02 Amazon Fine Food Reviews Analysis_TSNE

April 26, 2019

1 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.

1.1 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 [17]: %matplotlib inline
         import warnings
         warnings.filterwarnings("ignore")



         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
         # Tutorial about Python regular expressions: https://pymotw.com/2/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

         from tqdm import tqdm
         import os
```

2 [1]. Reading Data

```
In [19]: # using the SQLite Table to read data.
         con = sqlite3.connect(r'D:\Sayantan\Personal\MLnAI\Assignments\t-SNE\database.sqlite\
         #filtering only positive and negative reviews i.e.
         # not taking into consideration those reviews with Score=3
         # SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data poin
         # you can change the number to any other number based on your computing power

         # filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT
         # for tsne assignment you can take 5k data points
```

```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 500

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative 
def partition(x):
    if x < 3:
        return 0
    return 1

#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
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

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

```
Out[19]:    Id   ProductId          UserId                      ProfileName  \
         0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
         1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
         2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

            HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         0                     1                       1      1  1303862400
         1                     0                       0      0  1346976000
         2                     1                       1      1  1219017600

                          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...
```

```
In [20]: display = pd.read_sql_query("""
         SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
         FROM Reviews
         GROUP BY UserId
         HAVING COUNT(*)>1
         """, con)
```

```
In [21]: print(display.shape)
         display.head()
```

```
(80668, 7)
```

```
Out[21]:                UserId   ProductId             ProfileName        Time  Score  \
         0  #oc-R115TNMSPFT9I7  B005ZBZLT4                 Breyton  1331510400      2
```

```
1  #oc-R11D9D7SHXIJB9  B005HG9ESG  Louis E. Emory "hoppy"  1342396800      5
2  #oc-R11DNU2NBKQ23Z  B005ZBZLT4        Kim Cieszykowski  1348531200      1
3  #oc-R11O5J5ZVQE25C  B005HG9ESG            Penguin Chick  1346889600      5
4  #oc-R12KPBODL2B5ZD  B007OSBEV0   Christopher P. Presta  1348617600      1

                                                 Text  COUNT(*)
0  Overall its just OK when considering the price...         2
1  My wife has recurring extreme muscle spasms, u...         3
2  This coffee is horrible and unfortunately not ...         2
3  This will be the bottle that you grab from the...         3
4  I didnt like this coffee. Instead of telling y...         2
```

In [0]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[0]:
```
              UserId   ProductId                     ProfileName        Time  \
80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

       Score                                              Text  COUNT(*)
80638      5  I was recommended to try green tea extract to ...         5
```

In [0]:
```
display['COUNT(*)'].sum()
```

Out[0]:
```
393063
```

3 Exploratory Data Analysis

3.1 [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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[0]:
```
       Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
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

   HelpfulnessDenominator  Score        Time  \
0                       2      5  1199577600
```

```
1                          2      5  1199577600
2                          2      5  1199577600
3                          2      5  1199577600
4                          2      5  1199577600

                                Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  LOACKER QUADRATINI VANILLA WAFERS
3  LOACKER QUADRATINI VANILLA WAFERS
4  LOACKER QUADRATINI VANILLA WAFERS

                                                   Text
0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

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 [22]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fa
```

In [23]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep
final.shape
```

Out[23]: (4986, 10)

In [24]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[24]: 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 [0]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND Id=44737 OR Id=64422
        ORDER BY ProductID
        """, con)

        display.head()
```

```
Out[0]:       Id   ProductId          UserId              ProfileName  \
        0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
        1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

           HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
        0                     3                       1      5  1224892800
        1                     3                       2      4  1212883200

                                                Summary  \
        0               Bought This for My Son at College
        1  Pure cocoa taste with crunchy almonds inside

                                                        Text
        0  My son loves spaghetti so I didn't hesitate or...
        1  It was almost a 'love at first bite' - the per...
```

```
In [25]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [26]: #Before starting the next phase of preprocessing lets see the number of entries left
         print(final.shape)

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

```
(4986, 10)
```

```
Out[26]: 1    4178
         0     808
         Name: Score, dtype: int64
```

4 [3]. 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 [0]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
Why is this $[...] when the same product is available for $[...] here?<br />http://www.amazon.c
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The bes
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the oth
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />This k cup is great coffee
==================================================
```

In [0]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor
```

In [0]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-
from bs4 import BeautifulSoup
```

```
soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
Why is this $[...] when the same product is available for $[...] here? />The Victor M380 and M5
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The bes
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the ot
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cup is great coffee.  dca
```

In [30]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

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 [0]:
```
sent_1500 = decontracted(sent_1500)
```

```
print(sent_1500)
print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the oth
==================================================
```

In [0]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victo
```

In [0]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Wow So far two two star reviews One obviously had no idea what they were ordering the other wa
```

In [27]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', '
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
            'won', "won't", 'wouldn', "wouldn't"])
```

In [31]:
```
# Combining all the above stundents
from tqdm import tqdm
from bs4 import BeautifulSoup
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)
        # https://gist.github.com/sebleier/554280
        sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopw
        preprocessed_reviews.append(sentance.strip())
```

```
100%|| 4986/4986 [00:02<00:00, 1744.36it/s]
```

In [0]:
```
preprocessed_reviews[1500]
```

Out[0]:
```
'wow far two two star reviews one obviously no idea ordering wants crispy cookies hey
```

[3.2] Preprocess Summary

In [32]:
```
## Similartly you can do preprocessing for review summary also.
#Deduplication of entries
final1=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Summary"},
print(final1.shape)

#Checking to see how much % of data still remains
print((final1['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100)

#value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not pr
#hence these  rows too are removed from calcualtions
final1=final1[final1.HelpfulnessNumerator<=final1.HelpfulnessDenominator]

#Before starting the next phase of preprocessing lets see the number of entries left
print(final1.shape)

#How many positive and negative reviews are present in our dataset?
print(final1['Score'].value_counts())

from tqdm import tqdm
preprocessed_summary = []
# tqdm is for printing the status bar
for sentance in tqdm(final1['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)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwo
    preprocessed_summary.append(sentance.strip())
```

```
(4985, 10)
99.7
(4985, 10)
1    4178
0     807
Name: Score, dtype: int64


100%|| 4985/4985 [00:02<00:00, 2334.58it/s]
```

In [33]:
```
preprocessed_summary[1500]
```

Out[33]:
```
'reviewing mistakes cookies'
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

In [0]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", 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  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abbott', 'abby', 'abdominal
==================================================
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
```

5.2 [4.2] Bi-Grams and n-Grams.

In [0]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/stable/modu
# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
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_shape())
print("the number of unique words including both unigrams and bigrams ", final_bigram_c
```

```
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
```

5.3 [4.3] TF-IDF

```
In [0]: 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.get_feature_names
        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.
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'able find', 'able get',
==================================================
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
```

5.4 [4.4] Word2Vec

```
In [0]: # 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.split())
```

```
In [0]: # Using Google News Word2Vectors

        # in this project we are using a pretrained model by google
        # its 3.3G file, once you load this into your memory
        # it occupies ~9Gb, so please do this step only if you have >12G of ram
        # we will provide a pickle file wich contains a dict ,
        # and it contains all our courpus words as keys and  model[word] as values
        # To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
        # from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
        # it's 1.9GB in size.


        # http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
        # you can comment this whole cell
        # or change these varible according to your need
```

```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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, workers=4)
    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_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin
        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_train_w2v = True, to
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wonderful', 0.99460321664810
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('popcorn', 0.99927508831024
```

In [0]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'stinky', 'right', 'nearby
```

5.5 [4.4.1] Converting text into vectors using wAvg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [0]:
```
# 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 tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need to
    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]))
```

```
100%|| 4986/4986 [00:03<00:00, 1330.47it/s]


4986
50
```

[4.4.1.2] TFIDF weighted W2v

```
In [0]: # 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 [0]: # TF-IDF weighted Word2Vec
        tfidf_feat = model.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 li
        row=0;
        for sent in tqdm(list_of_sentance): # 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 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 [00:20<00:00, 245.63it/s]
```

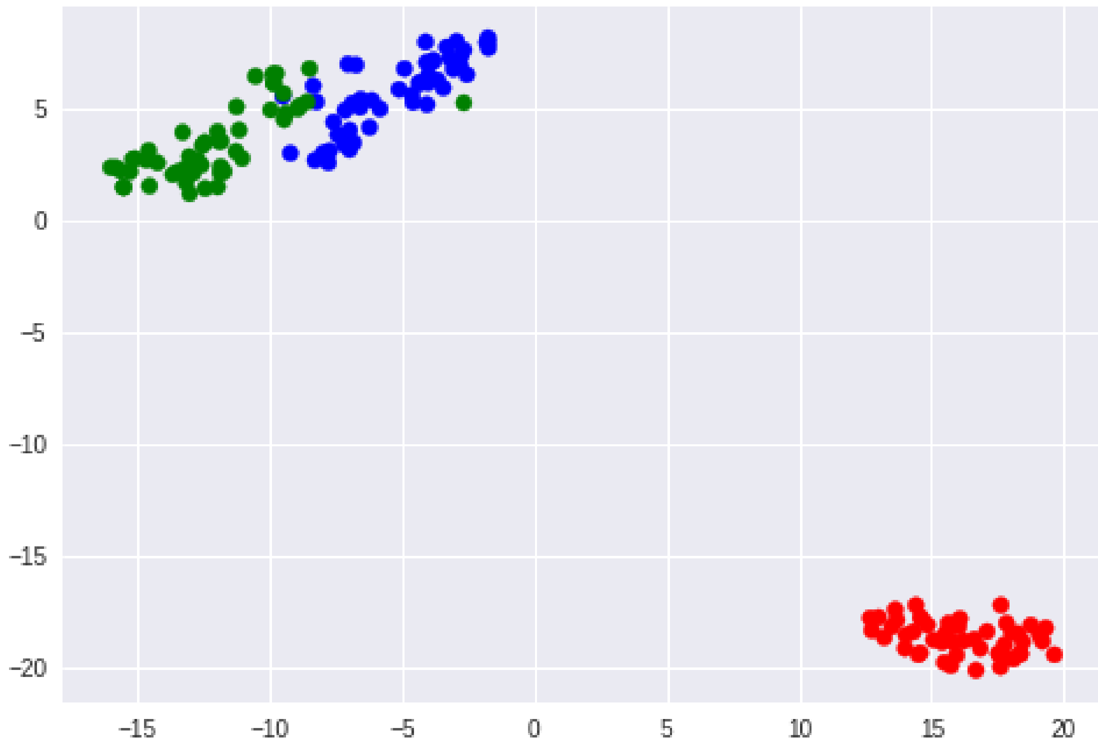
6 [5] Applying TSNE

```
<li> you need to plot 4 tsne plots with each of these feature set
```


    Review text, preprocessed one converted into vectors using (BOW)
    Review text, preprocessed one converted into vectors using (TFIDF)
    Review text, preprocessed one converted into vectors using (AVG W2v)
    Review text, preprocessed one converted into vectors using (TFIDF W2v)

 Note 1: The TSNE accepts only dense matrices
 Note 2: Consider only 5k to 6k data points

In [11]:
```
# https://github.com/pavlin-policar/fastTSNE you can try this also, this version is l
import numpy as np
from sklearn.manifold import TSNE
from sklearn import datasets
import pandas as pd
import matplotlib.pyplot as plt

iris = datasets.load_iris()
x = iris['data']
y = iris['target']

tsne = TSNE(n_components=2, perplexity=30, learning_rate=200)

X_embedding = tsne.fit_transform(x)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit_transform(x.t

for_tsne = np.hstack((X_embedding, y.reshape(-1,1)))
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimension_y','Score
colors = {0:'red', 1:'blue', 2:'green'}
plt.scatter(for_tsne_df['Dimension_x'], for_tsne_df['Dimension_y'], c=for_tsne_df['Sco
plt.show()
```



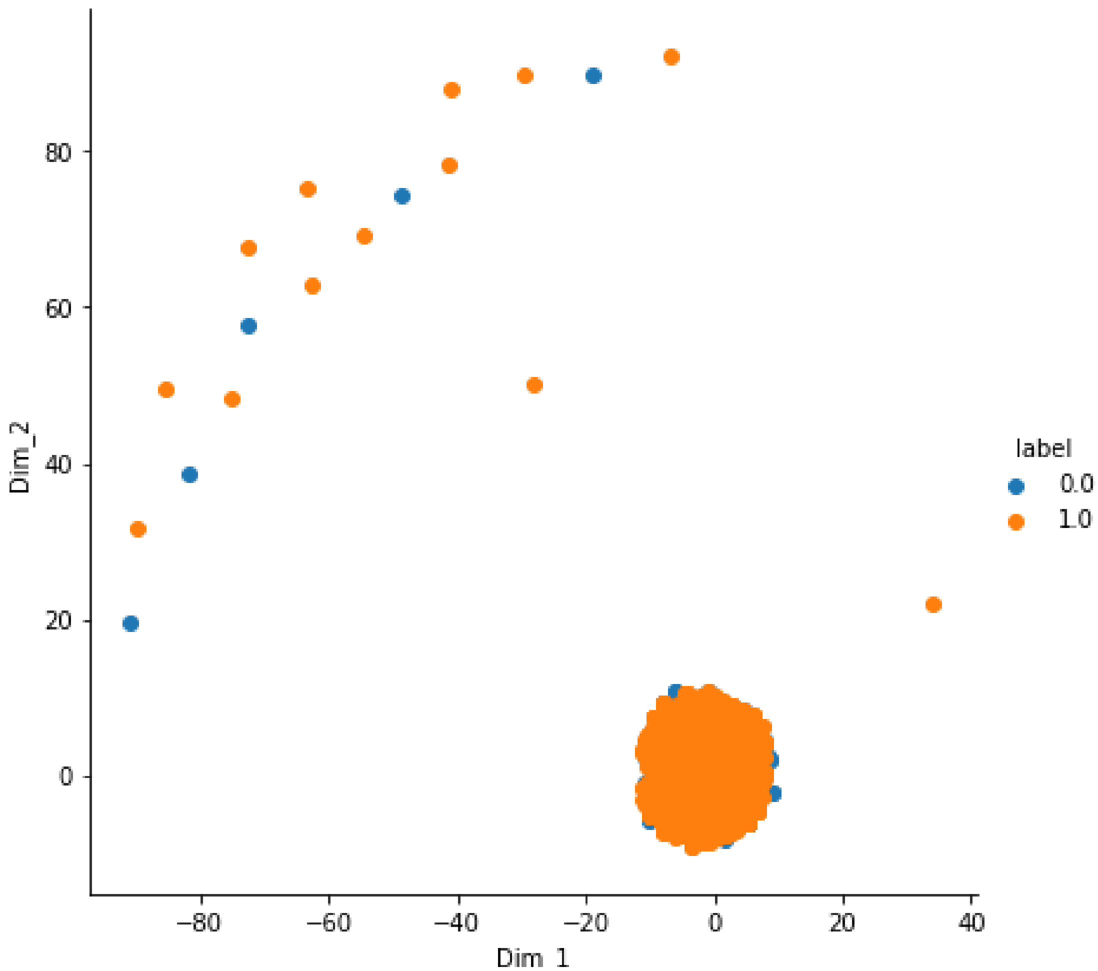
6.1 [5.1] Applying TNSE on Text BOW vectors

```
In [44]: # please write all the code with proper documentation, and proper titles for each sub
         # when you plot any graph make sure you use
             # a. Title, that describes your plot, this will be very helpful to the reader
             # b. Legends if needed
             # c. X-axis label
             # d. Y-axis label
         from sklearn.feature_extraction.text import CountVectorizer
         import seaborn as sn

         Y = final['Score'].values
         print(Y.shape)
         print(len(preprocessed_reviews))
         vectorizer = CountVectorizer()
         reviews_bow = vectorizer.fit_transform(preprocessed_reviews)

         print("the type of count vectorizer ",type(reviews_bow))
         print("the shape of out text BOW vectorizer ",reviews_bow.get_shape())
         print("the number of unique words ", reviews_bow.get_shape()[1])

         from sklearn.manifold import TSNE
         model = TSNE(n_components=2, perplexity=30, n_iter=5000, random_state=0)
```

```
tsne_data = model.fit_transform(reviews_bow.toarray())

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

```
(4986,)
4986
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
```

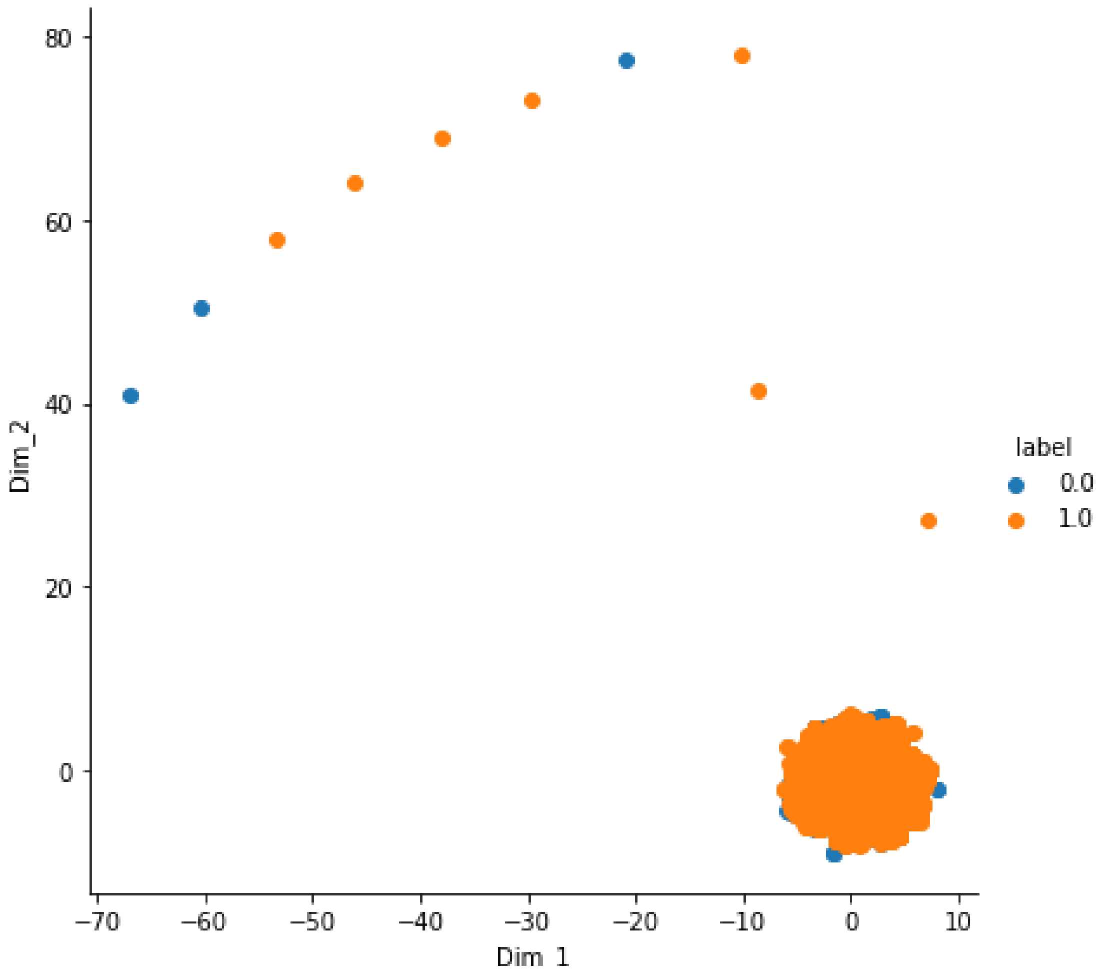
In [45]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



In [48]:
```
final['Score'].value_counts()
```

Out[48]: 1   4178
0   808
Name: Score, dtype: int64

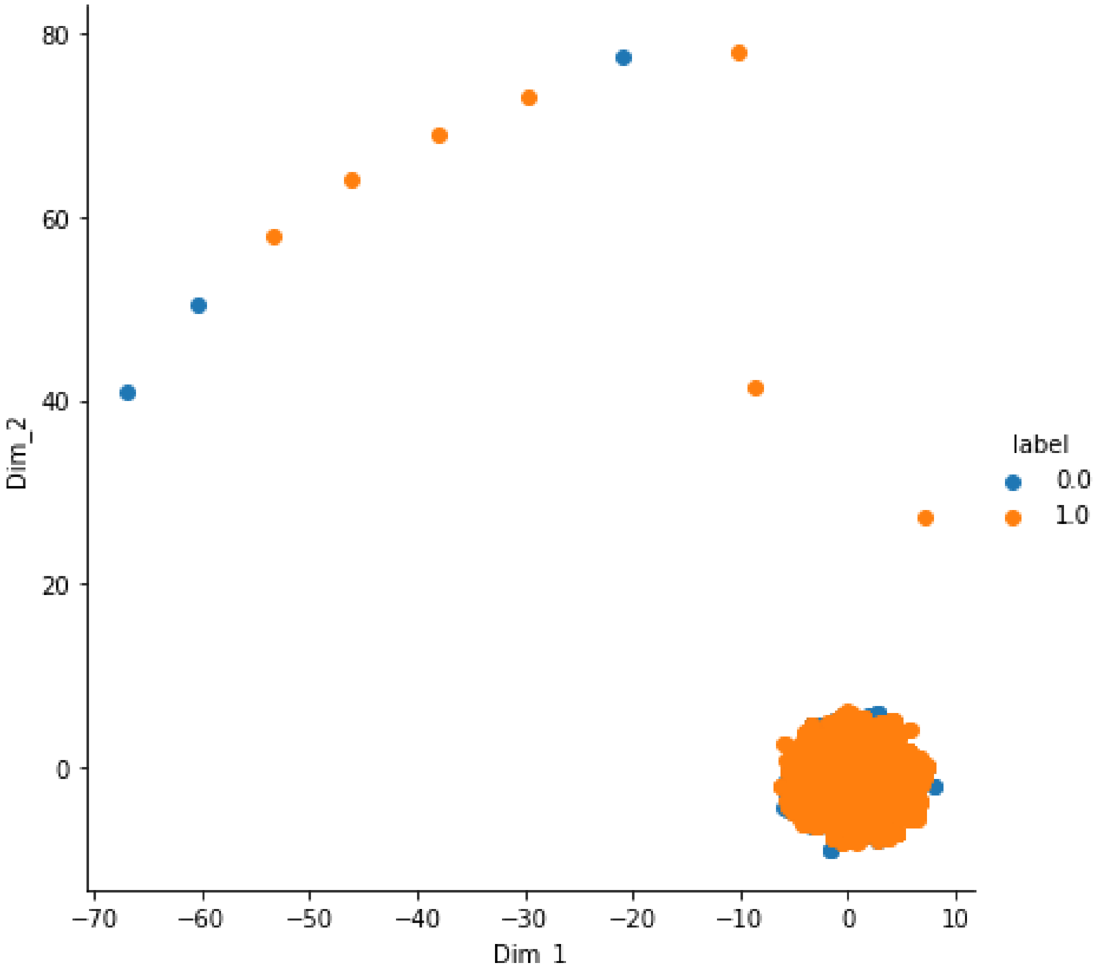
In [46]:
```
#increased perplexity to 50
model = TSNE(n_components=2, perplexity=50, n_iter=5000, random_state=0)
tsne_data = model.fit_transform(reviews_bow.toarray())

tsne_data = np.vstack((tsne_data.T, Y)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



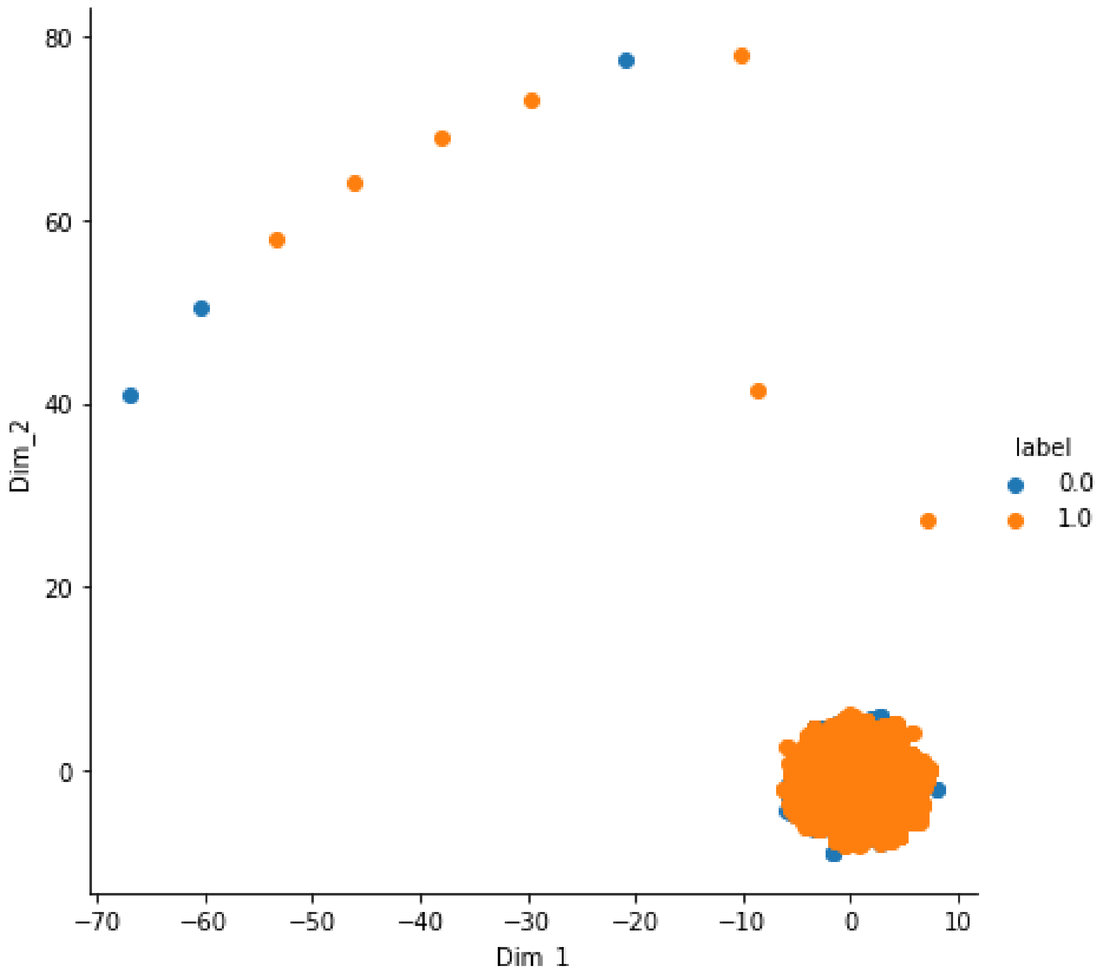
With perplexity 30 and 50 t-SNE stabilizes so not required further increasing the perplexity. Now increasing iterations to 6000

In [47]:
```
model = TSNE(n_components=2, perplexity=50, n_iter=6000, random_state=0)
tsne_data = model.fit_transform(reviews_bow.toarray())
```

```
tsne_data = np.vstack((tsne_data.T, Y)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```




```
In [75]: model = TSNE(n_components=2, perplexity=50, n_iter=10000, random_state=0)
         tsne_data = model.fit_transform(reviews_bow.toarray())

         tsne_data = np.vstack((tsne_data.T, Y)).T
         tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
         # Ploting the result of tsne
         sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
         plt.show()
```



In [ ]:

With the increment of iteration count as well the result is stabilized. So with perplexity = 30 and iteration 5000, and perplexity = 50 and iteration = 6000 and iteration 10000 almost same result. Though there are 800 odd -ve data still we don't have proper segregation with this model.

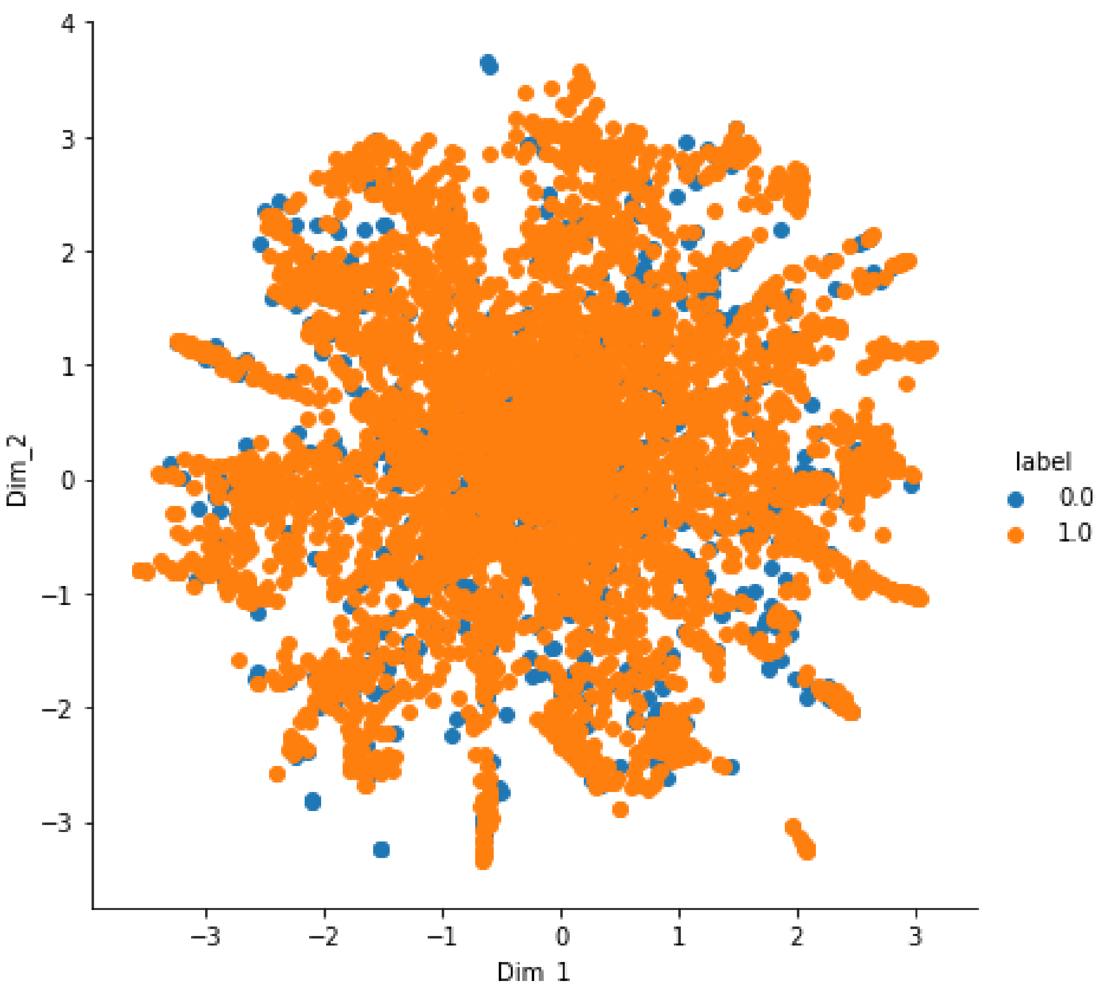
6.2 [5.1] Applying TNSE on Text TFIDF vectors

In [49]:
```
# please write all the code with proper documentation, and proper titles for each sub
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
reviews_tfidf = tf_idf_vect.fit_transform(preprocessed_reviews)
```

```
print("the type of count vectorizer ",type(reviews_tfidf))
print("the shape of out text tf-idf vectorizer ",reviews_tfidf.get_shape())
print("the number of unique words ", reviews_tfidf.get_shape()[1])

from sklearn.manifold import TSNE
model = TSNE(n_components=2, perplexity=30, n_iter=5000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(reviews_tfidf.toarray())

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

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text tf-idf vectorizer  (4986, 3144)
the number of unique words  3144
```

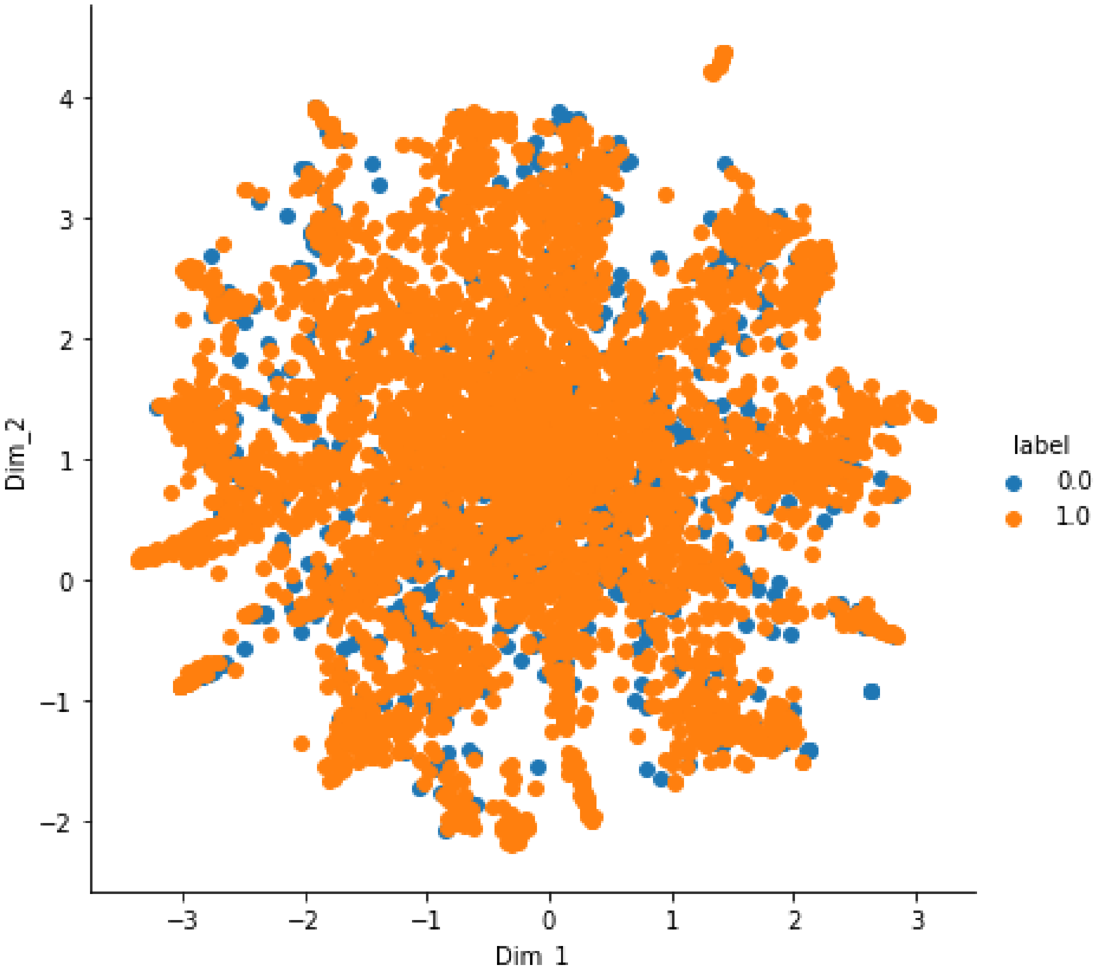
In [50]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



From the above plot we have overlapped data, so moving to higher perplexity value i.e. 40

In [52]:
```
model = TSNE(n_components=2, perplexity=40, n_iter=5000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(reviews_tfidf.toarray())

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

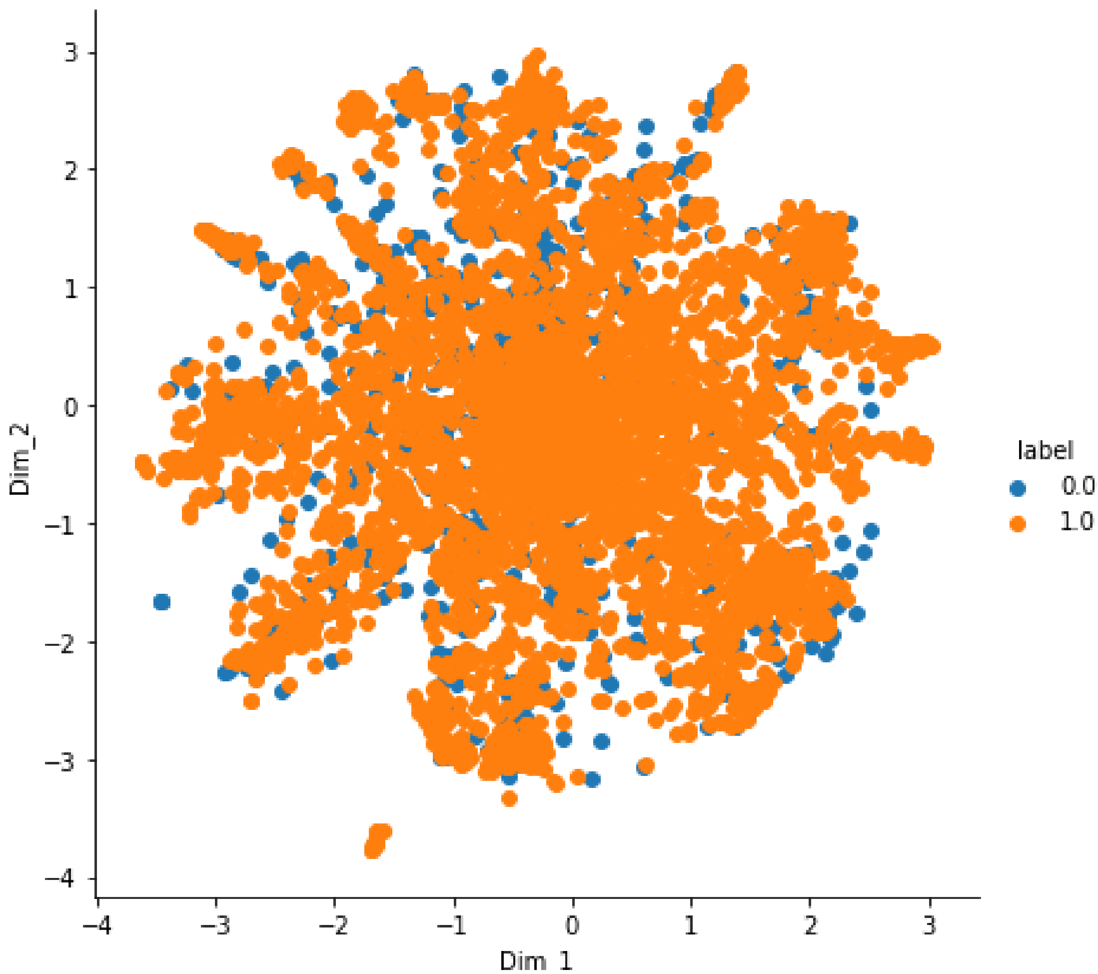
In [53]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



In [54]:
```
#Increasing further the perplexity value to 50
model = TSNE(n_components=2, perplexity=50, n_iter=5000, random_state=0)
```

```
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(reviews_tfidf.toarray())

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

In [55]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```

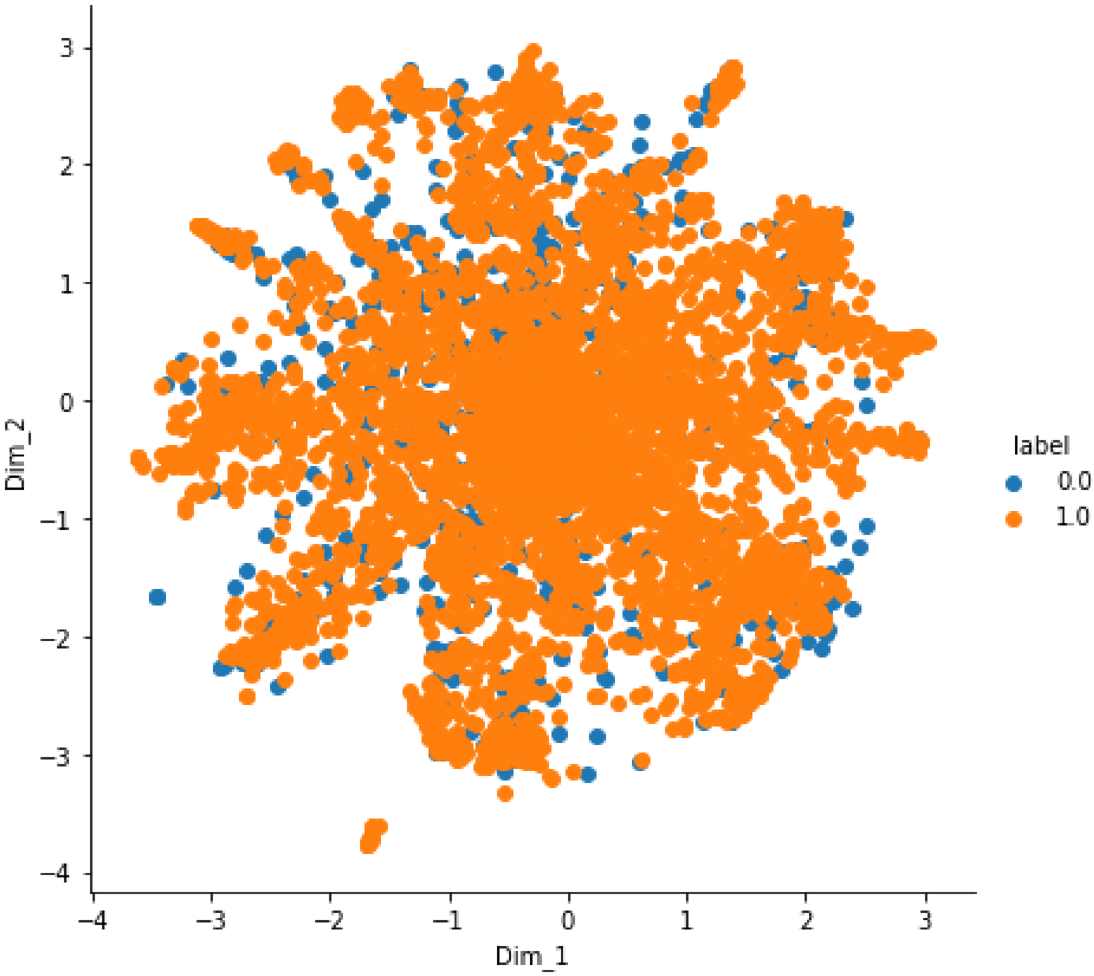


No improvement on changing perplexity values to higher range so now changing number of iterations to 6000

In [56]:
```
#Increasing further the perplexity value to 50
model = TSNE(n_components=2, perplexity=50, n_iter=6000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(reviews_tfidf.toarray())
```

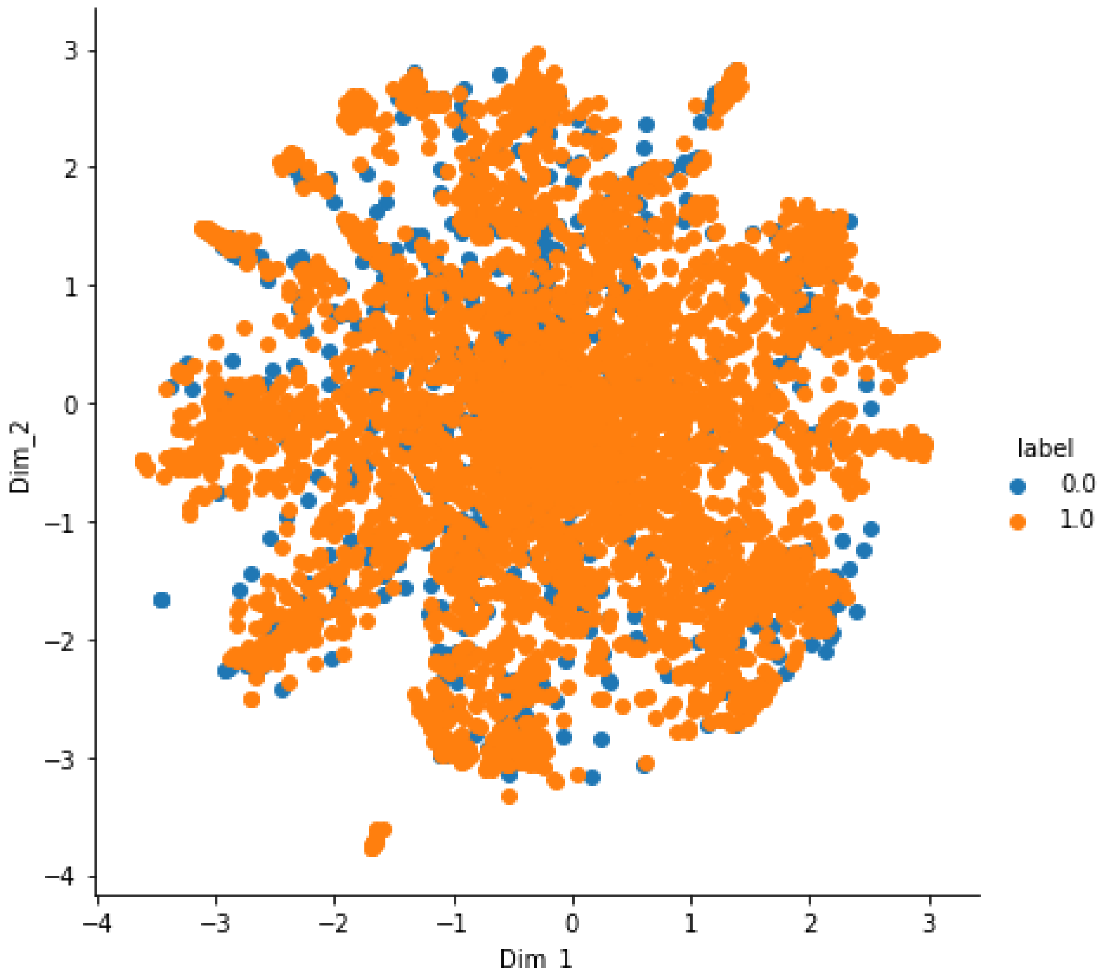
```
tsne_data = np.vstack((tsne_data.T, Y)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
```

In [57]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



In [58]:
```
#Increasing further the perplexity value to 50 and iteration to 7000
model = TSNE(n_components=2, perplexity=50, n_iter=7000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(reviews_tfidf.toarray())

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

In [59]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



With increasing value of perplexity and iterations there is no change in plotting much. It is almost same over the course. So no clear separation on +ve and -ve data

6.3 [5.3] Applying TNSE on Text Avg W2V vectors

In [61]:
```
# please write all the code with proper documentation, and proper titles for each sub
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label
from tqdm import tqdm
import numpy as np
from gensim.models import Word2Vec
from gensim.models import KeyedVectors

# Train your own Word2Vec model using your own text corpus
```

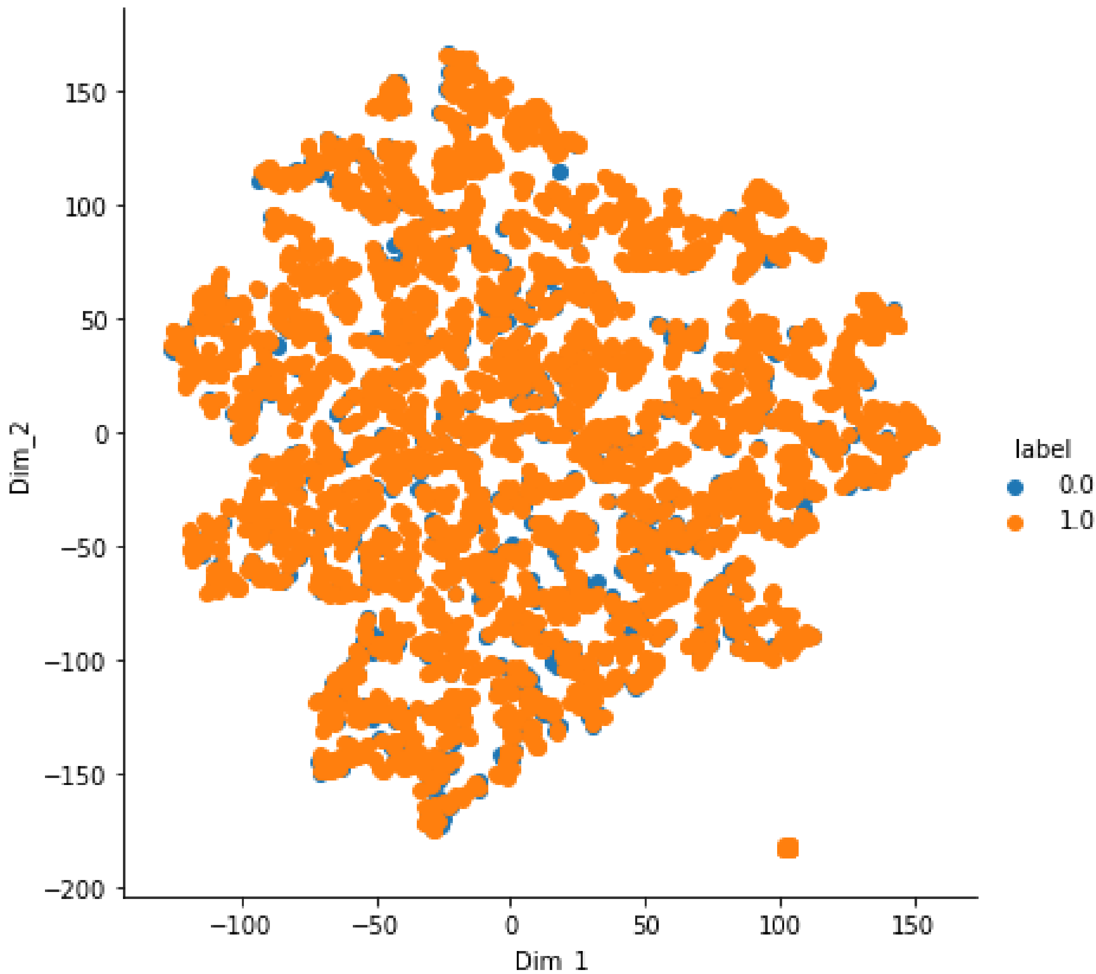
```
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())

# this line of code trains your w2v model on the give list of sentances
w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
```

In [62]:
```
# 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 tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50)
    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)
sent_vectors = np.array(sent_vectors)
print(sent_vectors.shape)
```

```
100%|| 4986/4986 [00:06<00:00, 778.83it/s]


(4986, 50)
```

In [63]:
```
model = TSNE(n_components=2, perplexity=10, n_iter=5000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(sent_vectors)

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

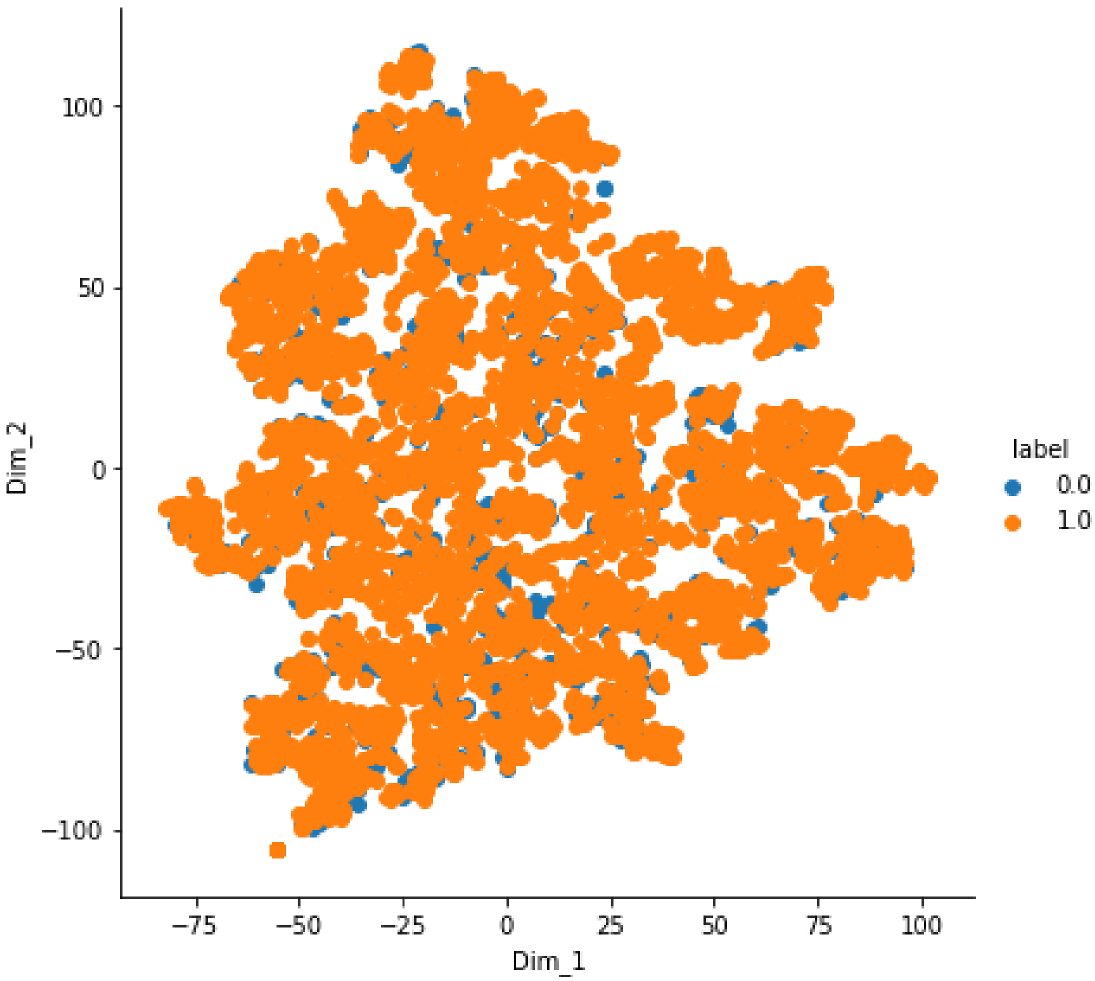
In [64]:
```
# Ploting the result of tsne
sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
plt.show()
```



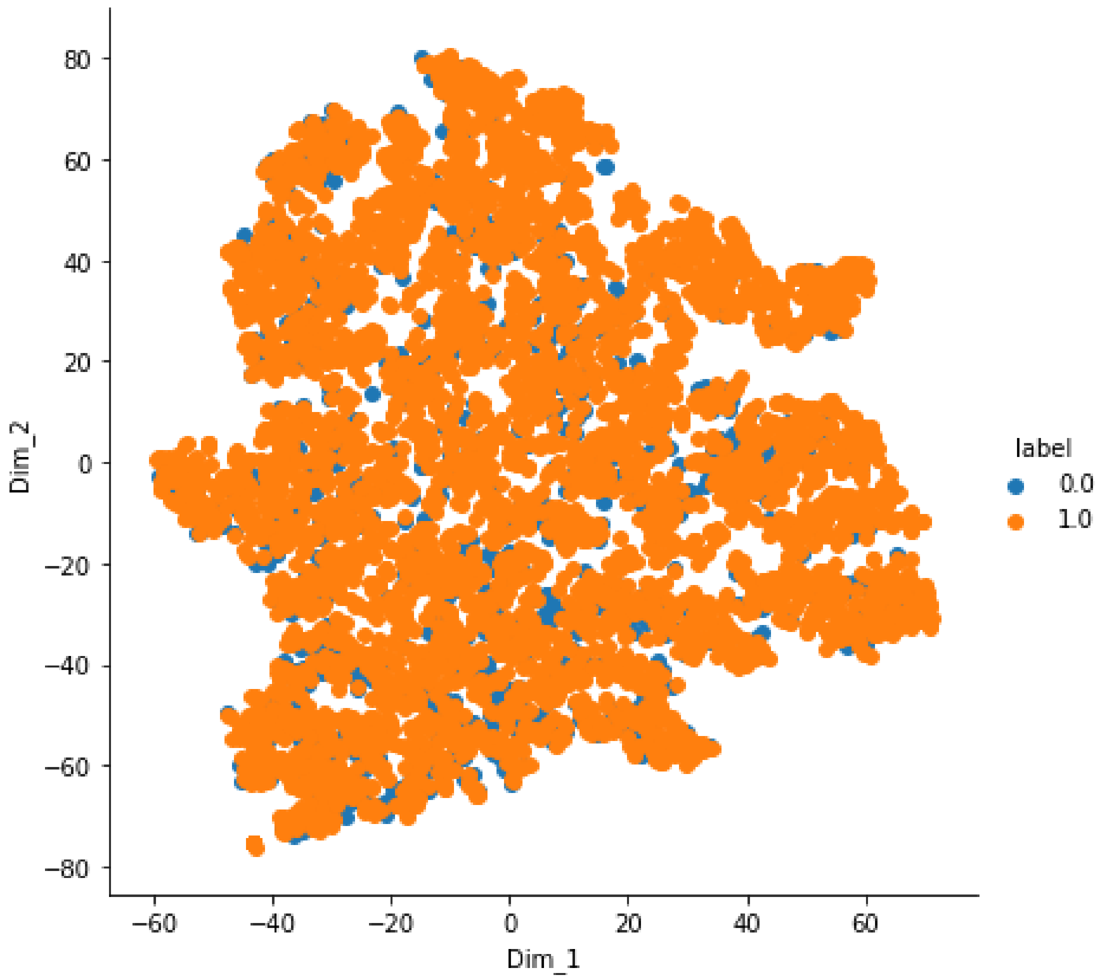
We have overlapping data, increasing perplexity to 30

```
In [65]: model = TSNE(n_components=2, perplexity=30, n_iter=5000, random_state=0)
         #as tf-idf gives sparse matrix, toarray() will convert it to dense one
         tsne_data = model.fit_transform(sent_vectors)

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

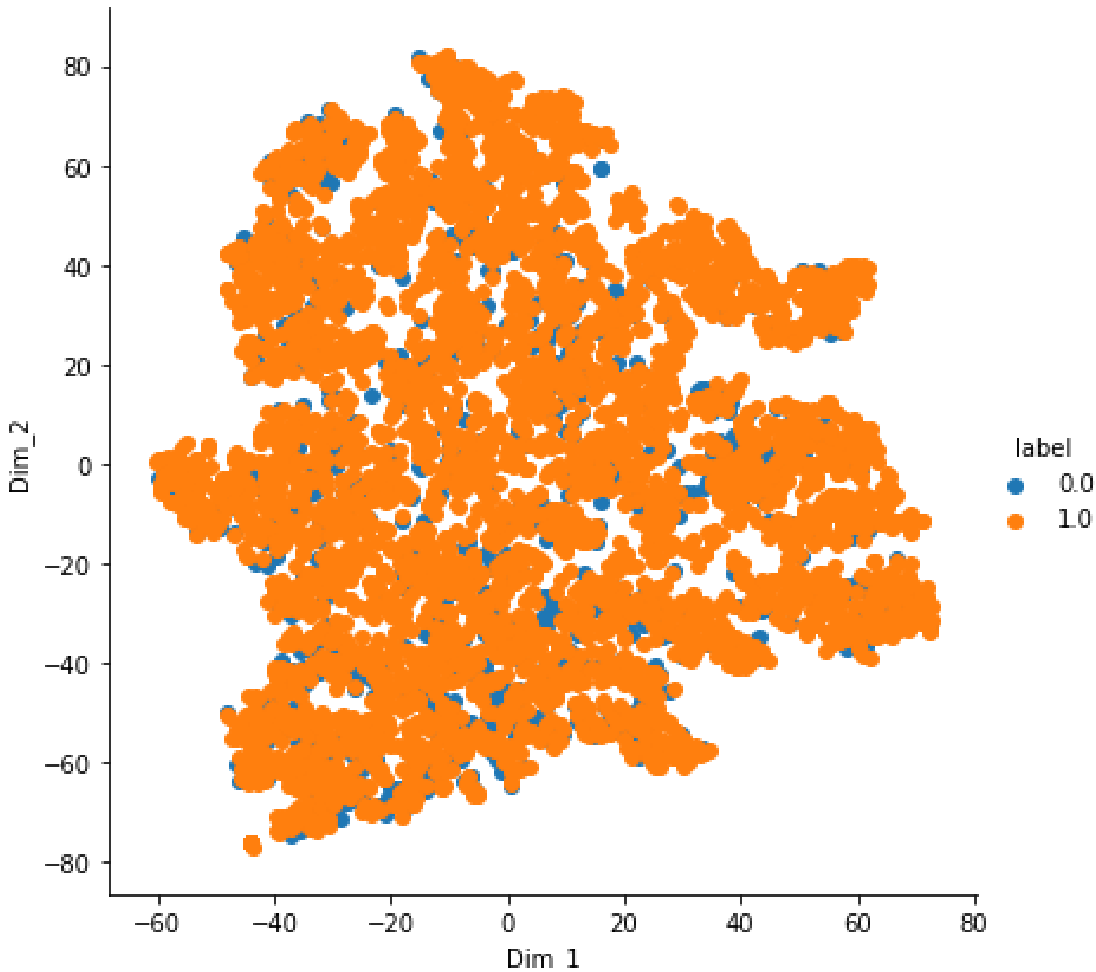
```
In [66]: # Ploting the result of tsne
         sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_lege
         plt.show()
```




```
In [67]: #perplexcity increasing furtehr to 50
         model = TSNE(n_components=2, perplexity=50, n_iter=5000, random_state=0)
         #as tf-idf gives sparse matrix, toarray() will convert it to dense one
         tsne_data = model.fit_transform(sent_vectors)

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

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




```
In [68]: #Changing perplxity there is no improvement on the data plotting, let change the numb
         model = TSNE(n_components=2, perplexity=50, n_iter=6000, random_state=0)
         #as tf-idf gives sparse matrix, toarray() will convert it to dense one
         tsne_data = model.fit_transform(sent_vectors)

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

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



Still overlapping and no change over the last few set. So we are not getting non-overlapping -ve and +ve data plot here as well.

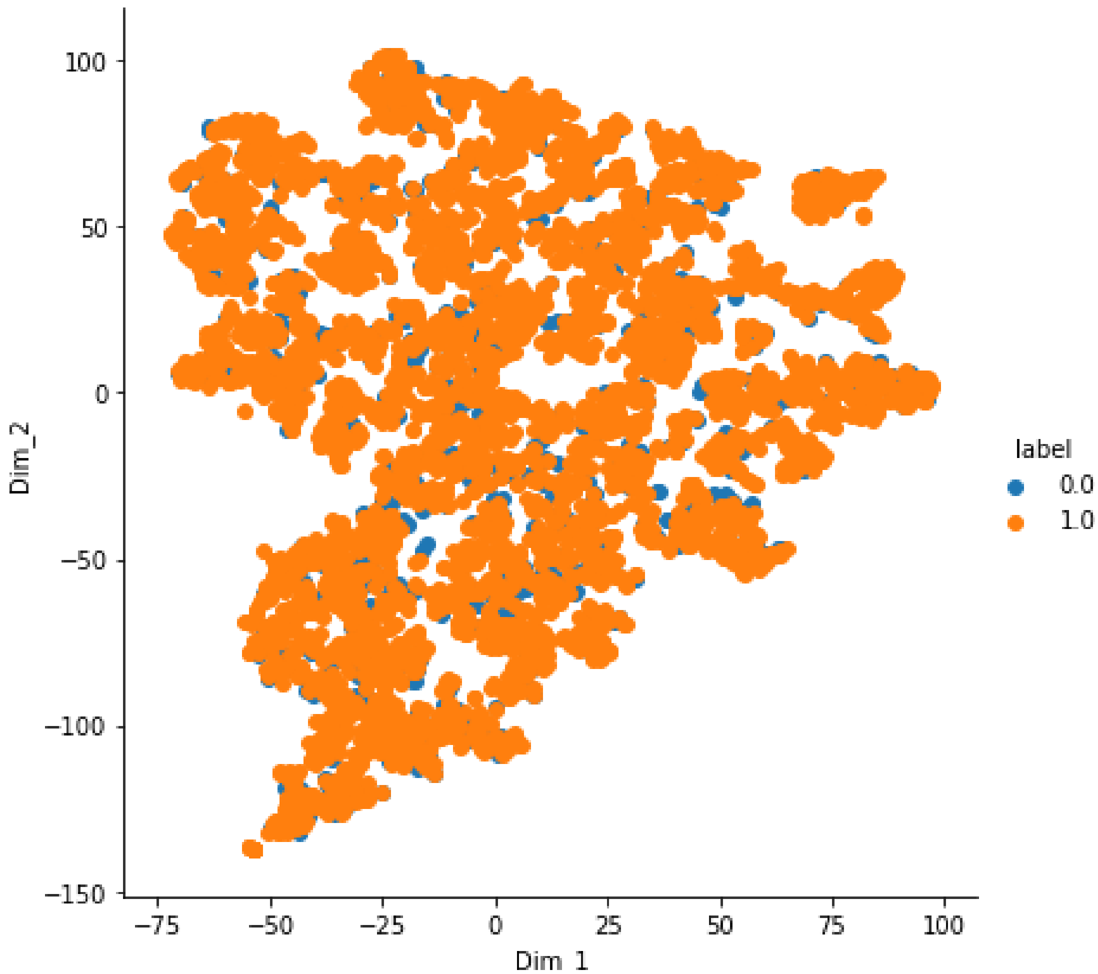
6.4 [5.4] Applying TNSE on Text TFIDF weighted W2V vectors

```
In [69]: # please write all the code with proper documentation, and proper titles for each sub
         # when you plot any graph make sure you use
             # a. Title, that describes your plot, this will be very helpful to the reader
             # b. Legends if needed
             # c. X-axis label
             # d. Y-axis label
         model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(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_)))

         # TF-IDF weighted Word2Vec
```

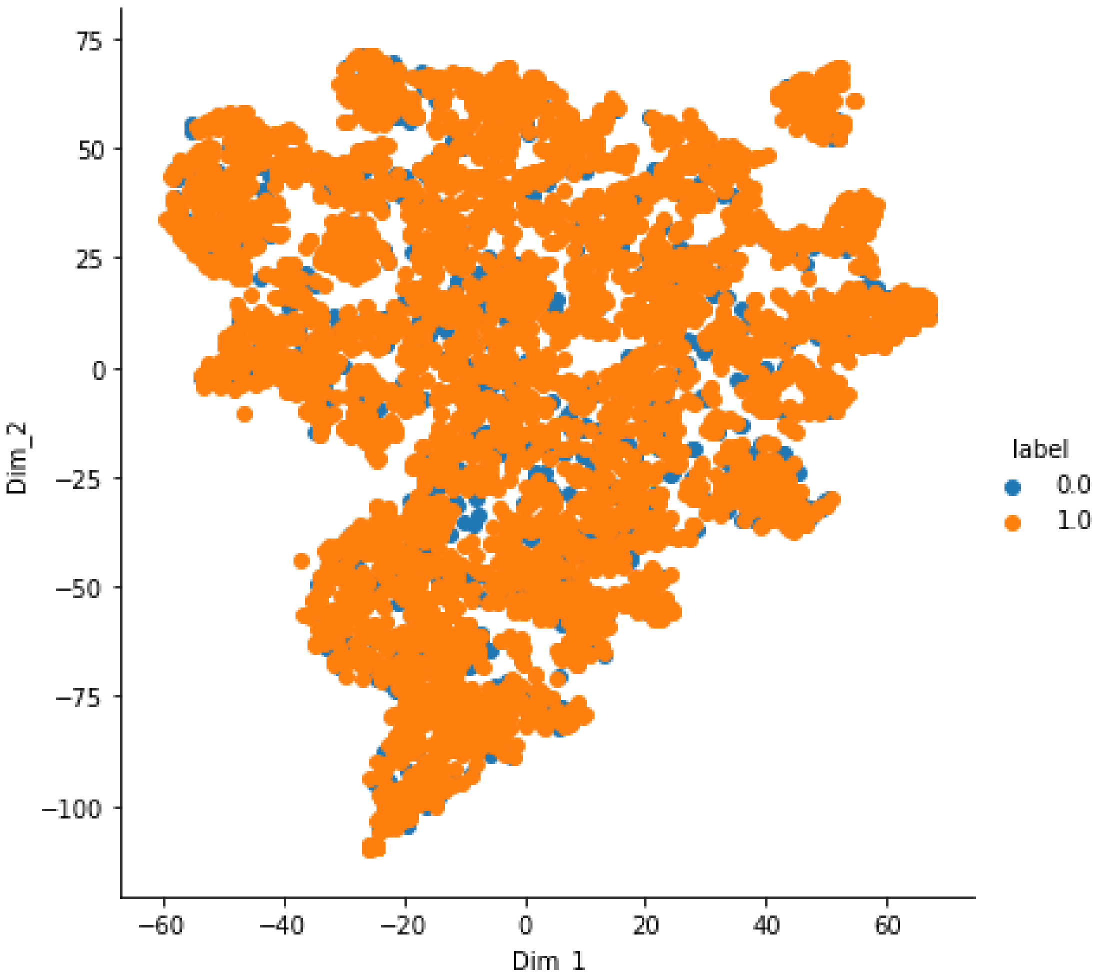
```
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
row=0;
for sent in tqdm(list_of_sentance): # 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 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 [00:45<00:00, 148.04it/s]
```

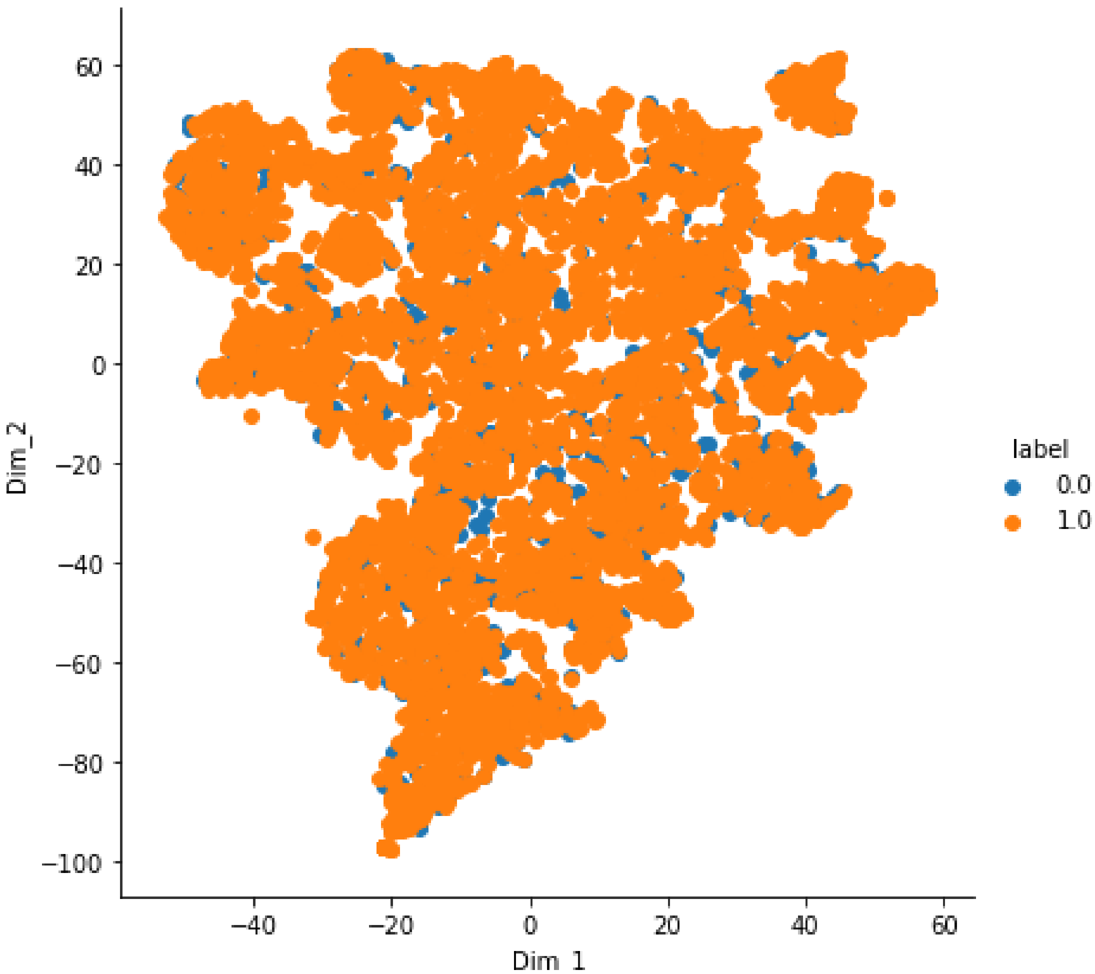
In [70]:
```
#Staring with perplexity 30 and iteration 5000
model = TSNE(n_components=2, perplexity=30, n_iter=5000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(tfidf_sent_vectors)

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

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



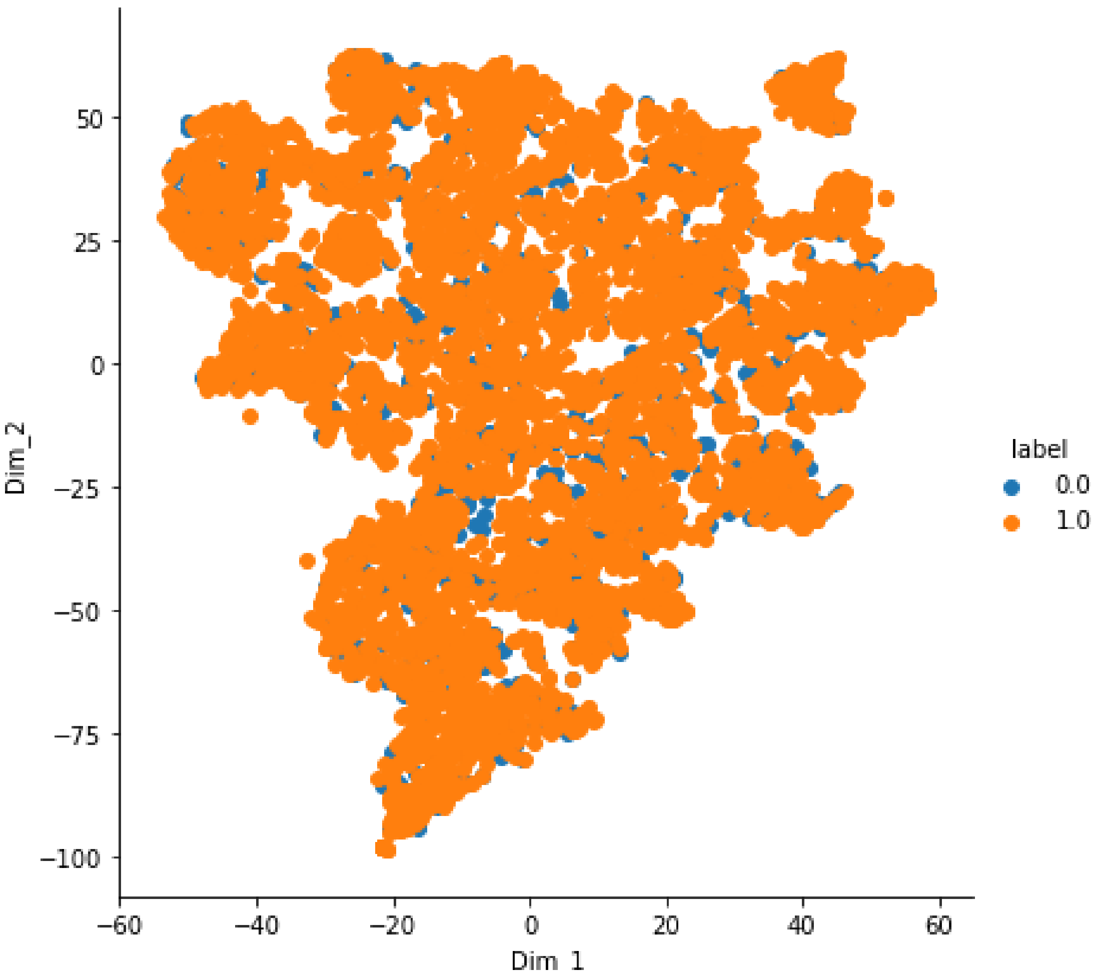

```
In [71]: #Changing perplexity to 50
         model = TSNE(n_components=2, perplexity=50, n_iter=5000, random_state=0)
         #as tf-idf gives sparse matrix, toarray() will convert it to dense one
         tsne_data = model.fit_transform(tfidf_sent_vectors)

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

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



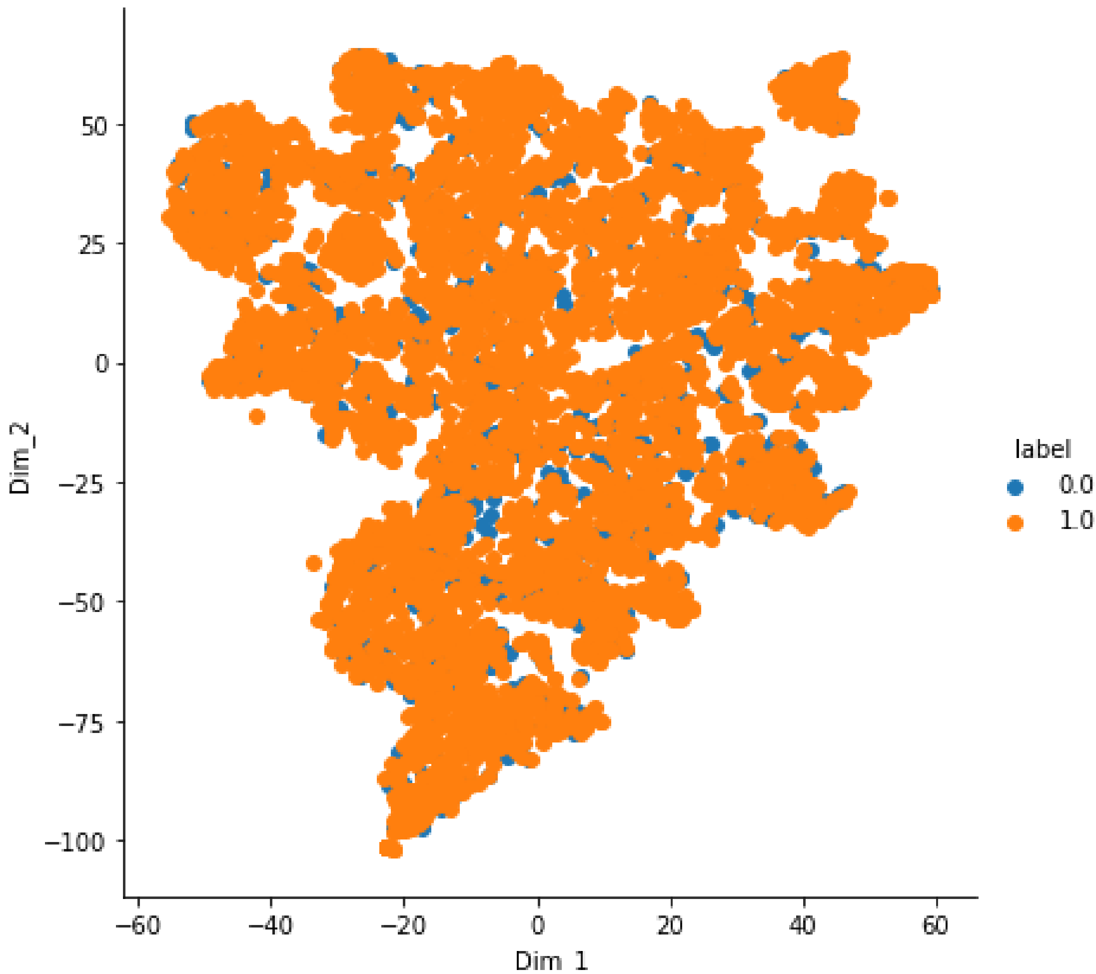
In [72]:
```
#Changing perplexity to 60
model = TSNE(n_components=2, perplexity=60, n_iter=5000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(tfidf_sent_vectors)

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

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




```
In [73]: #Changing perplexity to higher value have no improvement of the plot so now changing
         model = TSNE(n_components=2, perplexity=60, n_iter=6000, random_state=0)
         #as tf-idf gives sparse matrix, toarray() will convert it to dense one
         tsne_data = model.fit_transform(tfidf_sent_vectors)

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

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



In [74]:
```
#Changing iterations to 10000
model = TSNE(n_components=2, perplexity=60, n_iter=10000, random_state=0)
#as tf-idf gives sparse matrix, toarray() will convert it to dense one
tsne_data = model.fit_transform(tfidf_sent_vectors)

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

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



7 [6] Conclusions

None of the model above have given result of dividing two sets of data clearly. All are having overlapping data. Changing Hyperparameter have not changed the result. So none of the model is acceptable for this set of data

```
In [ ]:
```