Amazon Fine Food Reviews Analysis

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

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

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

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

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

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

Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

In [2]:
```
%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
```

```python
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
```

```
C:\Anaconda\lib\site-packages\gensim\utils.py:1209: UserWarning: detect
ed Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

[1]. Reading Data

In [3]:

```python
# using the SQLite Table to read data.
con = sqlite3.connect('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 50
0000 data points
# you can change the number to any other number based on your computing
 power
```

```python
# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

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

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

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

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [4]:

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

In [5]:

```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [6]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[6]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	5

In [7]:
```
display['COUNT(*)'].sum()
```

Out[7]: 393063

Exploratory Data Analysis

[2] Data Cleaning: Deduplication

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

In [8]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[8]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

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

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

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

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

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

In [9]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [10]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

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

In [11]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[11]:
```
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 [12]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)
```

```
display.head()
```

Out[12]:

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

In [13]:

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

In [14]:

```
#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[14]:

```
1    4178
0     808
Name: Score, dtype: int64
```

[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 [15]:
```
# 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.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<
br /><br />The Victor M380 and M502 traps are unreal, of course -- tota
l fly genocide. Pretty stinky, but only right nearby.
==================================================
```

```
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.<br /><br />These are chocolate-oatmeal cookies.  If you don't li
ke that combination, don't order this type of cookie.  I find the combo
quite nice, really.  The oatmeal sort of "calms" the rich chocolate fla
vor and gives the cookie sort of a coconut-type consistency.  Now let's
also remember that tastes differ; so, I've given my opinion.<br /><br /
>Then, these are soft, chewy cookies -- as advertised.  They are not "c
rispy" cookies, or the blurb would say "crispy," rather than "chewy."
I happen to like raw cookie dough; however, I don't see where these tas
te like raw cookie dough.  Both are soft, however, so is this the confu
sion?  And, yes, they stick together.  Soft cookies tend to do that.  T
hey aren't individually wrapped, which would add to the cost.  Oh yeah,
chocolate chip cookies tend to be somewhat sweet.<br /><br />So, if you
want something hard and crisp, I suggest Nabiso's Ginger Snaps.  If you
want a cookie that's soft, chewy and tastes like a combination of choco
late and oatmeal, give these a try.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />Thi
s k cup is great coffee.  dcaf is very good as well
==================================================
```

In [16]:

```python
# 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 M380 and M502 traps are unreal, of course -- t
otal fly genocide. Pretty stinky, but only right nearby.
```

In [16]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
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 M502 traps are unreal, of course -- total fly gen
ocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
```

```
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.These are chocolate-oatmeal cookies.  If you don't like that comb
ination, don't order this type of cookie.  I find the combo quite nice,
really.  The oatmeal sort of "calms" the rich chocolate flavor and give
s the cookie sort of a coconut-type consistency.  Now let's also rememb
er that tastes differ; so, I've given my opinion.Then, these are soft,
chewy cookies -- as advertised.  They are not "crispy" cookies, or the
blurb would say "crispy," rather than "chewy."  I happen to like raw co
okie dough; however, I don't see where these taste like raw cookie doug
h.  Both are soft, however, so is this the confusion?  And, yes, they s
tick together.  Soft cookies tend to do that.  They aren't individually
wrapped, which would add to the cost.  Oh yeah, chocolate chip cookies
tend to be somewhat sweet.So, if you want something hard and crisp, I s
uggest Nabiso's Ginger Snaps.  If you want a cookie that's soft, chewy
and tastes like a combination of chocolate and oatmeal, give these a tr
y.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cu
p is great coffee.  dcaf is very good as well
```

In [17]:

```python
# 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 [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I am sorry; but
these reviews do nobody any good beyond reminding us to look  before or
dering.<br /><br />These are chocolate-oatmeal cookies.  If you do not
like that combination, do not order this type of cookie.  I find the co
mbo quite nice, really.  The oatmeal sort of "calms" the rich chocolate
flavor and gives the cookie sort of a coconut-type consistency.  Now le
t is also remember that tastes differ; so, I have given my opinion.<br
/><br />Then, these are soft, chewy cookies -- as advertised.  They are
not "crispy" cookies, or the blurb would say "crispy," rather than "che
wy."  I happen to like raw cookie dough; however, I do not see where th
ese taste like raw cookie dough.  Both are soft, however, so is this th
e confusion?  And, yes, they stick together.  Soft cookies tend to do t
hat.  They are not individually wrapped, which would add to the cost.
Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br /><br />S
o, if you want something hard and crisp, I suggest Nabiso is Ginger Sna
ps.  If you want a cookie that is soft, chewy and tastes like a combina
tion of chocolate and oatmeal, give these a try.  I am here to place my
second order.
==================================================
```

In [18]:
```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
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 Victor  and  traps are unreal, of course -- total fly
genocide. Pretty stinky, but only right nearby.
```

In [19]:
```
#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 wer
e ordering the other wants crispy cookies Hey I m sorry but these revie
ws do nobody any good beyond reminding us to look before ordering br br
These are chocolate oatmeal cookies If you don t like that combination
don t order this type of cookie I find the combo quite nice really The
oatmeal sort of calms the rich chocolate flavor and gives the cookie so
rt of a coconut type consistency Now let s also remember that tastes di
ffer so I ve given my opinion br br Then these are soft chewy cookies a
s advertised They are not crispy cookies or the blurb would say crispy
rather than chewy I happen to like raw cookie dough however I don t see
where these taste like raw cookie dough Both are soft however so is thi
s the confusion And yes they stick together Soft cookies tend to do tha
t They aren t individually wrapped which would add to the cost Oh yeah
chocolate chip cookies tend to be somewhat sweet br br So if you want s
omething hard and crisp I suggest Nabiso s Ginger Snaps If you want a c
ookie that s soft chewy and tastes like a combination of chocolate and
oatmeal give these a try I m here to place my second order
```

In [20]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <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', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
```

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

In [23]:

```
# 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████████████████
██████████| 4986/4986 [00:01<00:00, 2735.03it/s]
```

In [24]:
```
preprocessed_reviews[1500]
```

Out[24]:
```
'wow far two two star reviews one obviously no idea ordering wants cris
py cookies hey sorry reviews nobody good beyond reminding us look order
ing chocolate oatmeal cookies not like combination not order type cooki
e find combo quite nice really oatmeal sort calms rich chocolate flavor
gives cookie sort coconut type consistency let also remember tastes dif
fer given opinion soft chewy cookies advertised not crispy cookies blur
b would say crispy rather chewy happen like raw cookie dough however no
t see taste like raw cookie dough soft however confusion yes stick toge
ther soft cookies tend not individually wrapped would add cost oh yeah
chocolate chip cookies tend somewhat sweet want something hard crisp su
ggest nabiso ginger snaps want cookie soft chewy tastes like combinatio
n chocolate oatmeal give try place second order'
```

[3.2] Preprocess Summary

In [25]:
```
## Similartly you can do preprocessing for review summary also.
from tqdm import tqdm
preprocessed_summary = []
#tqdm is for printing the status bar
for sentence in tqdm(final['Summary'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_summary.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████
██████████| 4986/4986 [00:01<00:00, 3468.14it/s]
```

In [26]:
```
preprocessed_summary[1500]
```

Out[26]:
```
'coffee supposedly premium tastes watery thin not good maybe old not su
re waste using line bottom sitting shoes trash cans rained luggage abso
rb smells used not drink not buy'
```

[4] Featurization

[4.1] BAG OF WORDS

In [27]:
```
score = final['Score'] #storing all scores in new series
print(type(score))
print(score.shape)
```

```
<class 'pandas.core.series.Series'>
(4986,)
```

In [28]:
```
#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', 'abb
ott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

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

In [29]:
```python
from sklearn.preprocessing import StandardScaler
std_data = StandardScaler(with_mean=False).fit_transform(final_counts)
std_data.shape
```

```
C:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConv
ersionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConv
ersionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

Out[29]:
```
(4986, 12997)
```

In [30]:
```python
type(std_data)
```

Out[30]:
```
scipy.sparse.csr.csr_matrix
```

In [31]:
```python
std_data = std_data.todense()
type(std_data)
```

Out[31]:
```
numpy.matrixlib.defmatrix.matrix
```

[4.2] Bi-Grams and n-Grams.

In [32]:
```python
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.
org/stable/modules/generated/sklearn.feature_extraction.text.CountVecto
rizer.html
```

```
# you can choose these numebrs min_df=10, max_features=5000, of your ch
oice
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_s
hape())
print("the number of unique words including both unigrams and bigrams "
, final_bigram_counts.get_shape()[1])
```

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

[4.3] TF-IDF

In [33]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape
())
print("the number of unique words including both unigrams and bigrams "
, final_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble find', 'able get', 'absolute', 'absolutely', 'absolutely deliciou
s', 'absolutely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.4] Word2Vec

In [34]:
```
# 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 [35]:
```
# 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 val
ues
# To use this code-snippet, download "GoogleNews-vectors-negative300.bi
n"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edi
t
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17
SRFAzZPY
# 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', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
[('snack', 0.9960731863975525), ('alternative', 0.9960423111915588),
('mellow', 0.9956516623497009), ('satisfying', 0.995613157749176), ('ta
sty', 0.9955406188964844), ('excellent', 0.9955399036407471), ('wonderf
ul', 0.9952979683876038), ('bad', 0.9952245354652405), ('especially',
0.9951435923576355), ('crunch', 0.9951103925704956)]
==================================================
[('comes', 0.9995228052139282), ('actual', 0.9994649887084961), ('bee
f', 0.9994617700576782), ('oh', 0.9994484782218933), ('sound', 0.999448
1205940247), ('wow', 0.9994404911994934), ('wife', 0.9994165897369385),
('major', 0.9994014501571655), ('person', 0.999396562576294), ('lays',
0.9993849992752075)]
```

In [36]:

```
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', 'st
inky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'receiv
ed', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'ins
tead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use',
'car', 'windows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fu
n', 'everywhere', 'like', 'tv', 'computer', 'really', 'good', 'idea',
'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'mad
e']
```

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

[4.4.1.1] Avg W2v

In [37]:
```
# 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 change this to 300 if you use google's w2v
    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, 1247.48it/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [38]:
```
# 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 v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [39]:

```
# 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 ce
ll_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is st
ored in this list
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/r
eview
    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 [00:23<00:00, 212.18it/s]
```

[5] Applying TSNE

1. you need to plot 4 tsne plots with each of these feature set

   A. Review text, preprocessed one converted into vectors using (BOW)
   B. Review text, preprocessed one converted into vectors using (TFIDF)
   C. Review text, preprocessed one converted into vectors using (AVG W2v)
   D. Review text, preprocessed one converted into vectors using (TFIDF W2v)
2. Note 1: The TSNE accepts only dense matrices
3. Note 2: Consider only 5k to 6k data points

TSNE is an iterative algorithm: tries to process all the data in iterations.

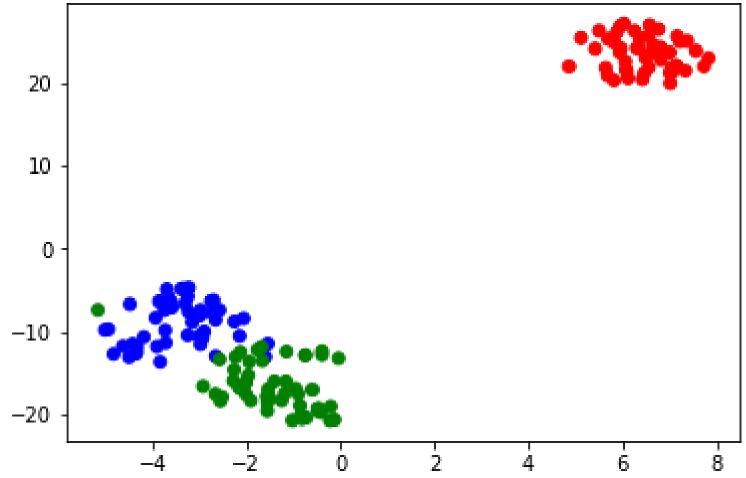
Eventually it reaches a stage of clusters are not more moving.

Parameters of TSNE : perplexity, StepSize.

In [40]:

```
# https://github.com/pavlin-policar/fastTSNE you can try this also, thi
s version is little faster than sklearn
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.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix

for_tsne = np.hstack((X_embedding, y.reshape(-1,1)))
```

```
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimen
sion_y','Score'])
colors = {0:'red', 1:'blue', 2:'green'}
plt.scatter(for_tsne_df['Dimension_x'], for_tsne_df['Dimension_y'], c=f
or_tsne_df['Score'].apply(lambda x: colors[x]))
plt.show()
```



[5.1] Applying TNSE on Text BOW vectors

In [40]:

```
# please write all the code with proper documentation, and proper title
s for each subsection
# 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.preprocessing import StandardScaler
print(final_bigram_counts.shape)
std_data = StandardScaler(with_mean= False).fit_transform(final_bigram_
counts)
```

```
print(std_data.shape)
type(std_data)
std_data=std_data.todense()
print(type(std_data))
```

```
(4986, 3144)
```

```
C:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data with input dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data with input dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

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

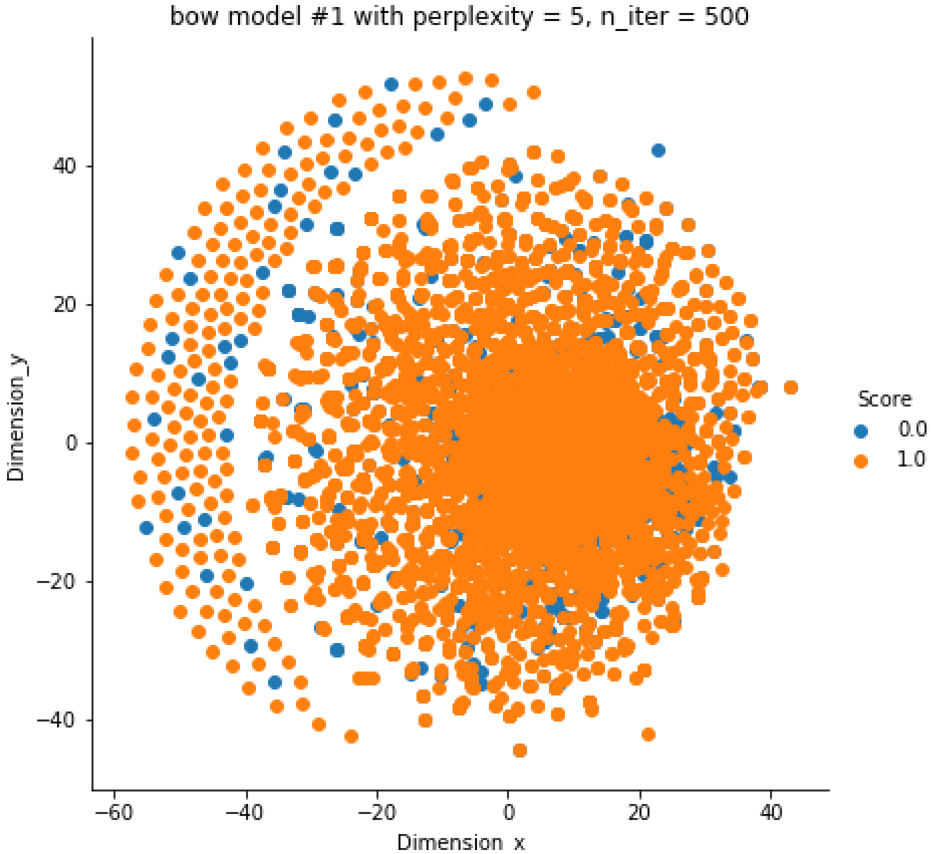
Perplexity: No of neighbors loosely to when the distances preserved.

StepSize: No of iterations better the solution.

In [41]:

```
from sklearn.manifold import TSNE
from sklearn import datasets
import pandas as pd
import matplotlib.pyplot as plt

model = TSNE(n_components=2, perplexity=5, n_iter=500, learning_rate=200, random_state=0)
for_tsne = model.fit_transform(std_data)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit_transform(x.toarray()) , .toarray() will convert the sparse matrix into dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
```

```
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimen
sion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('bow model #1 with perplexity = 5, n_iter = 500')
plt.show()
```

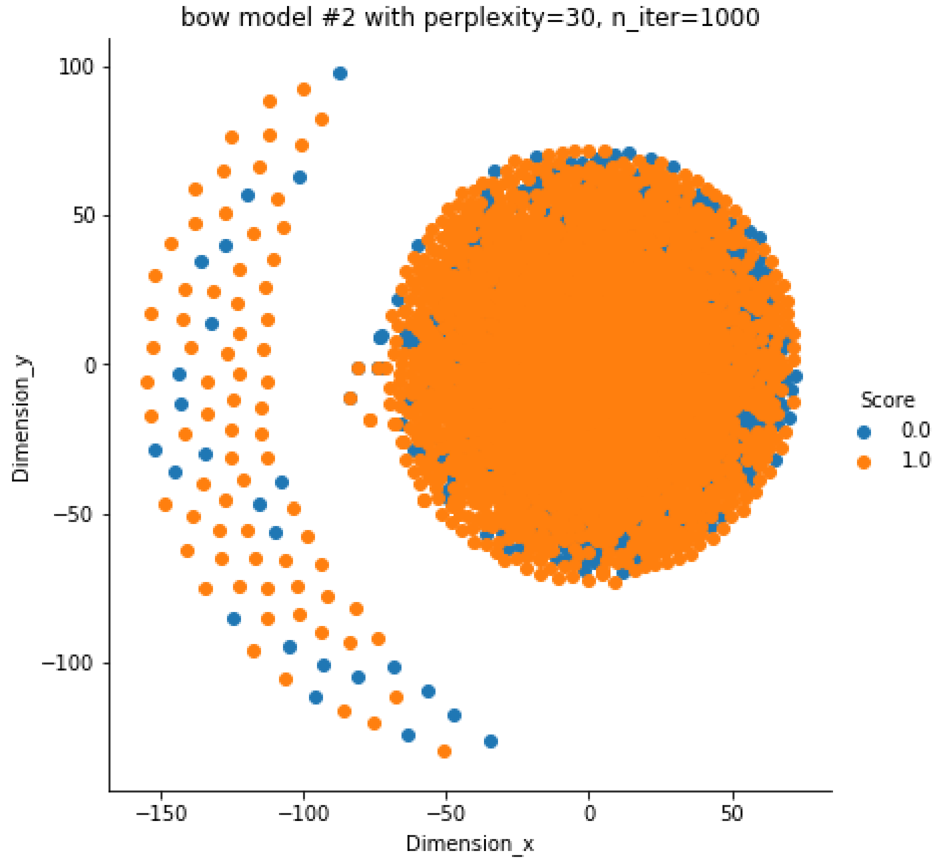


Observation:

1. Bow model at 500 iterations is not classifying positive and negative reviews of the preprocessed text it's unable to distinguish since the points formed cluster of overlapped(crowded) .

2. Let's increase the n_iter, perplexity and see whether it's going to distinguish b/w positive and negative text.

In [42]:
```
model = TSNE(n_components=2, perplexity=30, n_iter=1000, learning_rate=400, random_state=0)
for_tsne = model.fit_transform(std_data)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit_transform(x.toarray()) , .toarray() will convert the sparse matrix into dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimension_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dimension_x', 'Dimension_y').add_legend()
plt.title('bow model #2 with perplexity=30, n_iter=1000')
plt.show()
```

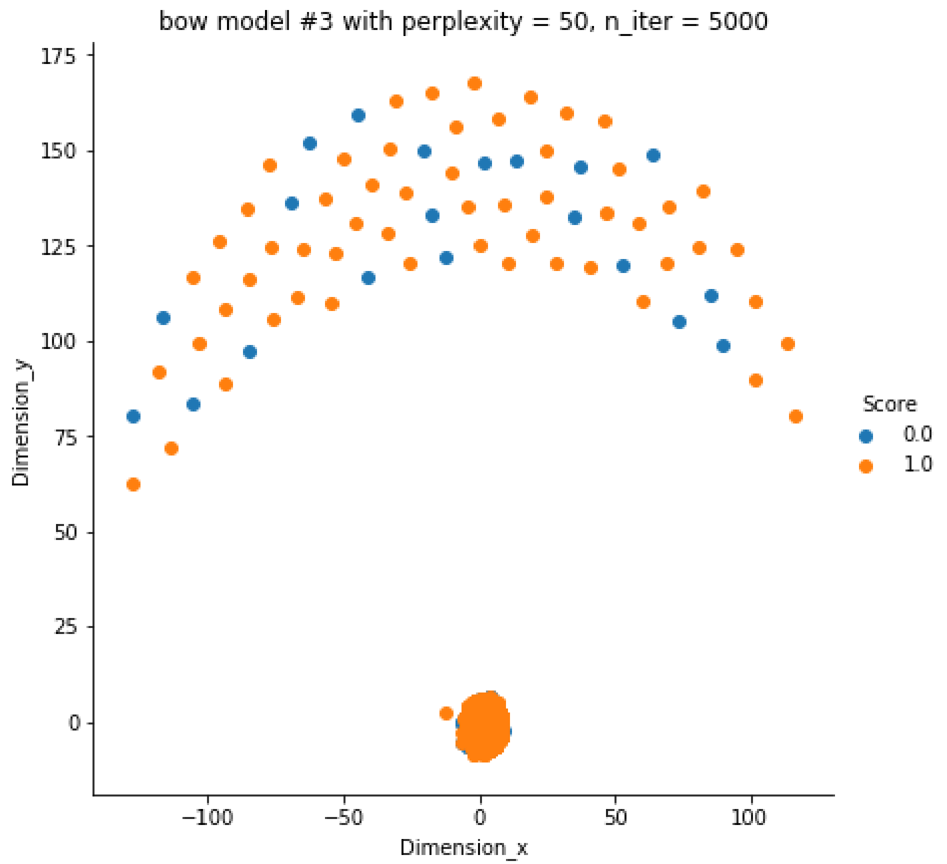


Observation:

1. Bow model2 with increment in itertion to 1000 is also unable to distinguish b/w positive and negative text.
2. let's increment the iteration and perplexity and check whether model is going to stable.
3. The points are more grouped as compared to above plot where points are scattered.

In [44]:
```
model = TSNE(n_components=2, perplexity=50, n_iter=5000, learning_rate=
600, random_state=0)
for_tsne = model.fit_transform(std_data)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit
```

```
_transform(x.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimen
sion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('bow model #3 with perplexity = 50, n_iter = 5000')
plt.show()
```



Observation:

1. Bow model3 with increased iteration of 5000, we can infer that model became stable. it's unable to classify text reviews.
2. Still we cannot determine whether the reviews of text are positive or not.

[5.1] Applying TNSE on Text TFIDF vectors

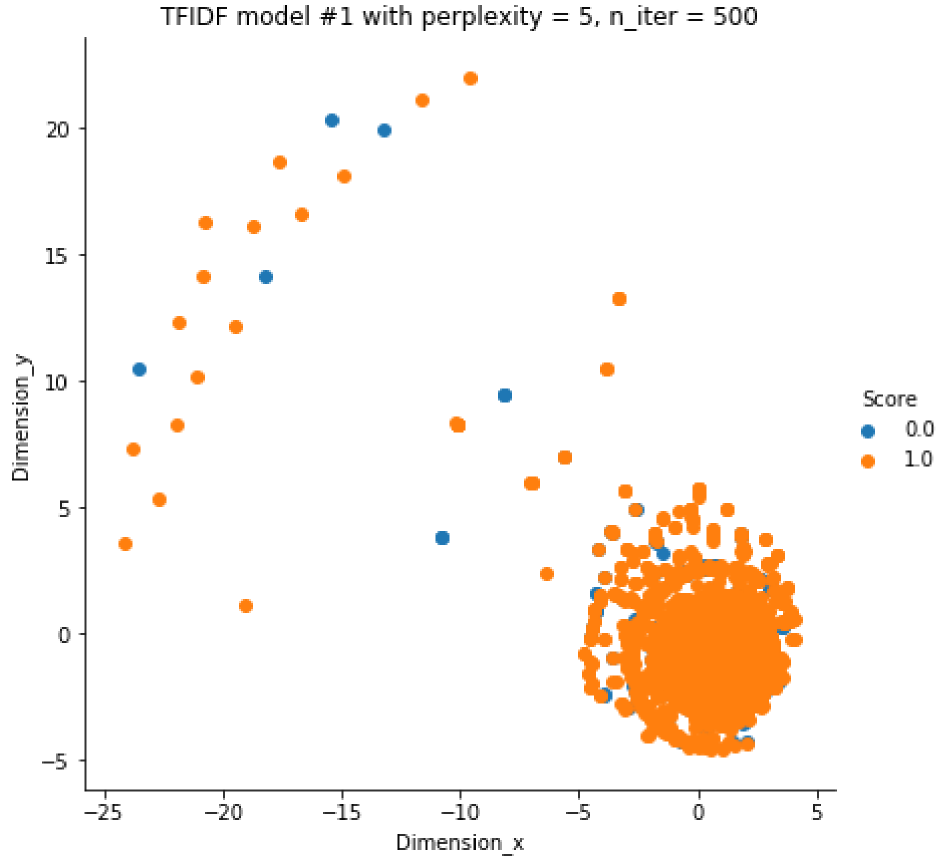
In [45]:
```
# please write all the code with proper documentation, and proper title
s for each subsection
# when you plot any graph make sure you use
    # a. Title, that describes your plot, this will be very helpful to
 the reader
    # b. Legends if needed
    # c. X-axis label
    # d. Y-axis label

from sklearn.preprocessing import StandardScaler
std_data1 = StandardScaler(with_mean = False).fit_transform(final_tf_id
f)
print(std_data1.shape)
type(std_data1)
std_data1 = std_data1.todense()
type(std_data1)
```

```
(4986, 3144)
```

Out[45]:
```
numpy.matrixlib.defmatrix.matrix
```

In [57]:
```
model = TSNE(n_components=2, perplexity=5, n_iter=500, learning_rate=20
0, random_state=0)
for_tsne = model.fit_transform(std_data1)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit
_transform(x.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimen
```

```
sion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('TFIDF model #1 with perplexity = 5, n_iter = 500')
plt.show()
```

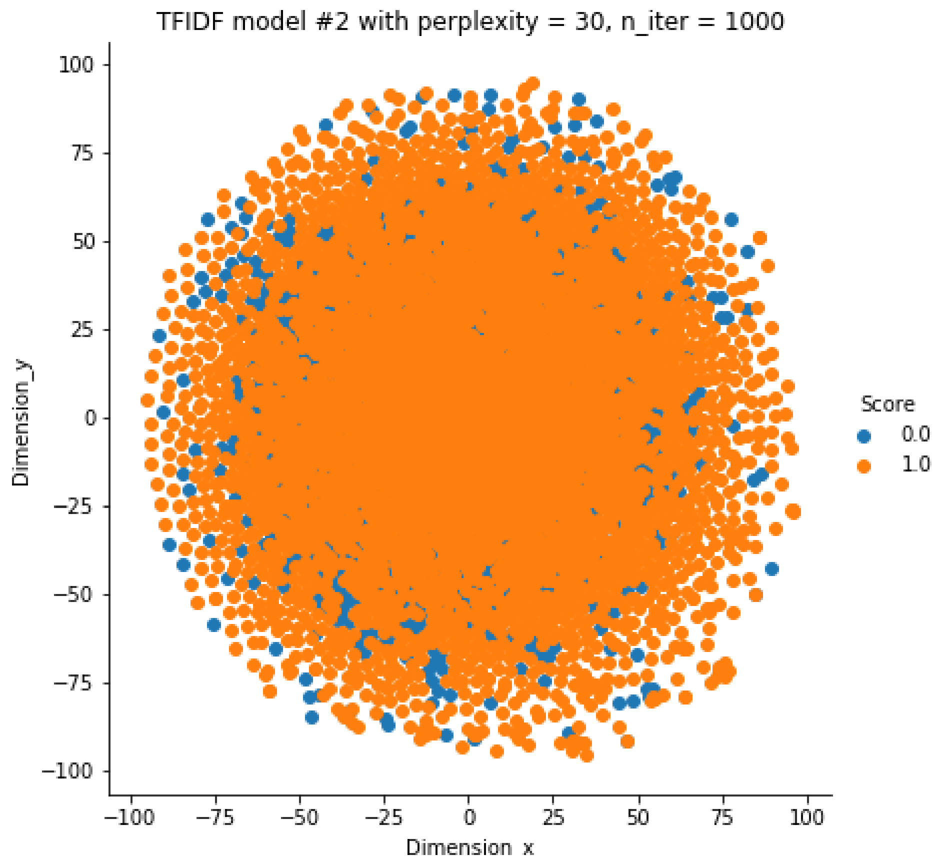


Observation:

1. Plot became dispersed still it's not stable with iter(500).

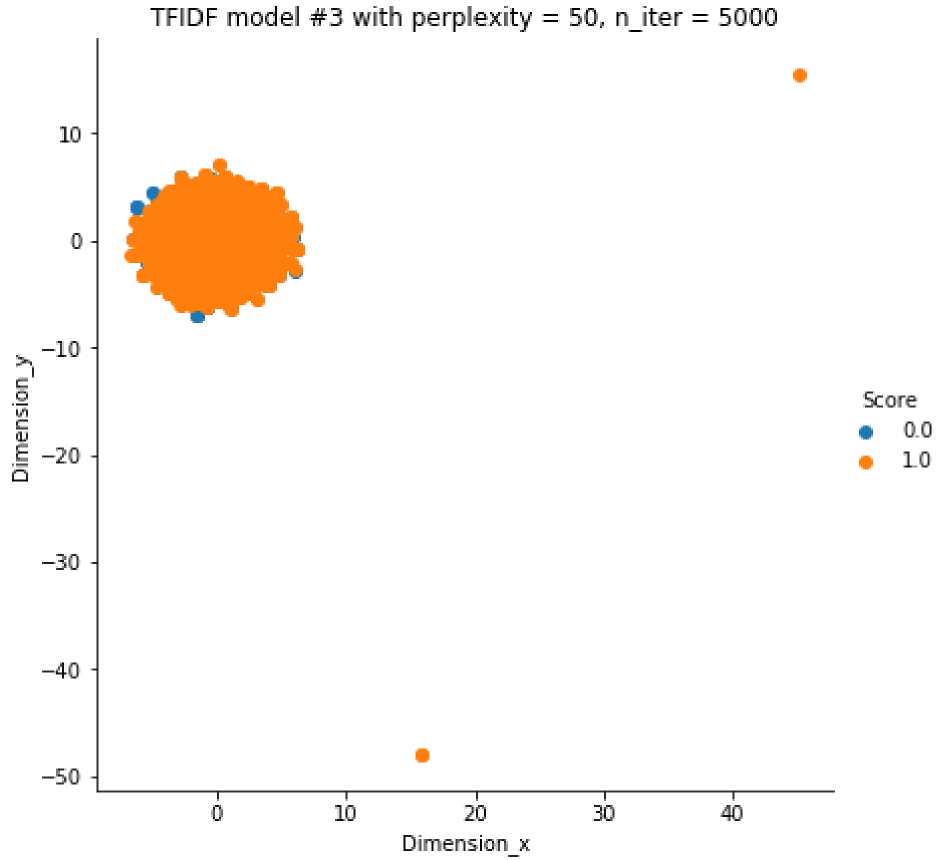
In [58]:
```
model = TSNE(n_components=2, perplexity=30, n_iter=1000, learning_rate=
```

```
400, random_state=0)
for_tsne = model.fit_transform(std_data1)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit
_transform(x.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimen
sion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('TFIDF model #2 with perplexity = 30, n_iter = 1000')
plt.show()
```



Observation: Plot became Stable at 1000 iter, due to class imbalance of more positive points and less negative points. '1' : Positive points. '2' : Negative Points.

In [59]:
```
model = TSNE(n_components=2, perplexity=50, n_iter=5000, learning_rate=
600, random_state=0)
for_tsne = model.fit_transform(std_data1)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit
_transform(x.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x','Dimen
sion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('TFIDF model #3 with perplexity = 50, n_iter = 5000')
plt.show()
```



Observation: Most of the points are clustered around top left handside of the plot and is not stable.

[5.3] Applying TNSE on Text Avg W2V vectors

In [49]:
```
# please write all the code with proper documentation, and proper title
s for each subsection
# 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.preprocessing import StandardScaler
std_data2 = StandardScaler(with_mean= False).fit_transform(sent_vectors
)
print(std_data2.shape)
type(std_data2)
```

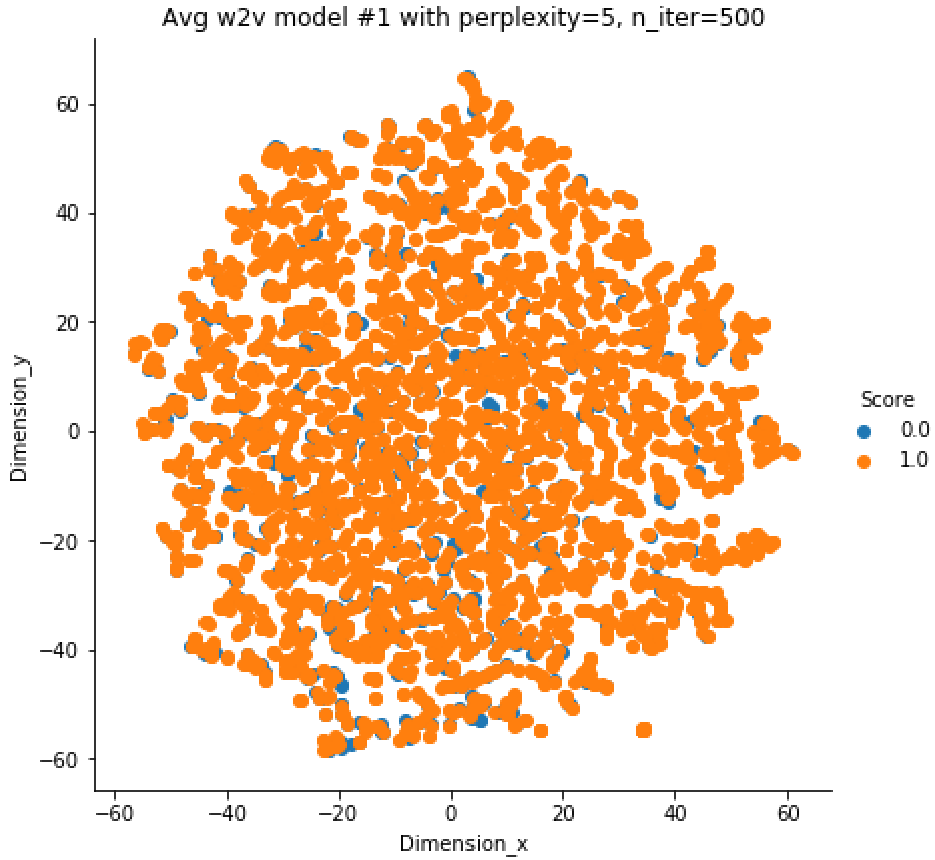
```
(4986, 50)
```

Out[49]:

```
numpy.ndarray
```

In [50]:

```
model = TSNE(n_components=2, perplexity=5, learning_rate=200, n_iter=50
0, random_state=0)
for_tsne = model.fit_transform(std_data2)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit
_transform(x.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix

for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns= ['Dimension_x', 'Dim
ension_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('Avg w2v model #1 with perplexity=5, n_iter=500')
plt.show()
```

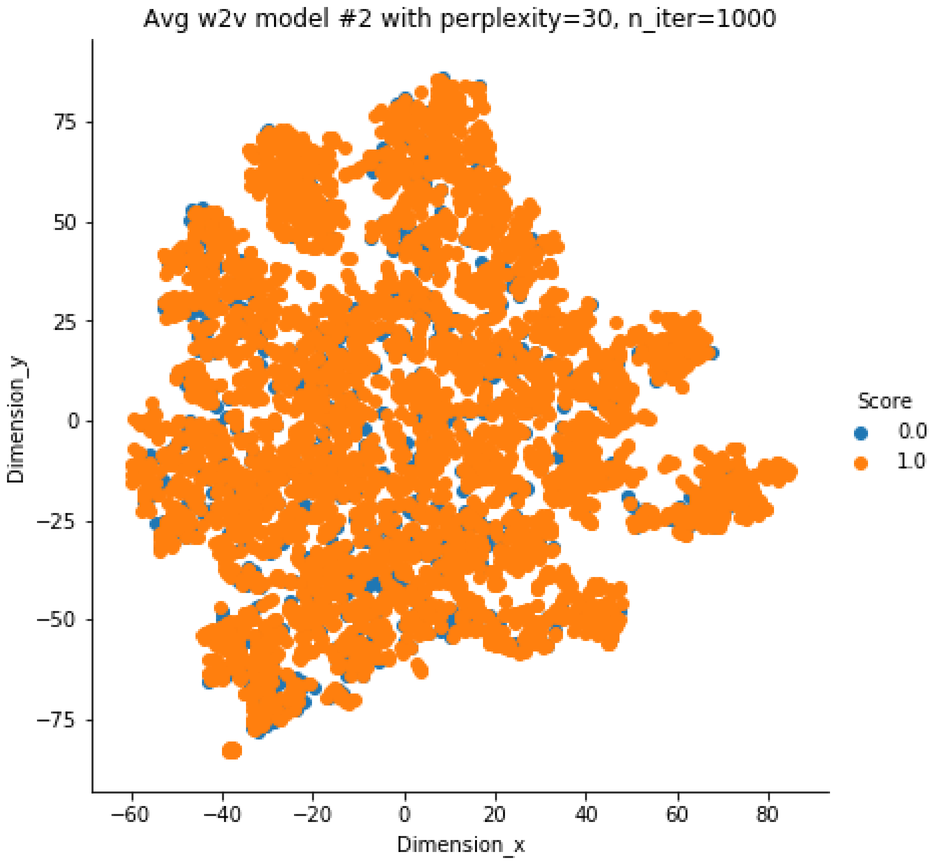


Observation:

1. Due to class imbalance plot is scattered at 500 iter. More no of Positive points are observed than negative points.

In [51]:
```
model = TSNE(n_components=2, perplexity=30, learning_rate=400, n_iter=1
000, random_state=0)
for_tsne = model.fit_transform(std_data2)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit
_transform(x.toarray()) , .toarray() will convert the sparse matrix int
o dense matrix
```

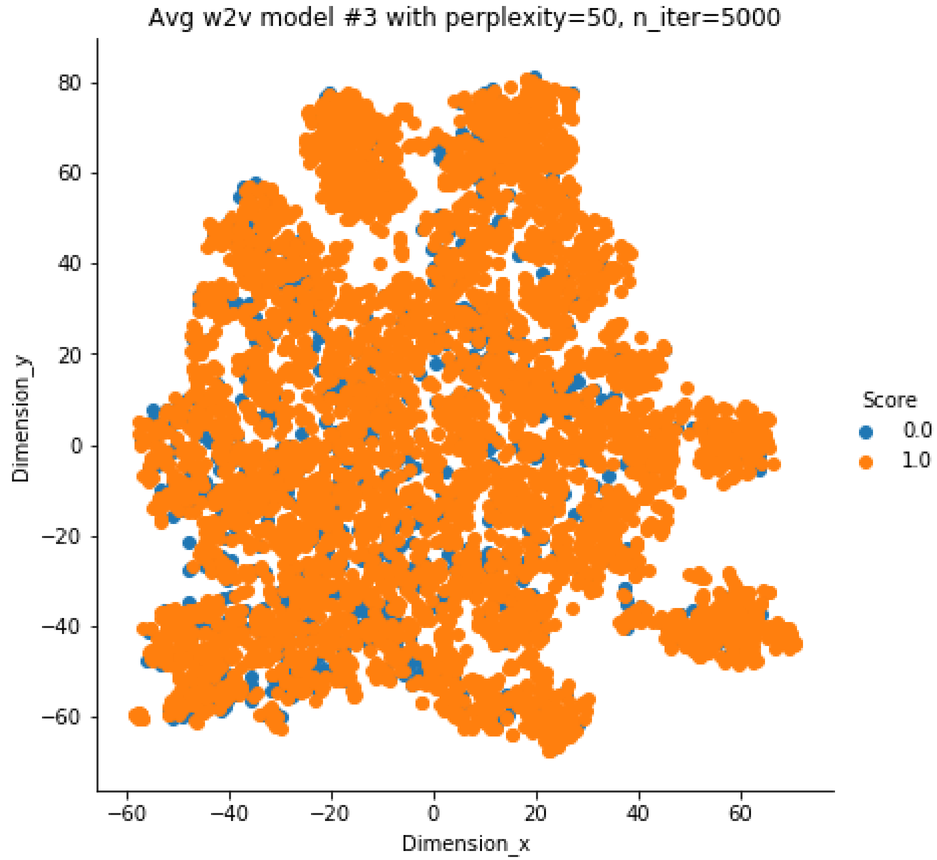
```
for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x', 'Dime
nsion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue="Score", height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('Avg w2v model #2 with perplexity=30, n_iter=1000')
plt.show()
```



Observation:

1. we can observe that points overlap massively and form different clusters with more no of positive points.

In [52]:
```
model = TSNE(n_components=2, perplexity=50, learning_rate= 600, n_iter=
5000, random_state=0)
for_tsne = model.fit_transform(std_data2)
for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x', 'Dime
nsion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue='Score', height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('Avg w2v model #3 with perplexity=50, n_iter=5000')
plt.show()
```



Observation: At model 3 of Avg w2v with 5000 iter also we can see overlap of +ve and -ve points.

[5.4] Applying TNSE on Text TFIDF weighted W2V vectors

In [53]:

```
# please write all the code with proper documentation, and proper title
s for each subsection
# 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.preprocessing import StandardScaler
std_data3 = StandardScaler(with_mean = False).fit_transform(tfidf_sent_vectors)
print(std_data3.shape)
type(std_data3)
```

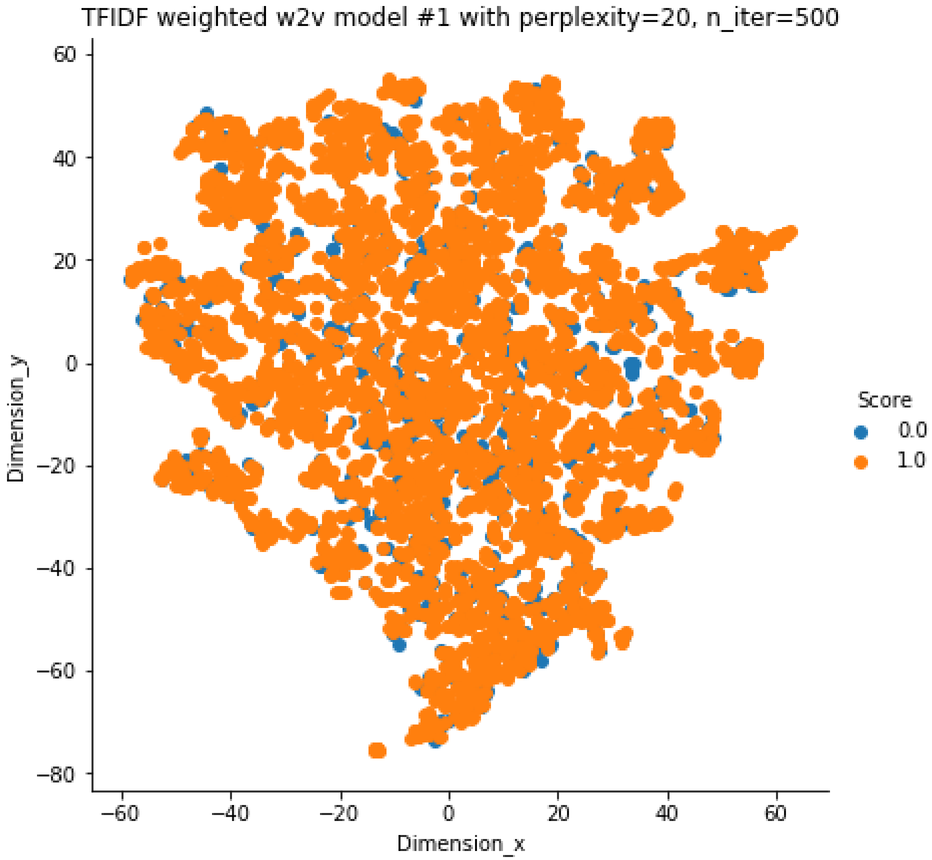
```
(4986, 50)
```

Out[53]:

```
numpy.ndarray
```

In [54]:

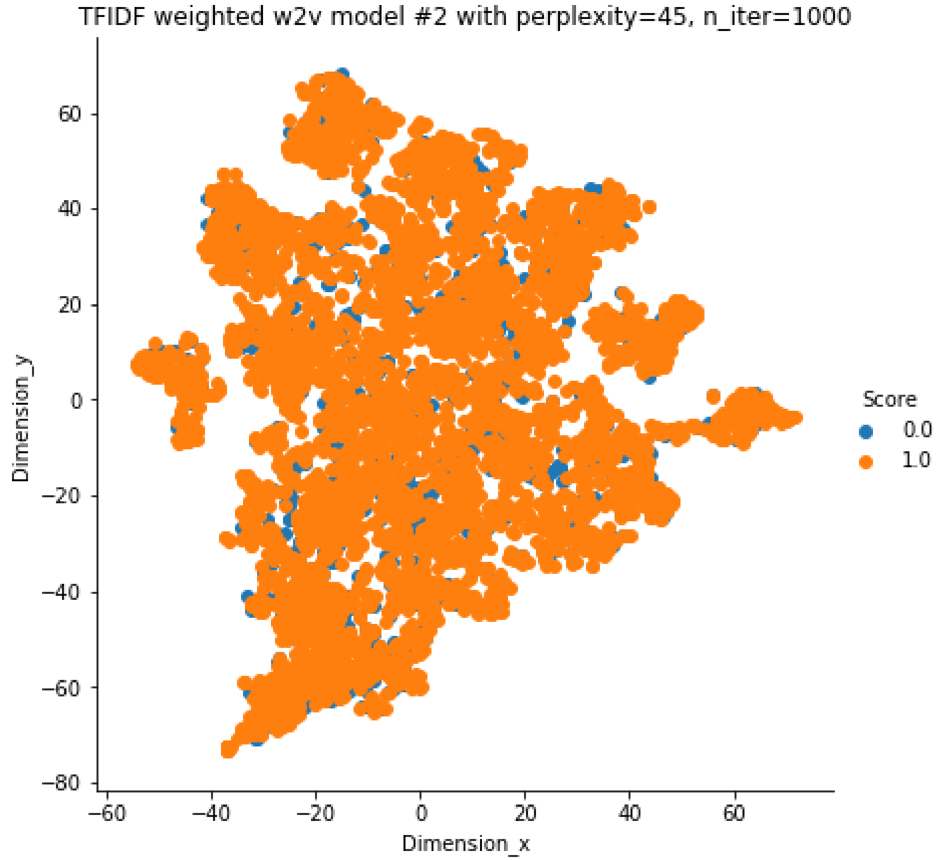
```
model = TSNE(n_components=2, perplexity=20, n_iter=500, learning_rate=600, random_state=0)
for_tsne = model.fit_transform(std_data3)
for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x', 'Dimension_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue='Score', height=6).map(plt.scatter, 'Dimension_x', 'Dimension_y').add_legend()
plt.title('TFIDF weighted w2v model #1 with perplexity=20, n_iter=500')
plt.show()
```



Observation: we can observe that both the classes are not going to seperable.

In [55]:
```
model = TSNE(n_components=2, perplexity=45, n_iter=1000, learning_rate=
400, random_state=0)
for_tsne = model.fit_transform(std_data3)
for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x', 'Dime
nsion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue='Score', height=6).map(plt.scatter, 'Dim
ension_x', 'Dimension_y').add_legend()
plt.title('TFIDF weighted w2v model #2 with perplexity=45, n_iter=1000'
```

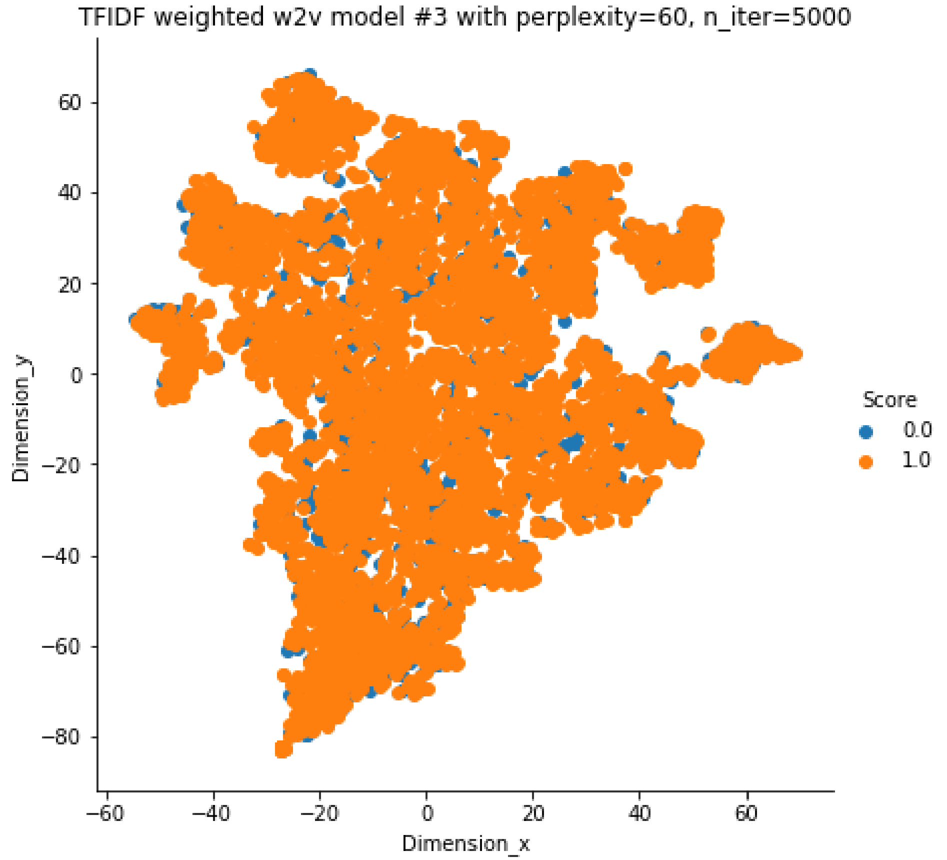
```
)
plt.show()
```



Observation: None of the measurements of TSNE helpful to determine the class labels.

In [56]:
```
model = TSNE(n_components=2, perplexity= 60, n_iter=5000, learning_rate
=200, random_state=0)
for_tsne = model.fit_transform(std_data3)
for_tsne = np.vstack((for_tsne.T, score)).T
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dimension_x', 'Dime
nsion_y', 'Score'])
sns.FacetGrid(for_tsne_df, hue='Score', height=6).map(plt.scatter, 'Dim
```

```
ension_x', 'Dimension_y').add_legend()
plt.title('TFIDF weighted w2v model #3 with perplexity=60, n_iter=5000'
)
plt.show()
```



Observation: By expermenting with increasing iterartions and perplexity also plots are not differentaited well.

[6] Conclusions

1. Experimenting with multiple no of iterations, and perplexity until the plot becomes stable.
2. Due to class imbalance we cannot determine the review points, as it belongs to positive class or negative class label. Certain words occur in both the class labels.
3. More no iterations and perplexity better is the plot. It becomes stable at certain iteration.
4. TSNE expands dense clusters, shrinks sparse clusters.
5. TSNE group points based on their visual similarity.
6. Points which are visually similar group togetehr, points less similar are far away.

In [ ]:

```

```