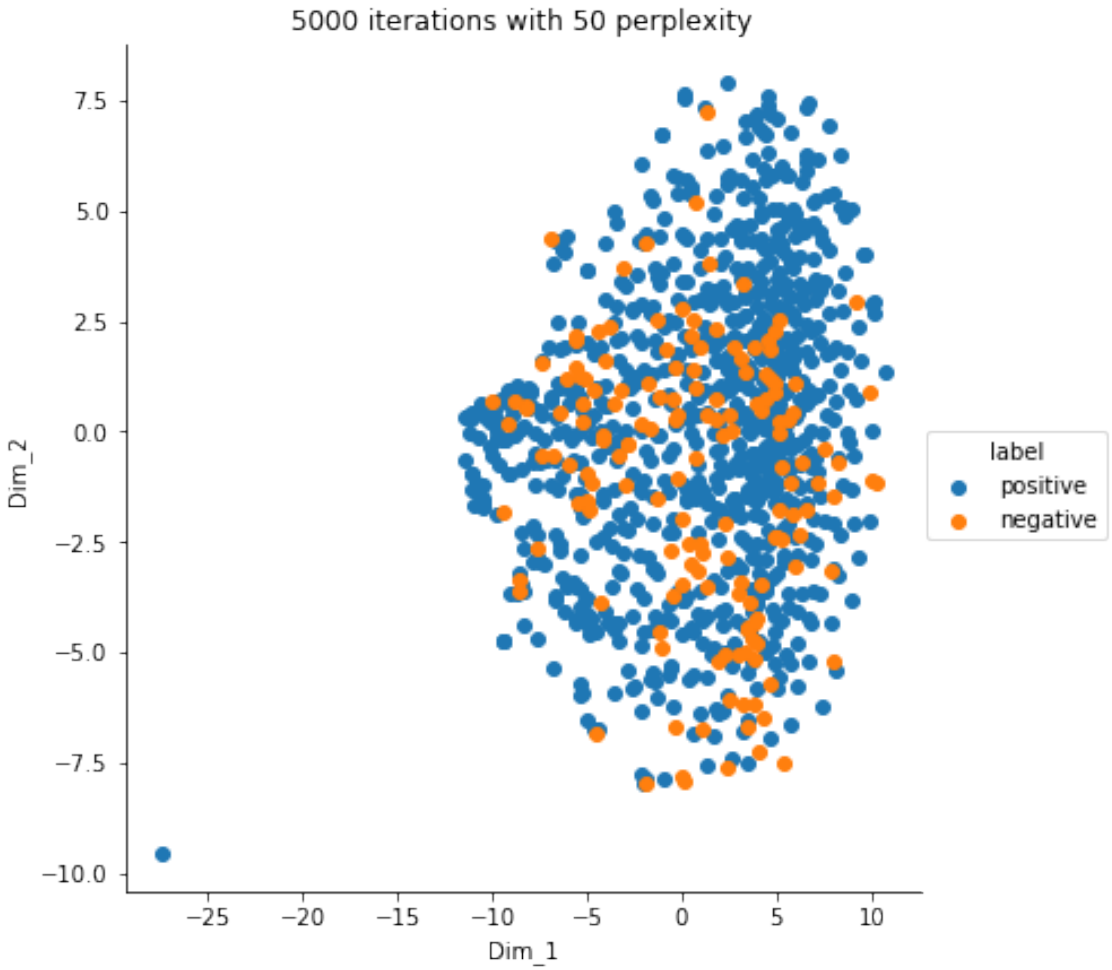
```
Out[50]: [('tastey', 0.885934054851532),
          ('satisfying', 0.8553158044815063),
          ('yummy', 0.8509554862976074),
          ('filling', 0.8147091865539551),
          ('delicious', 0.8125235438346863),
          ('flavorful', 0.7986399531364441),
          ('tasteful', 0.7899627089500427),
          ('addicting', 0.7626280784606934),
          ('versatile', 0.7522609233856201),
          ('delish', 0.7506635785102844)]
```

```
In [51]: count_vect_feat = count_vect.get_feature_names() # list of words in the BoW
         count_vect_feat.index('tasty')
         print(count_vect_feat[64055])
```

```
keylime
```

```
In [70]: from sklearn.manifold import TSNE
         data_1000 = final_counts[0:1000,:]
         top_1000 = data_1000.toarray()
         labels = final['Score']
         labels_1000 = labels[0:1000]

         model = TSNE(n_components=2,random_state=0,perplexity=50,n_iter=5000)
         tsne_data = model.fit_transform(top_1000)

         # creating a new data frame which help us in ploting the result data

         tsne_data = np.vstack((tsne_data.T, labels_1000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

         print(tsne_df.head())
         print(tsne_df.shape)
         print(tsne_df['label'].unique())

         sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
         .add_legend()
         plt.title("5000 iterations with 50 perplexity")
         plt.show()
```

```
     Dim_1     Dim_2     label
0 -8.48749  -3.44611  positive
1 -2.49999   -5.7627  positive
2  1.72465   4.95329  positive
3  4.23387 -0.756875  positive
4  3.36928   3.15518  positive
(1000, 3)
['positive' 'negative']
```



In [ ]: *# Observation=>When we take 1000 data points,perpexity=50 and iterations 5000*

Here we seen that all positive and negative data points are overlapping each other so we cannot easily distinguish the positive and negative data points but here we also seen that a single positive point is shown far from all the points

8 Classification of avg word2vec using tsne

In [55]:
```
# 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/revi
    for word in sent:           # for each word in a review/sentence
```

```
                try:
                    vec = w2v_model.wv[word]
                    sent_vec += vec
                    cnt_words += 1
                except:
                    pass
            sent_vec /= cnt_words
            sent_vectors.append(sent_vec)
        print(len(sent_vectors))
        print(len(sent_vectors[0]))
```

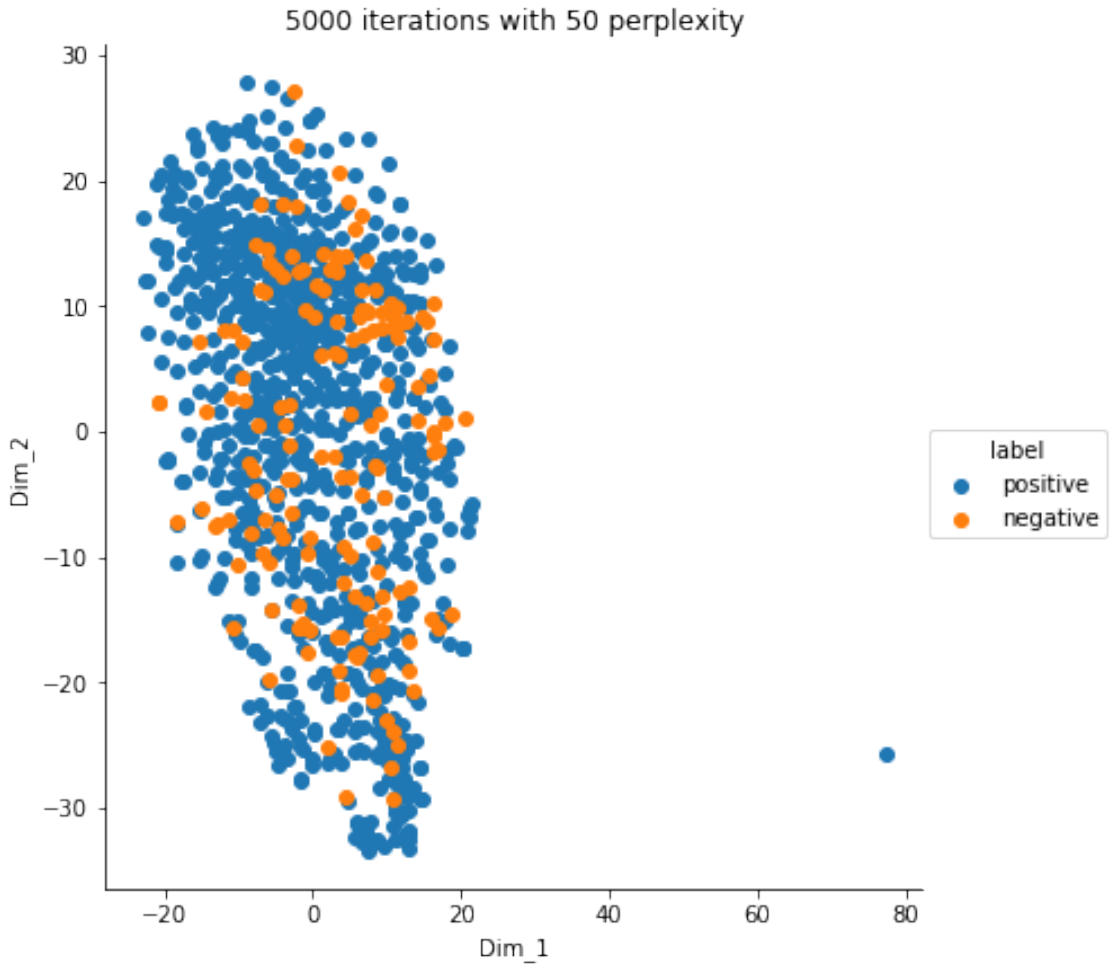
```
C:\Users\Saurabh\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: RuntimeWarning: invalid
```

```
393931
50
```

```
In [71]: from sklearn.manifold import TSNE
         data_1000 = final_counts[0:1000,:]
         top_1000 = data_1000.toarray()
         labels = final['Score']
         labels_1000 = labels[0:1000]

         model = TSNE(n_components=2,random_state=0,perplexity=20,n_iter=1000)
         tsne_data = model.fit_transform(top_1000)

         # creating a new data frame which help us in ploting the result data

         tsne_data = np.vstack((tsne_data.T, labels_1000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

         print(tsne_df.head())
         print(tsne_df.shape)
         print(tsne_df['label'].unique())

         sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
         .add_legend()
         plt.title("5000 iterations with 50 perplexity")
         plt.show()
```

```
      Dim_1    Dim_2     label
0   16.5019 -15.0289  positive
1  0.880632 -6.49288  positive
2  -8.43573  -11.717  positive
3  -2.18549  7.97556  positive
4  -6.28254  16.4617  positive
(1000, 3)
```

```
['positive' 'negative']
```



In [ ]: Observation => When we take 1000 data pointsperpexity=50 and iterations 5000

Here we seen that all positive and negative data points are overlapping each other so we cannot easily distinguish the positive and negative data points but here we also seen that a single positive point is shown far from all the points

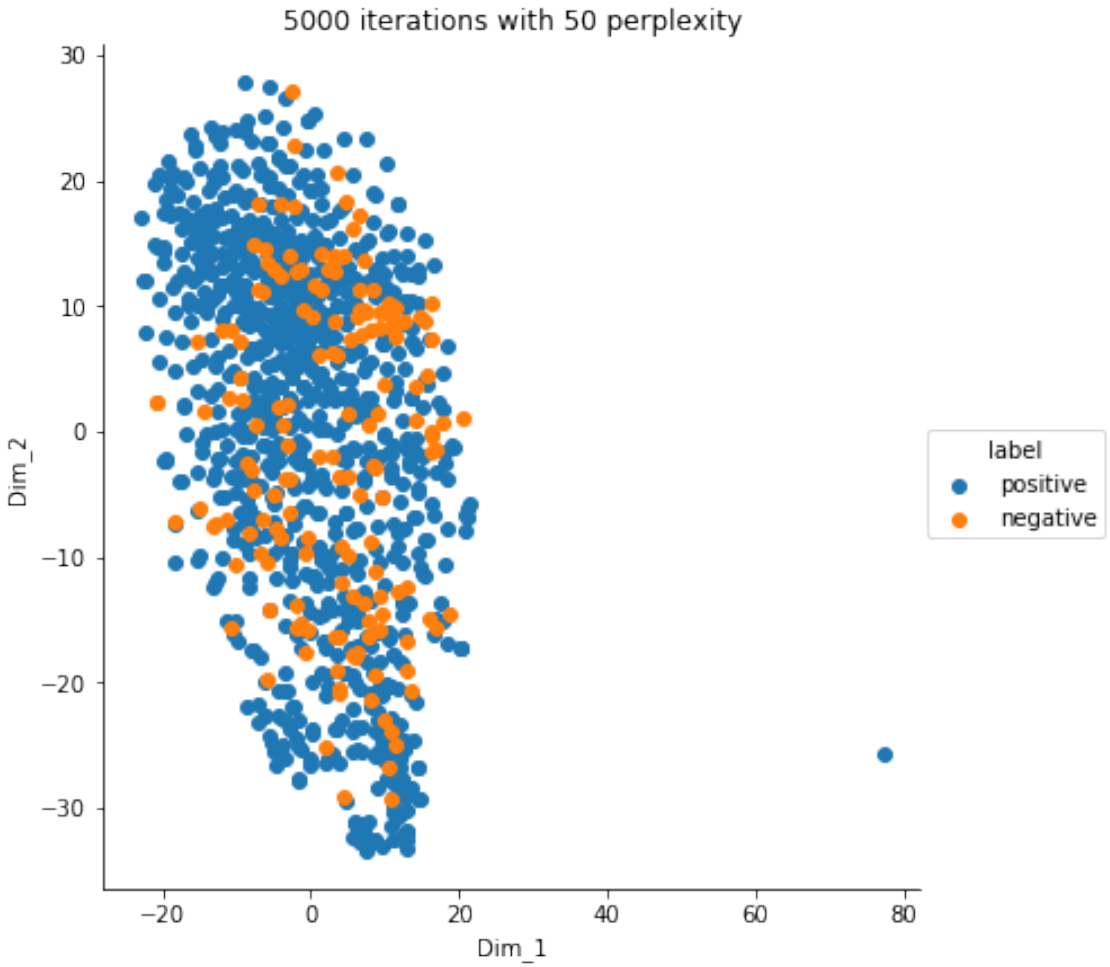
9 TF-IDF Weighted Word2Vec Using TSNE Visulaization

In [ ]:
```
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
row=0;
```

```
        for sent in list_of_sent: # for each review/sentence
            sent_vec = np.zeros(50) # as word vectors are of zero length
            weight_sum =0; # num of words with a valid vector in the sentence/review
            for word in sent: # for each word in a review/sentence
                try:
                    vec = w2v_model.wv[word]
                    # obtain the tf_idfidf of a word in a sentence/review
                    tfidf = final_tf_idf[row, tfidf_feat.index(word)]
                    sent_vec += (vec * tfidf)
                    weight_sum += tfidf

                except:
                    pass
            sent_vec /= weight_sum
            tfidf_sent_vectors.append(sent_vec)
            row += 1
```

```
In [73]: from sklearn.manifold import TSNE
         data_1000 = final_counts[0:1000,:]
         top_1000 = data_1000.toarray()
         labels = final['Score']
         labels_1000 = labels[0:1000]

         model = TSNE(n_components=2,random_state=0,perplexity=20,n_iter=1000)
         tsne_data = model.fit_transform(top_1000)

         # creating a new data frame which help us in ploting the result data

         tsne_data = np.vstack((tsne_data.T, labels_1000)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2","label"))

         print(tsne_df.head())
         print(tsne_df.shape)
         print(tsne_df['label'].unique())

         sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, "Dim_1","Dim_2")
         .add_legend()
         plt.title("5000 iterations with 50 perplexity")
         plt.show()
```

```
      Dim_1    Dim_2     label
0   16.5019 -15.0289  positive
1  0.880632 -6.49288  positive
2  -8.43573  -11.717  positive
3  -2.18549  7.97556  positive
4  -6.28254  16.4617  positive
(1000, 3)
['positive' 'negative']
```



In [ ]: Observation=>When we take 1000 data pointsperpexity=50 and iterations 2000

Here we seen that all positive and negative data points are overlapping each other so we cannot easily distinguish the positive and negative data points but here we also seen that a single positive point is shown far from all the points

10 Conclusion:

In [ ]: In this assignment we see that how we change the score, text values into numeric and make the text(reviews) data into numeric data. So the conclusion driven from this assignment is that we can easily use numeric data to make the plots using tsne in this assignment. We can easily figure out the positive eand negative reviews using the tsne plots.