Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (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 [3]:

```
%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
```

[1]. Reading Data

In [4]:

```

# 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 500000 data point:
# 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 5(
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 100(

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r(
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 (10000, 10)
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [5]:

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

In [6]:

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

(80668, 7)

Out[6]:

	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
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [7]:

```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[7]:

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

In [8]:

```
display['COUNT(*)'].sum()
```

Out[8]:

```
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 [9]:

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

Out[9]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDen
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 [10]:

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

In [11]:

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

Out[11]:

```
(9564, 10)
```

In [12]:

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

Out[12]:

```
95.64
```

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 [13]:

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

display.head()
```

Out[13]:

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

In [14]:

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

In [15]:

```
#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=final.sample(5000)
Score1=final['Score']
final['Score'].value_counts()
```

```
(9564, 10)
```

Out[15]:

```
1    4190
0     810
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 [16]:

```python
# 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)
```

```
Most Caribou coffees are too weak for me. This one is a delicious exception.
It's right up there with Revv, Emeril's bold, or Van Houtte's eclipse. A Dar
k bold coffee without tasting burned or bitter.
==================================================
Ok - so this is the best flavored coffee ever.  No after taste that seems to
always occur w/flavored coffees & its not even really flavored, it has hint
of coconut taste but it really still tastes like coffee just the best coffee
ever... mmmmmm... add honey.. yummy!!!!!<br />Highly recommend!
==================================================
Gum made without sugar substitutes isn't easily obtained these days, so I wa
s happy to find Chiclets through Amazon Prime.  Sugar substitutes present pr
oblems for persons sensitive to them, so it's good to have the option of gum
made the old-fashioned way. Another source for this and other gum from yeste
ryear is Vermont Country Store online; however VCS sells the same box of Chi
clets for $14.95, so clearly Amazon is a better deal.  Amazon Prime (free sh
ipping) makes it a much better deal.<br /><br />My Great-Grandpa used to com
e home with Chiclets from time to time, so this gum isn't just loaded with l
ong-lasting peppermint flavor, but long-lasting, happy memories, as well.  I
guess you can say there's a lot packed into such a little piece of gum.  Hop
e you enjoy as much as I do.
==================================================
Coffee beans did not seem fresh.  No oil on them what so ever.  I have taste
d much better and fresher.  Will not order again.
==================================================
```

In [17]:

```
# 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)
```

```
Most Caribou coffees are too weak for me. This one is a delicious exception.
It's right up there with Revv, Emeril's bold, or Van Houtte's eclipse. A Dar
k bold coffee without tasting burned or bitter.
```

In [18]:

```
# 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)
```

```
Most Caribou coffees are too weak for me. This one is a delicious exception.
It's right up there with Revv, Emeril's bold, or Van Houtte's eclipse. A Dar
k bold coffee without tasting burned or bitter.
==================================================
Ok - so this is the best flavored coffee ever.  No after taste that seems to
always occur w/flavored coffees & its not even really flavored, it has hint
of coconut taste but it really still tastes like coffee just the best coffee
ever... mmmmmm... add honey.. yummy!!!!!Highly recommend!
==================================================
Gum made without sugar substitutes isn't easily obtained these days, so I wa
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made the old-fashioned way. Another source for this and other gum from yeste
ryear is Vermont Country Store online; however VCS sells the same box of Chi
clets for $14.95, so clearly Amazon is a better deal.  Amazon Prime (free sh
ipping) makes it a much better deal.My Great-Grandpa used to come home with
Chiclets from time to time, so this gum isn't just loaded with long-lasting
peppermint flavor, but long-lasting, happy memories, as well.  I guess you c
an say there's a lot packed into such a little piece of gum.  Hope you enjoy
as much as I do.
==================================================
Coffee beans did not seem fresh.  No oil on them what so ever.  I have taste
d much better and fresher.  Will not order again.
```

In [19]:

```
# 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 [20]:

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

```
Gum made without sugar substitutes is not easily obtained these days, so I w
as happy to find Chiclets through Amazon Prime.  Sugar substitutes present p
roblems for persons sensitive to them, so it is good to have the option of g
um made the old-fashioned way. Another source for this and other gum from ye
steryear is Vermont Country Store online; however VCS sells the same box of
Chiclets for $14.95, so clearly Amazon is a better deal.  Amazon Prime (free
shipping) makes it a much better deal.<br /><br />My Great-Grandpa used to c
ome home with Chiclets from time to time, so this gum is not just loaded wit
h long-lasting peppermint flavor, but long-lasting, happy memories, as well.
I guess you can say there is a lot packed into such a little piece of gum.
Hope you enjoy as much as I do.
==================================================
```

In [21]:

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

```
Most Caribou coffees are too weak for me. This one is a delicious exception.
It's right up there with Revv, Emeril's bold, or Van Houtte's eclipse. A Dar
k bold coffee without tasting burned or bitter.
```

In [22]:

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

```
Gum made without sugar substitutes is not easily obtained these days so I wa
s happy to find Chiclets through Amazon Prime Sugar substitutes present prob
lems for persons sensitive to them so it is good to have the option of gum m
ade the old fashioned way Another source for this and other gum from yestery
ear is Vermont Country Store online however VCS sells the same box of Chicle
ts for 14 95 so clearly Amazon is a better deal Amazon Prime free shipping m
akes it a much better deal br br My Great Grandpa used to come home with Chi
clets from time to time so this gum is not just loaded with long lasting pep
permint flavor but long lasting happy memories as well I guess you can say t
here is a lot packed into such a little piece of gum Hope you enjoy as much
as I do
```

In [23]:

```
# 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', "t
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'h
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'o
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'an
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mig
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", '
            'won', "won't", 'wouldn', "wouldn't"])
```

In [24]:

```
# Combining all the above statements
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwo
    preprocessed_reviews.append(sentance.strip())
```

```
100%|█████████████████████████████████████████████
█████| 5000/5000 [00:01<00:00, 3208.75it/s]
```

In [25]:

```
len(preprocessed_reviews)
```

Out[25]:

```
5000
```

In [26]:

```
preprocessed_reviews[1500]
```

Out[26]:

```
'gum made without sugar substitutes not easily obtained days happy find chic
lets amazon prime sugar substitutes present problems persons sensitive good
option gum made old fashioned way another source gum yesteryear vermont coun
try store online however vcs sells box chiclets clearly amazon better deal a
mazon prime free shipping makes much better deal great grandpa used come hom
e chiclets time time gum not loaded long lasting peppermint flavor long last
ing happy memories well guess say lot packed little piece gum hope enjoy muc
h'
```

[3.2] Preprocess Summary

In [27]:

```
## Similartly you can do preprocessing for review summary also.

warnings.filterwarnings("ignore")

preprocessed_summary = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Summary'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # 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())
```

```
100%|████████████████████████████████████████████████████████████████████
█████| 5000/5000 [00:01<00:00, 4594.37it/s]
```

In [28]:

```
len(preprocessed_summary)
```

Out[28]:

```
5000
```

In [29]:

```
preprocessed_summary[4848]
```

Out[29]:

```
'great chip substitute'
```

[4] Featurization

[4.1] BAG OF WORDS

In [66]:

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

```
some feature names  ['aa', 'aahhhs', 'ab', 'abates', 'abberline', 'abbott',
'abby', 'abdominal', 'ability', 'able']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (5000, 13786)
the number of unique words  13786
```

[4.2] Bi-Grams and n-Grams.

In [30]:

```
#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_
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (5000, 3246)
the number of unique words including both unigrams and bigrams  3246
```

[4.3] TF-IDF

In [32]:

```
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 f
ind', 'able get', 'absolute', 'absolutely', 'absolutely delicious', 'absolut
ely love', 'absolutely loves', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (5000, 3192)
the number of unique words including both unigrams and bigrams  3192
```

[4.4] Word2Vec

In [33]:

```
# 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 [34]:

```
# 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.bi
        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
```

```
[('surprised', 0.9939281940460205), ('wonderful', 0.9930830001831055), ('bud
s', 0.9930804371833801), ('yum', 0.9929231405258179), ('caramel', 0.99270868
3013916), ('others', 0.9926697015762329), ('outstanding', 0.992548465728759
8), ('say', 0.9925089478492737), ('darker', 0.9924708604812622), ('awful',
0.9923328161239624)]
==================================================
[('varieties', 0.9992631077766418), ('hands', 0.9991902112960815), ('doubl
e', 0.99913489818573), ('pod', 0.9990931153297424), ('pleasantly', 0.9990634
322166443), ('pre', 0.9990385174751282), ('name', 0.9989603757858276), ('lef
t', 0.998951256275177), ('husband', 0.9989496469497681), ('types', 0.9989420
771598816)]
```

In [35]:

```
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  3938
sample words  ['caribou', 'coffees', 'weak', 'one', 'delicious', 'exceptio
n', 'right', 'emeril', 'bold', 'van', 'houtte', 'dark', 'coffee', 'without',
'tasting', 'burned', 'bitter', 'awesome', 'ordered', 'pack', 'bags', 'twic
e', 'getting', 'ready', 'order', 'third', 'like', 'dunkin', 'donuts', 'hazel
nut', 'not', 'price', 'great', 'inexpensive', 'alternative', 'favorite', 'wa
ter', 'add', 'think', 'really', 'crisp', 'clean', 'taste', 'hint', 'tea', 't
end', 'settle', 'bottom', 'bottle', 'left']
```

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

[4.4.1.1] Avg W2v

In [36]:

```
# 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%|████████████████████████████████████████
█████| 5000/5000 [00:03<00:00, 1431.69it/s]

5000
50
```

[4.4.1.2] TFIDF weighted W2v

In [37]:

```
# 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 [38]:

```
# 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
```

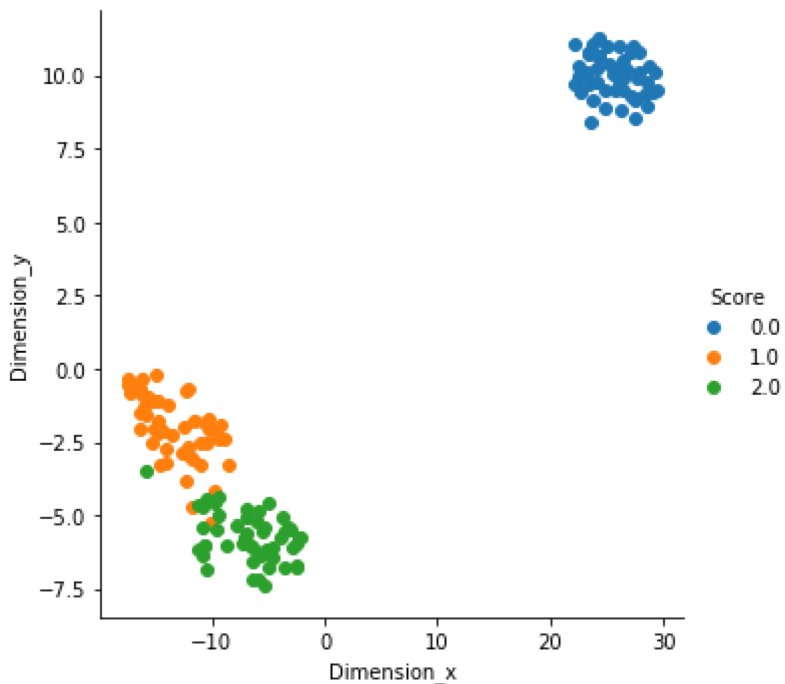
```
100%|████████████████████████████████████████████████████████████████████████
██████| 5000/5000 [00:24<00:00, 200.52it/s]
```

[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

In [39]:

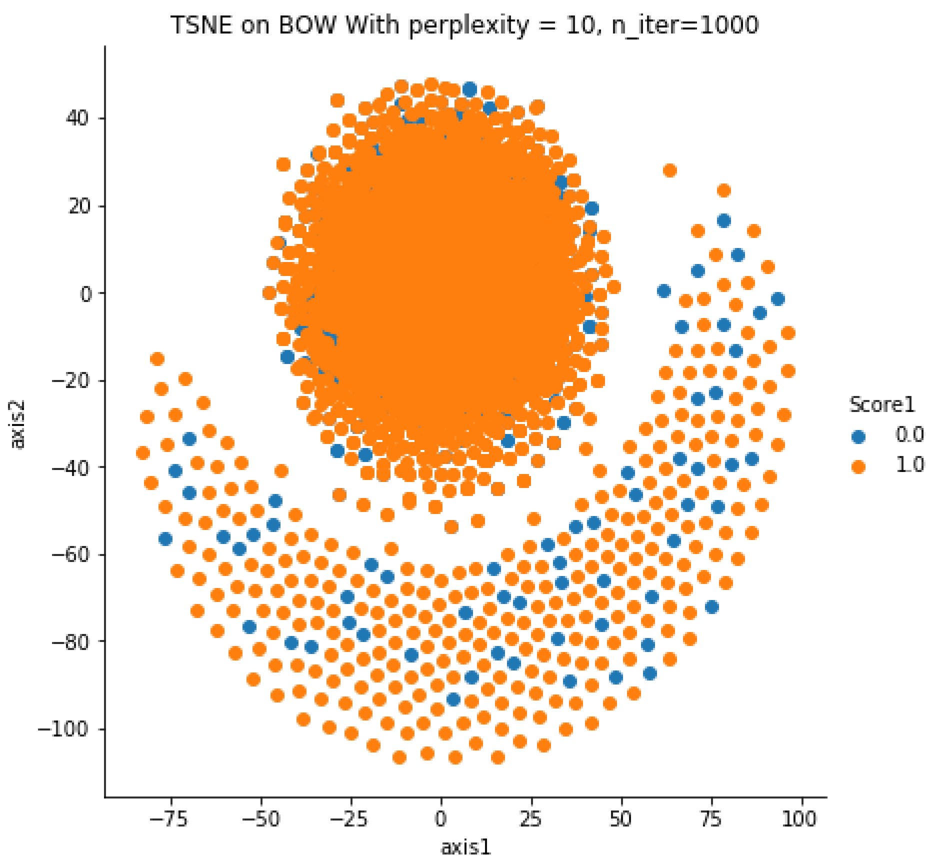
```
# https://github.com/pavlin-policar/fastTSNE you can try this also, this version is li
import numpy as np
from sklearn.manifold import TSNE
from sklearn import datasets
import pandas as pd
import matplotlib.pyplot as plt

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.to

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'}

sns.FacetGrid(for_tsne_df, hue="Score", height=5).map(plt.scatter,'Dimension_x','Dimen
```



[5.1] Applying TNSE on Text BOW vectors

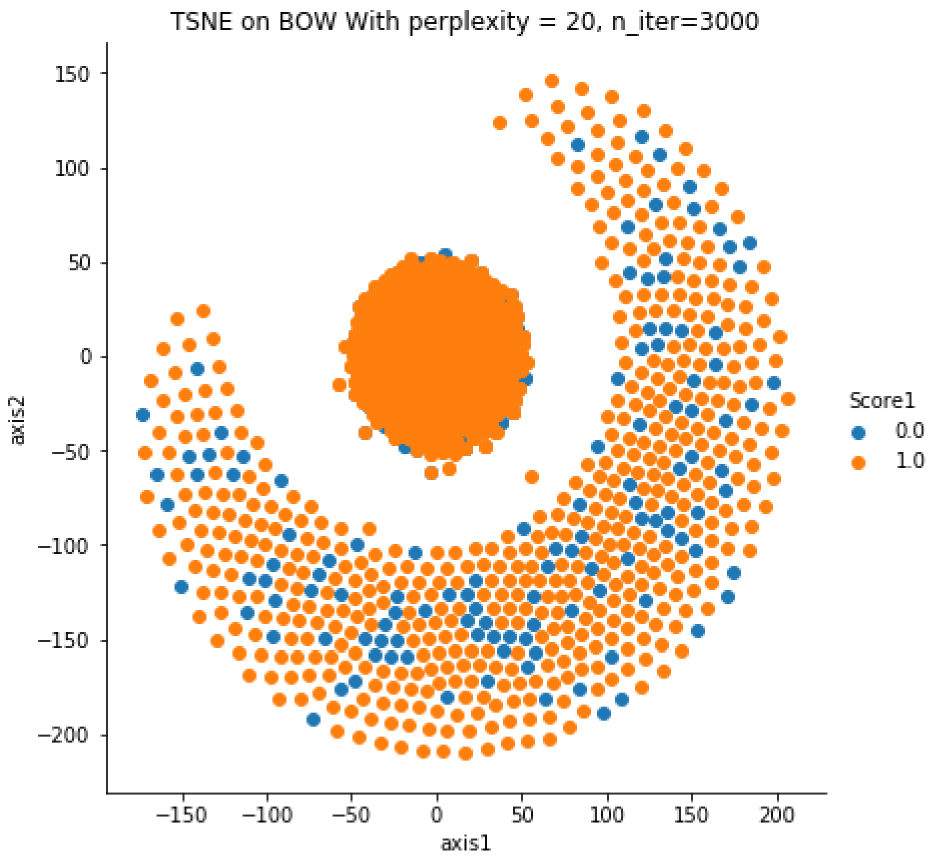
In [67]:

```
# please write all the code with proper documentation, and proper titles for each subse
# 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
import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import StandardScaler

final_BOW=StandardScaler(with_mean= False).fit_transform(final_BOW)
data=final_BOW.todense()

model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter
tsne_data = model.fit_transform(data)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on BOW With perplexity = 10, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



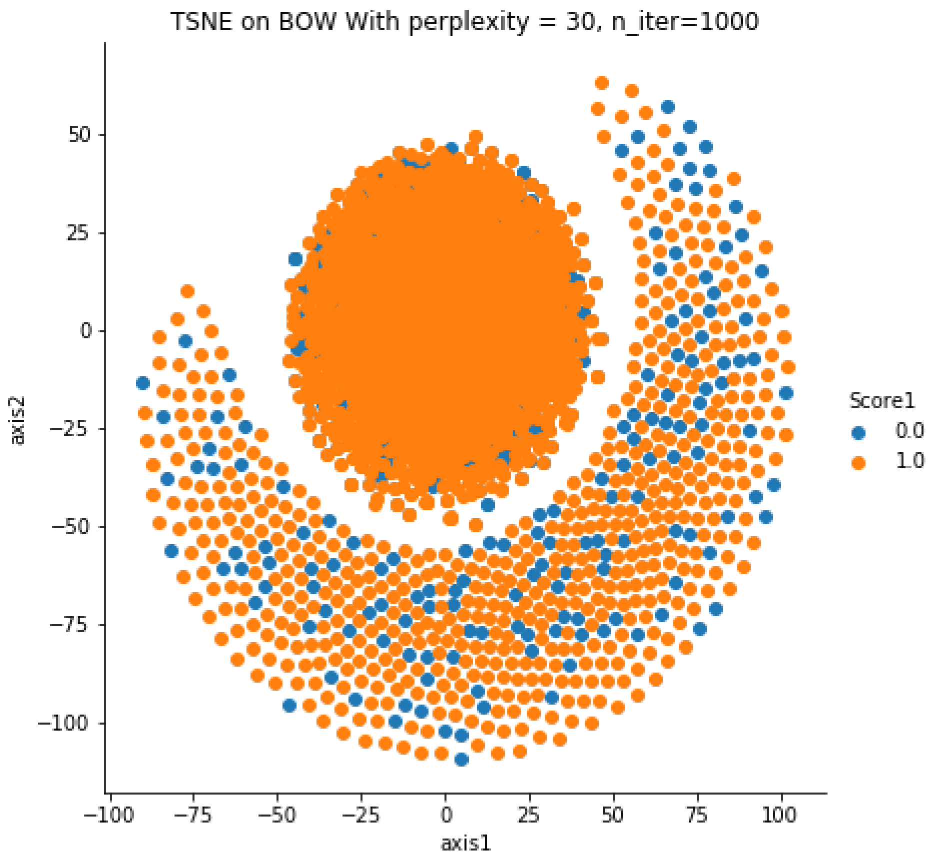
In [68]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=20,  n_iter
tsne_data = model.fit_transform(data)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on BOW With perplexity = 20, n_iter=3000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



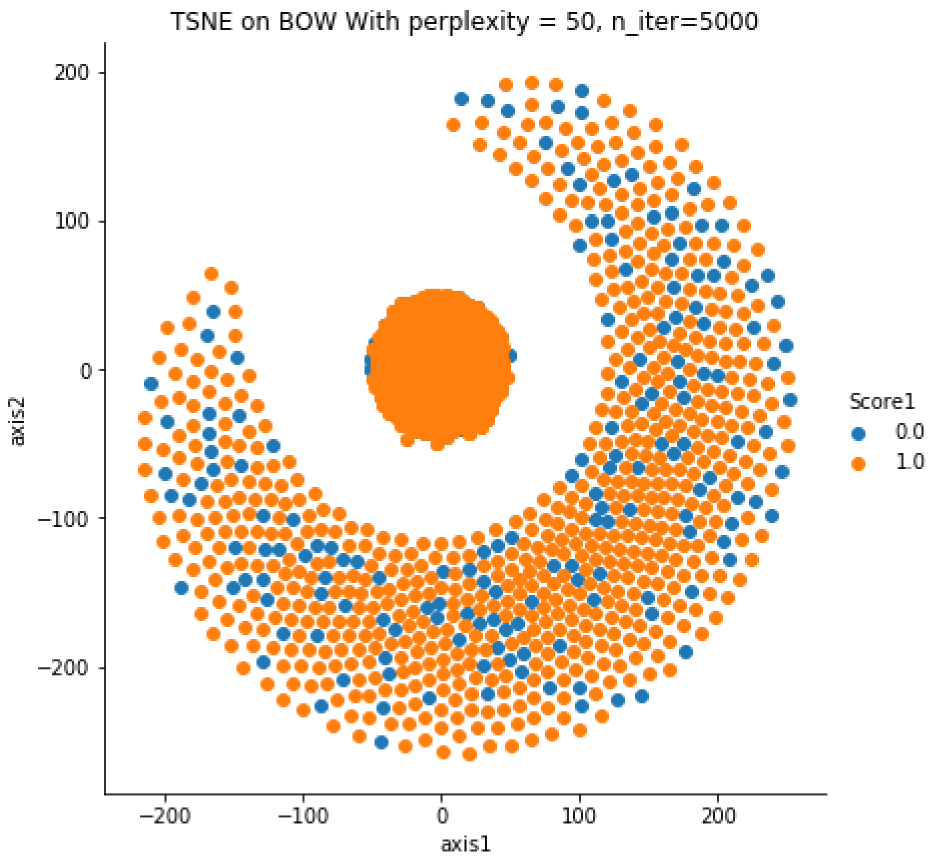
In [69]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=30,  n_iter
tsne_data = model.fit_transform(data)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on BOW With perplexity = 30, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



In [70]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=50,  n_iter
tsne_data = model.fit_transform(data)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on BOW With perplexity = 50, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



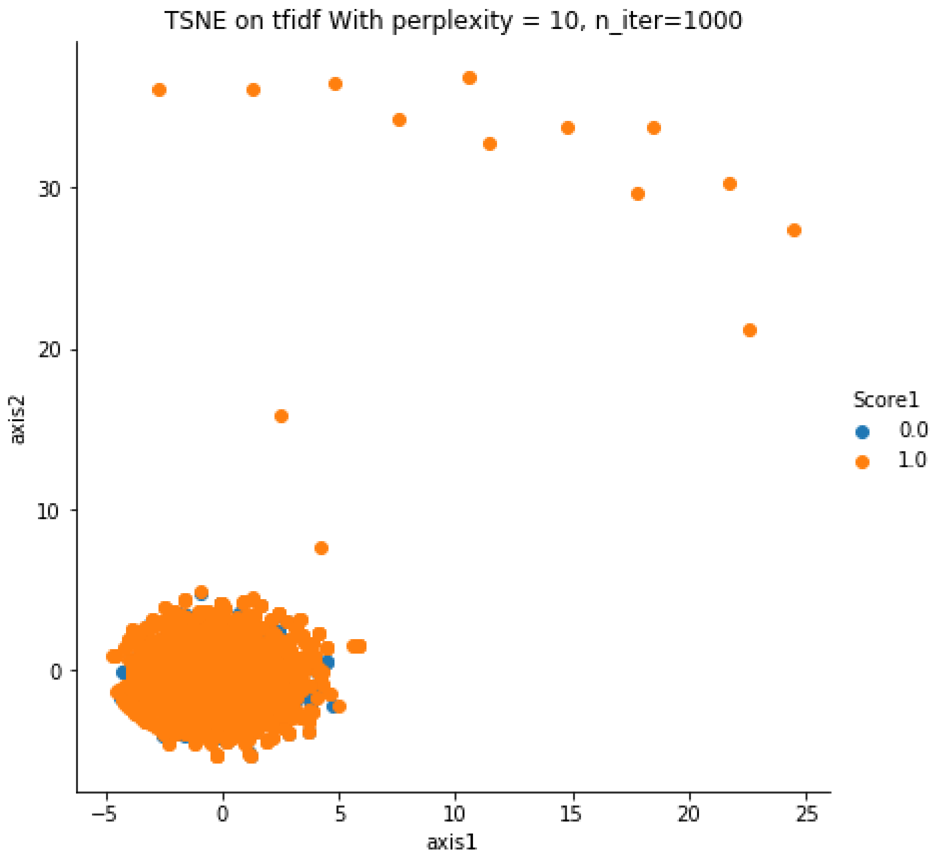
Observation

1. Applying TSNE on BOW with different number of iterations and perplexity yeilds almost the same result with some rotation in the image.
2. The result of application of TSNE on BOW yeilds a crammed and cluttered result, where making a distinction between positive and neagative review would be inconceivable .

[5.2] Applying TNSE on Text TFIDF vectors

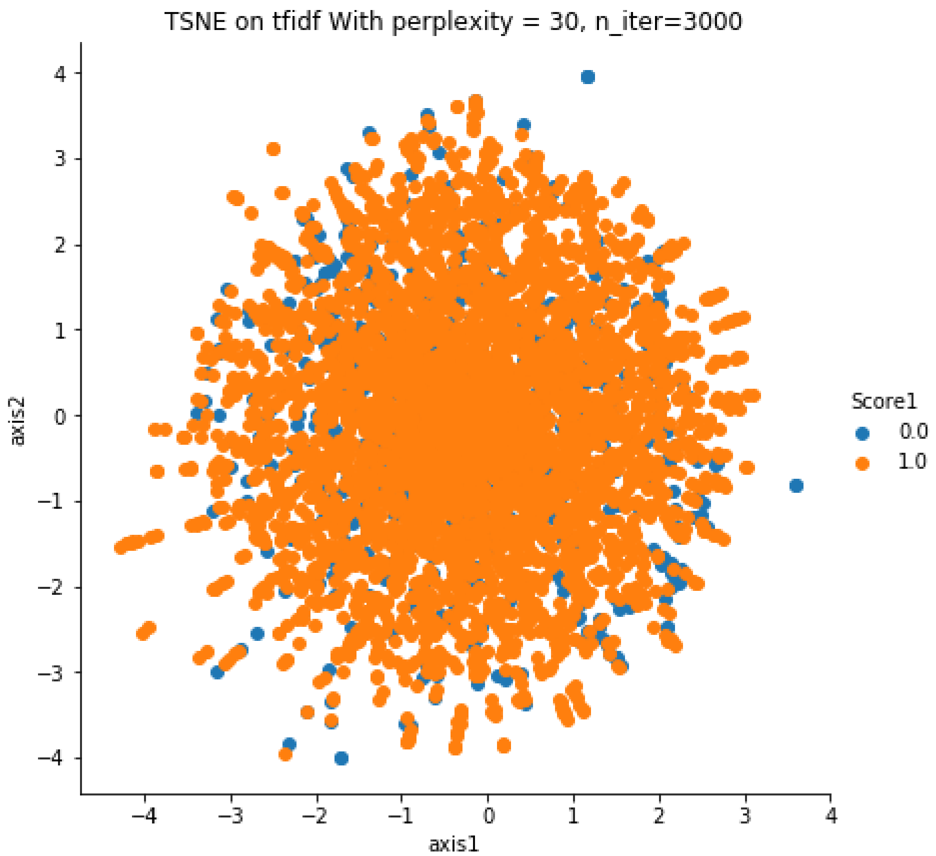
In [61]:

```
# please write all the code with proper documentation, and proper titles for each subse
# 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

final_tf_idf=StandardScaler(with_mean= False).fit_transform(final_tf_idf)

final_tf_idf=final_tf_idf.todense()

model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter
tsne_data = model.fit_transform(final_tf_idf)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on tfidf With perplexity = 10, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



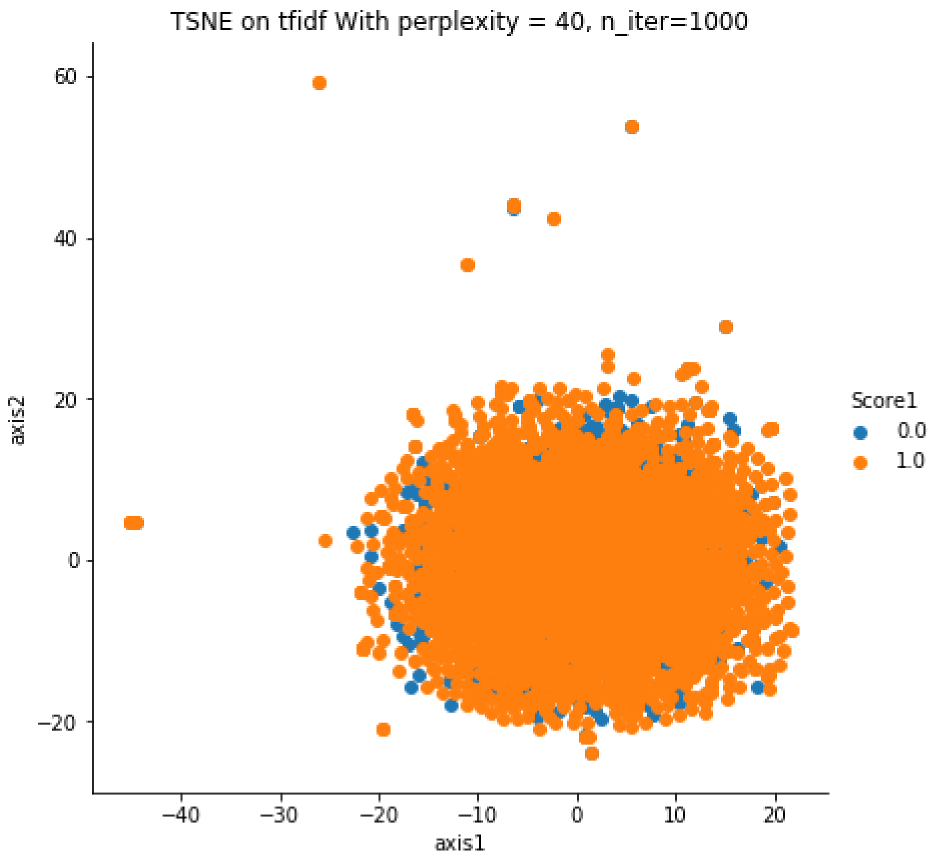
In [78]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=30,  n_iter
tsne_data = model.fit_transform(final_tf_idf)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on tfidf With perplexity = 30, n_iter=3000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



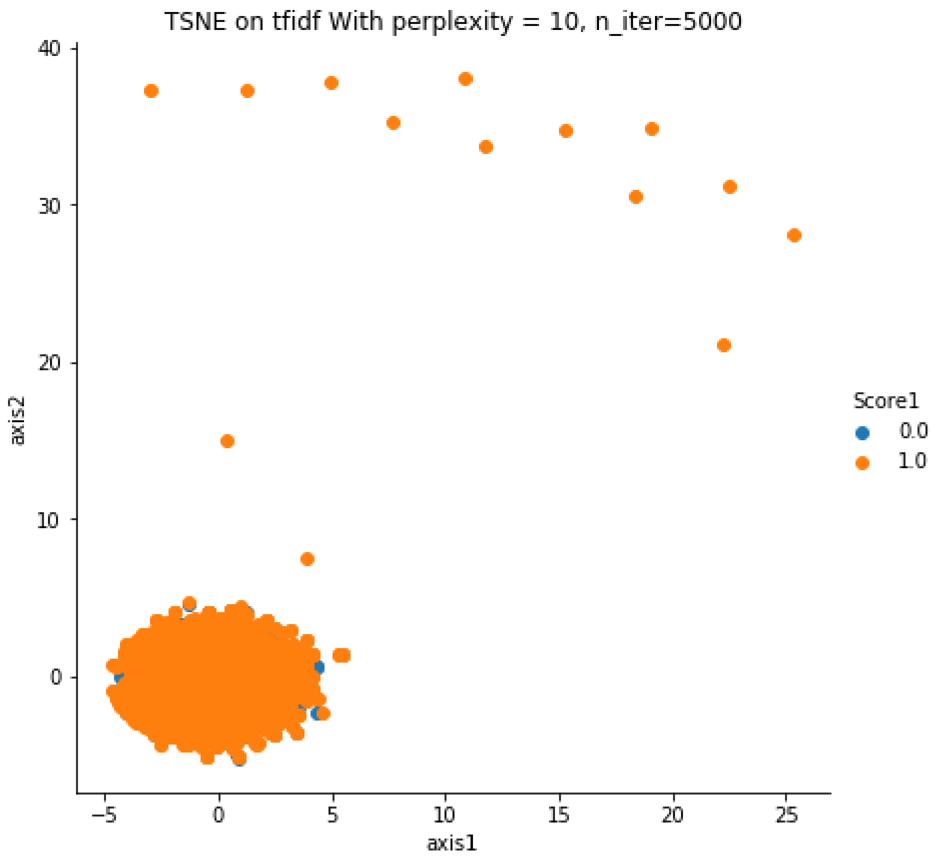
In [63]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=40,  n_iter
tsne_data = model.fit_transform(final_tf_idf)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on tfidf With perplexity = 40, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



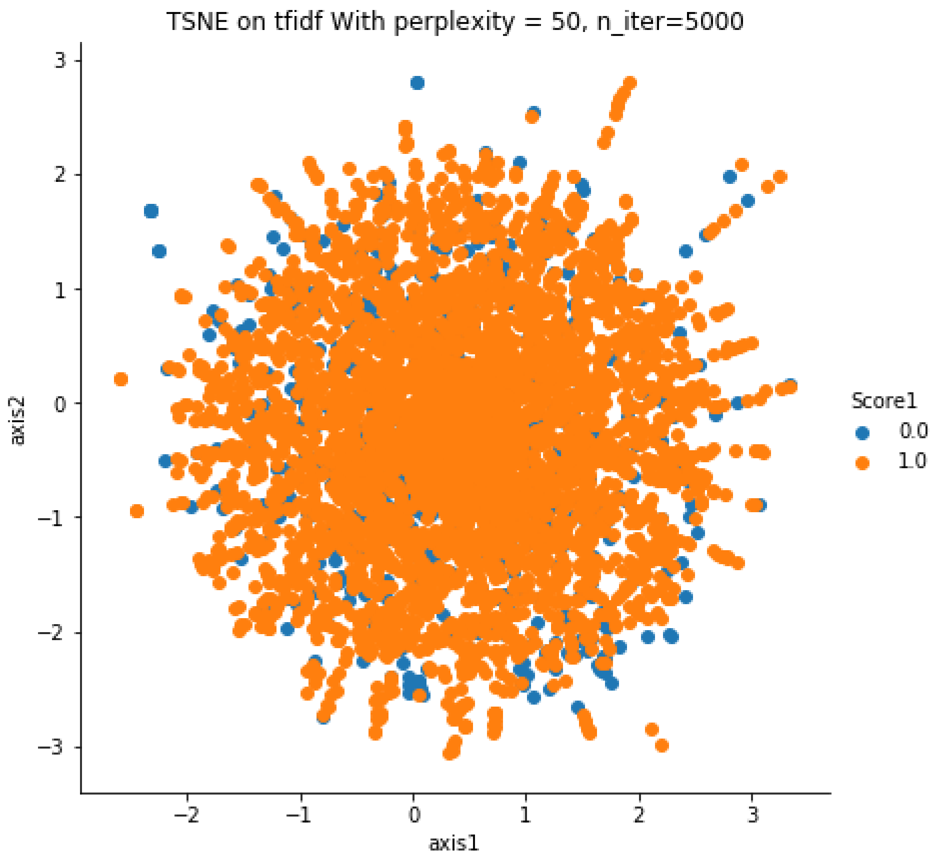
In [64]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter=
tsne_data = model.fit_transform(final_tf_idf)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_l
plt.title('TSNE on tfidf With perplexity = 10, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



In [65]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=50,  n_iter
tsne_data = model.fit_transform(final_tf_idf)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on tfidf With perplexity = 50, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



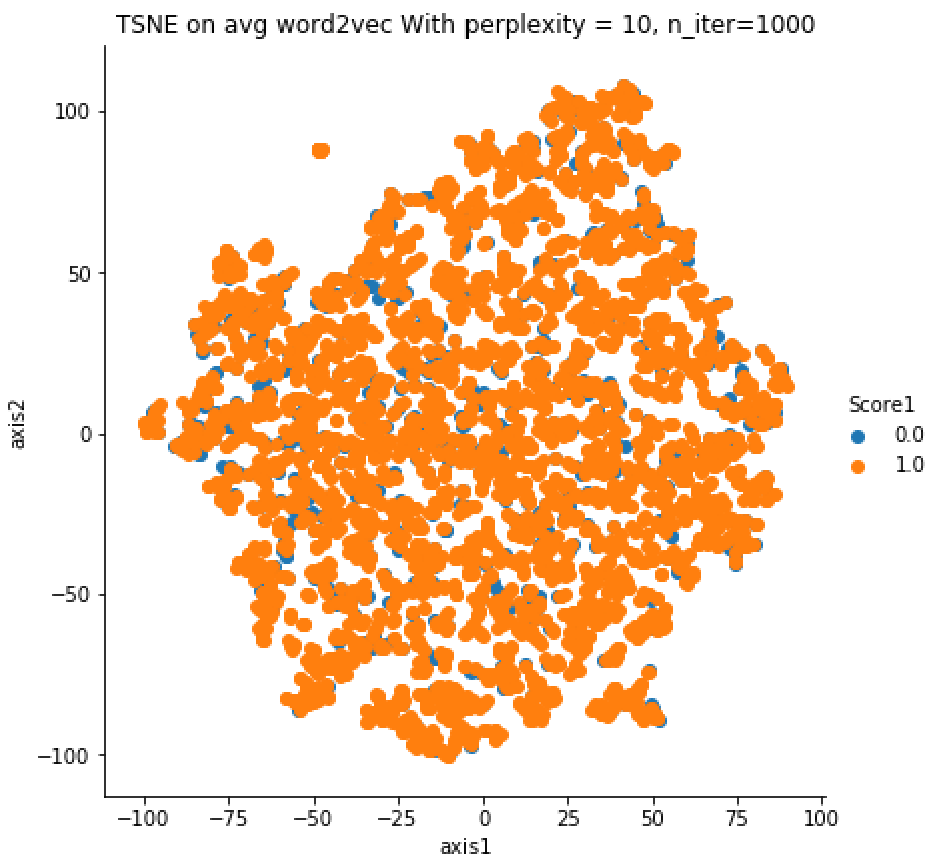
Observation

1. The result of application of TSNE on tfidf yeilds a clodded mass of review points with high degree of overlapping.
2. The high degree of overlap makes the segregation of points unsurmountable.

[5.3] Applying TNSE on Text Avg W2V vectors

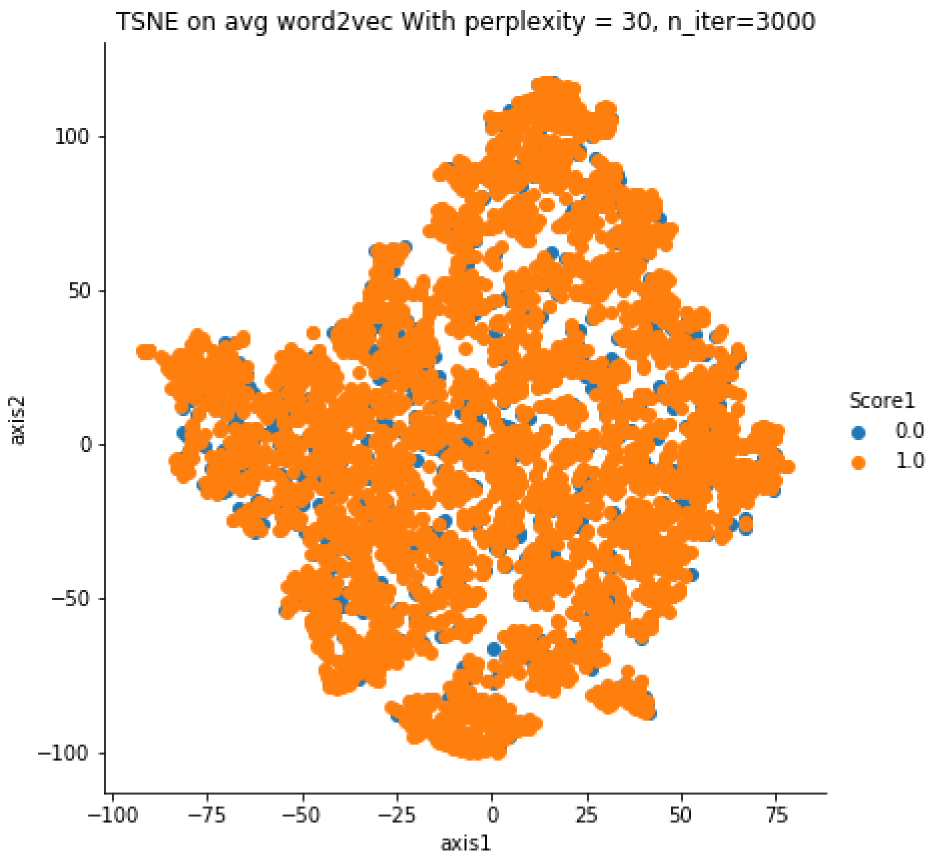
In [75]:

```
# please write all the code with proper documentation, and proper titles for each subse
# 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

sent_vectors=StandardScaler(with_mean= False).fit_transform(sent_vectors)

sent_vectors=sent_vectors

model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter
tsne_data = model.fit_transform(sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 10, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



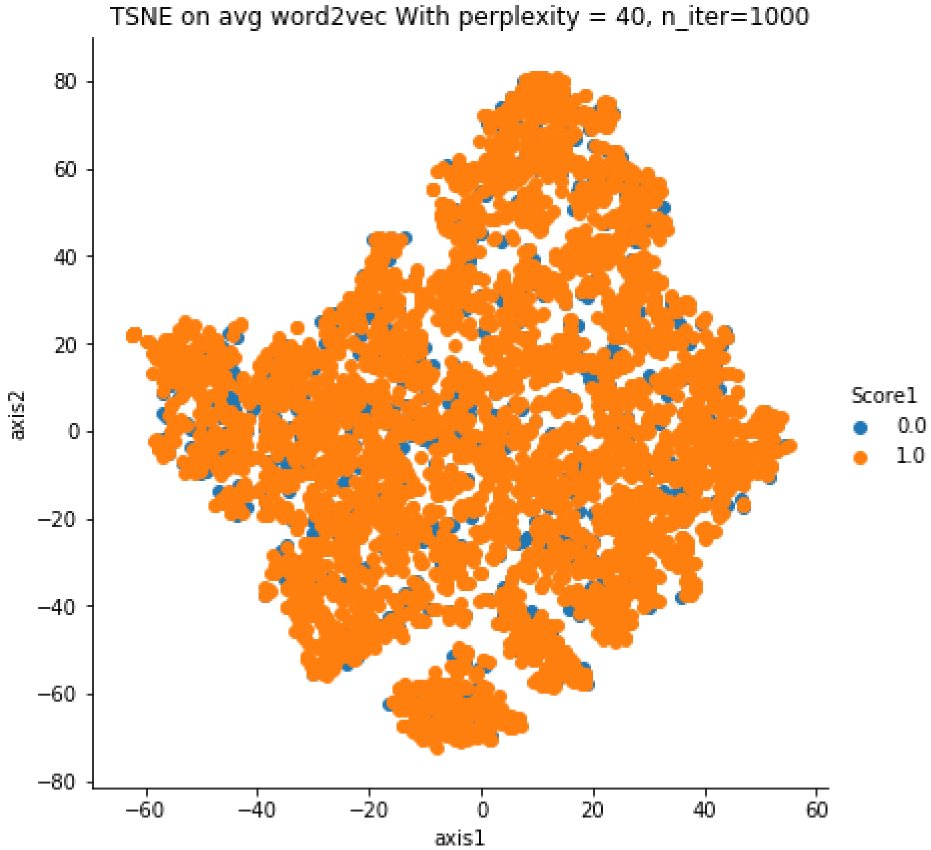
In [79]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=30,  n_iter
tsne_data = model.fit_transform(sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 30, n_iter=3000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



In [80]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=40,  n_iter
tsne_data = model.fit_transform(sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 40, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```

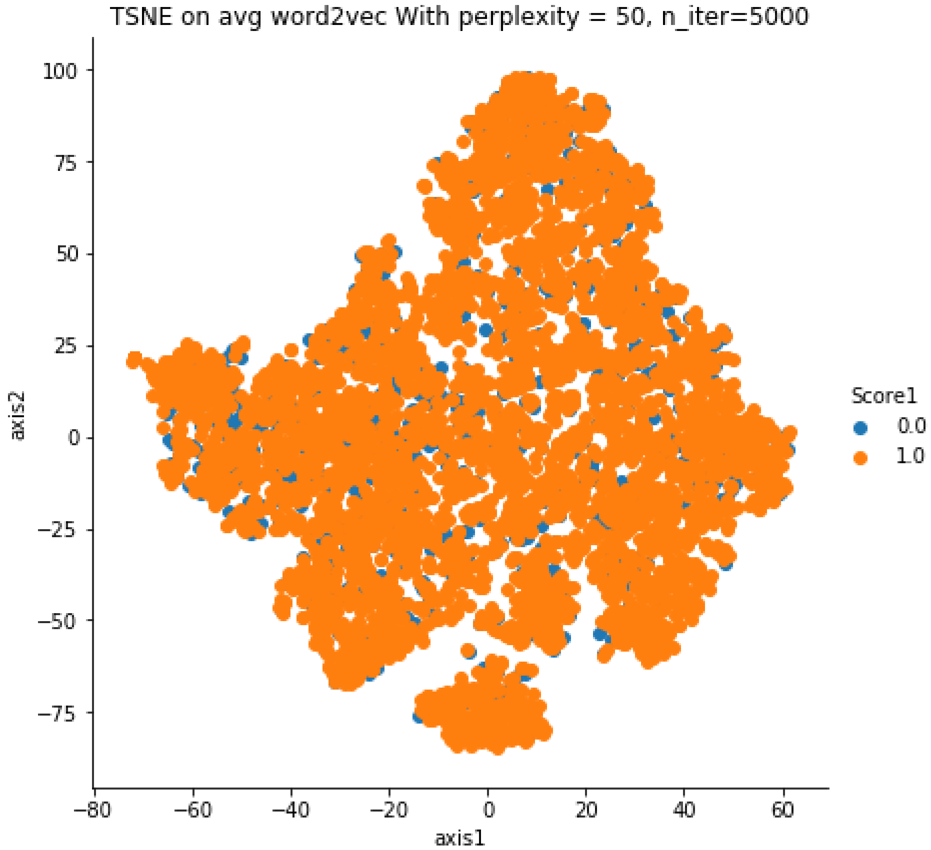


In [81]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter
tsne_data = model.fit_transform(sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 10, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```

In [82]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=50,  n_iter
tsne_data = model.fit_transform(sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 50, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



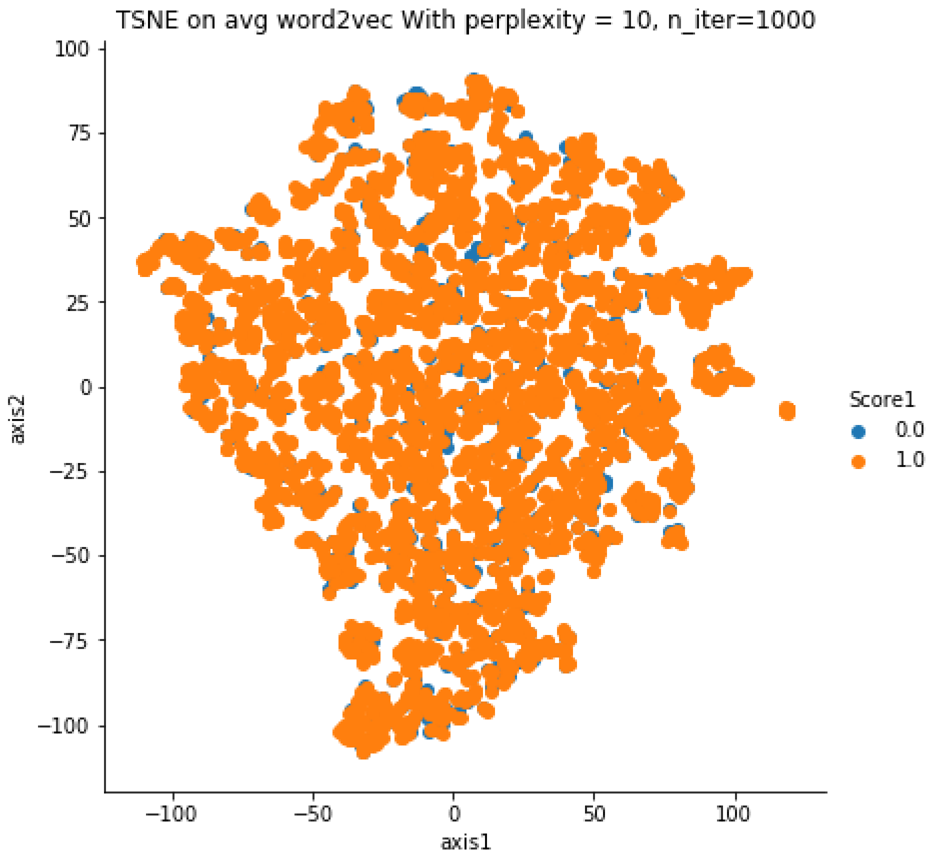
Observation

1. The Yeild here also shows a cluttered mass, with indistinguishable positive and negative review points.

[5.4] Applying TNSE on Text TFIDF weighted W2V vectors

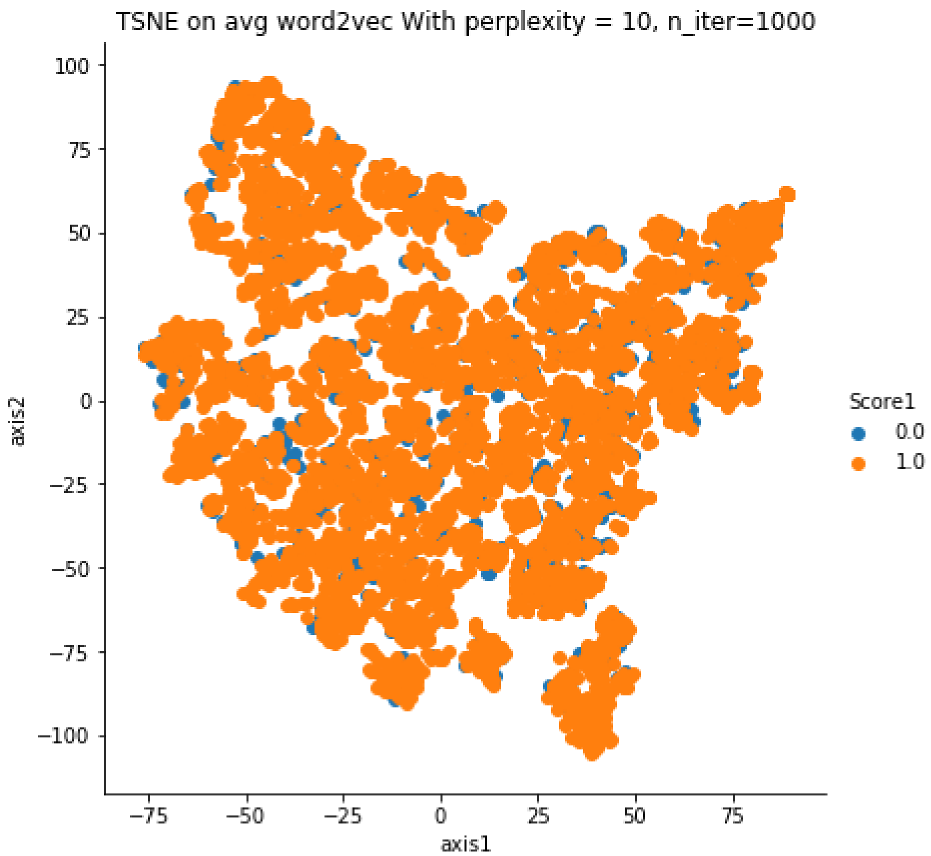
In [41]:

```
# please write all the code with proper documentation, and proper titles for each subse
# 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

tfidf_sent_vectors=StandardScaler(with_mean= False).fit_transform(tfidf_sent_vectors)

tfidf_sent_vectors=tfidf_sent_vectors

model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter
tsne_data = model.fit_transform(tfidf_sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T ,Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 10, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



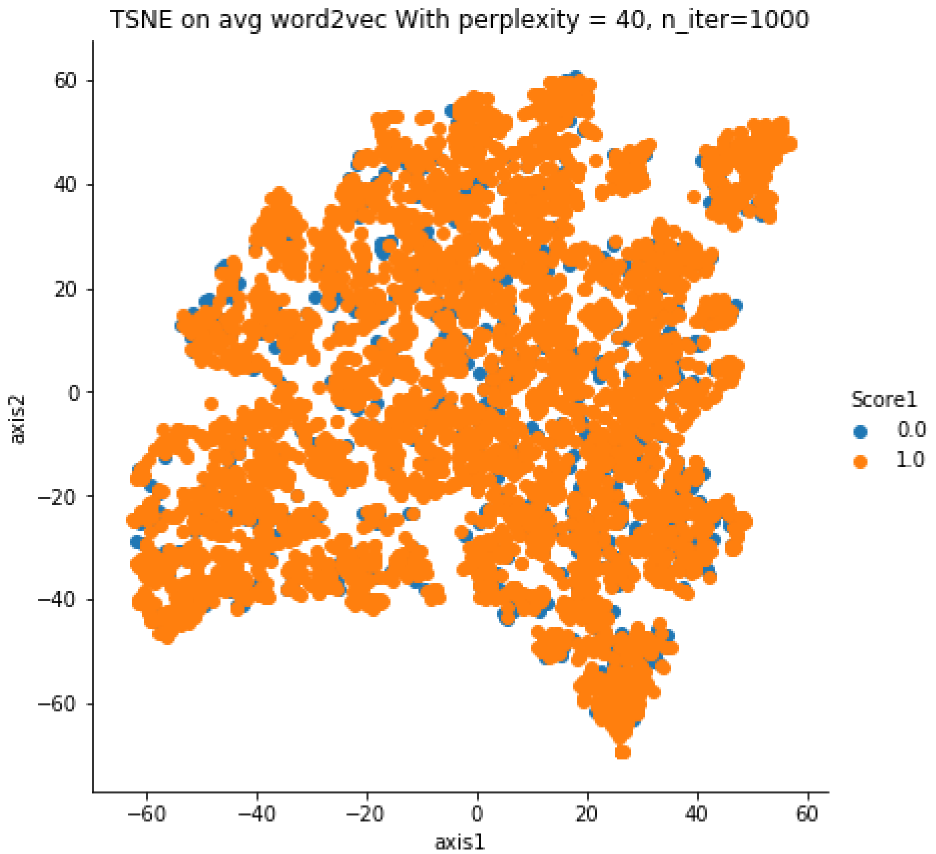
In [42]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=30,  n_iter
tsne_data = model.fit_transform(tfidf_sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T ,Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 10, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



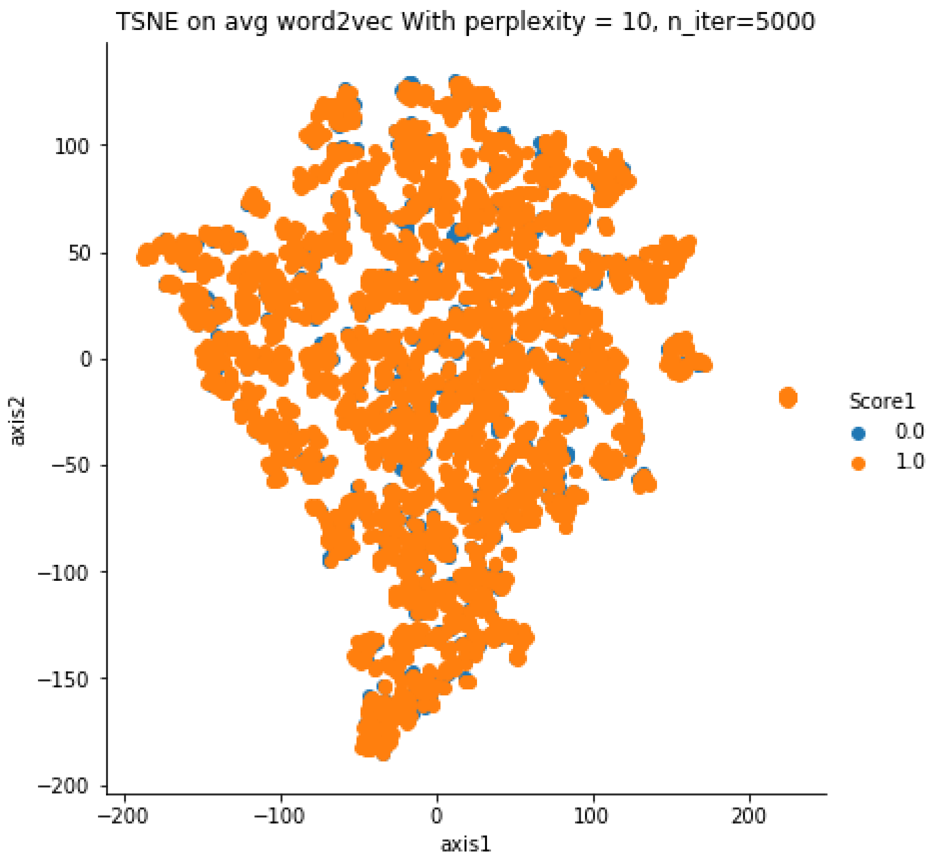
In [43]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=40,  n_iter
tsne_data = model.fit_transform(tfidf_sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T ,Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 40, n_iter=1000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



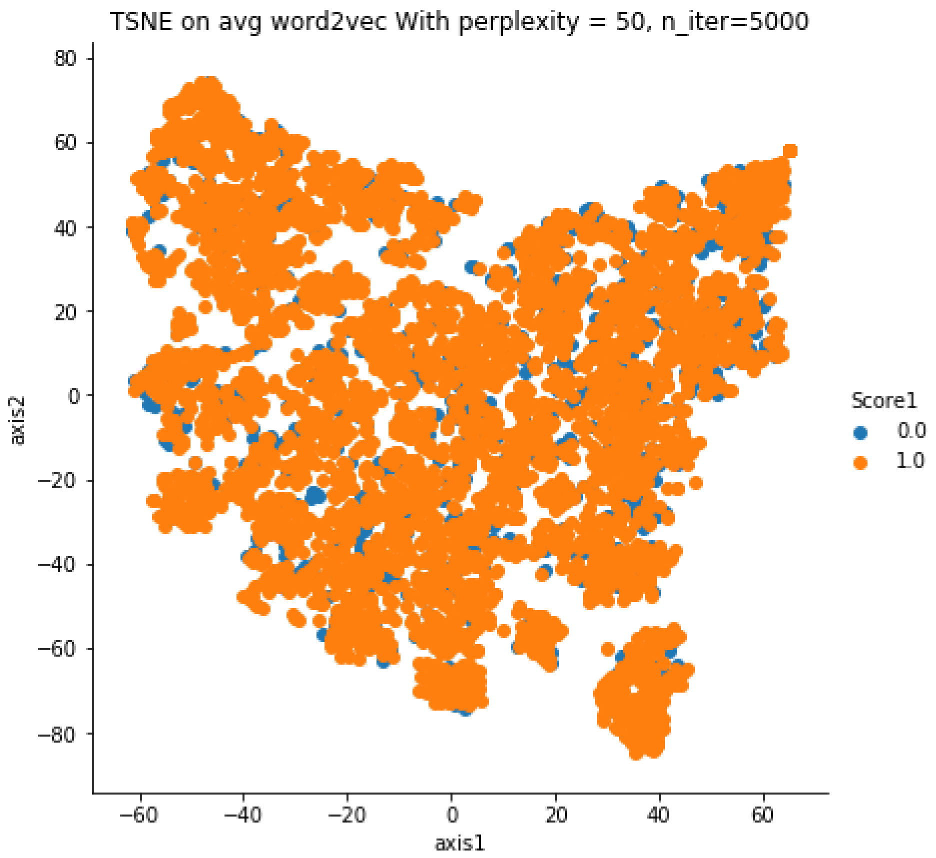
In [44]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=10,  n_iter
tsne_data = model.fit_transform(tfidf_sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T ,Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 10, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



In [45]:

```
model = TSNE(n_components=2, random_state=0, learning_rate=200, perplexity=50,  n_iter
tsne_data = model.fit_transform(tfidf_sent_vectors)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T ,Score1)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Axis_1", "Axis_2", "Score1"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="Score1", size=6).map(plt.scatter, 'Axis_1', 'Axis_2').add_
plt.title('TSNE on avg word2vec With perplexity = 50, n_iter=5000')
plt.xlabel("axis1")
plt.ylabel("axis2")
plt.show()
```



Observation ¶

1. Not a clear representation of points again, same indistinguishable overlapping positive and negative review points.

[6] Conclusions

1. In the TSNE application on the different vector representaions of words, the results vary in shape but fail to achieve the end goal of segregation of points into positive and negative review. The yeild is always a crammed and clutterd mass of indistinguishable overlapped points. Might this be a case where more number of TSNE plots are required to interpret what's going on with the data.