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 [6]:

```
%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
```

[1]. Reading Data

In [8]:

```python
# using the SQLite Table to read data.

import os

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

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
```

```python
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 6000""", 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 (6000, 10)
```

Out[8]:

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

In [9]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [10]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[10]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [11]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[11]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	5

In [12]:

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

Out[12]: 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 [13]:

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

Out[13]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon

	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 [14]:
```
#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 [15]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[15]:
```
(5979, 10)
```

In [16]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[16]:
```
99.65
```

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 [17]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)
```

```
display.head()
```

Out[17]:

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

In [18]:

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

In [19]:

```
#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()
```

```
(5979, 10)
```

Out[19]:

```
1    5014
0     965
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 [20]:

```
# 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 Love these chips for its unique taste and incredible crispy texture.
Used to get them at Henry's in San Diego, CA before we moved out of the
re and have been ordering them from Amazon since. Running out of them c
onstantly!
==================================================
I dont like the taste of this at all.  I have some other fennel tea fro
m another company not on amazon and it is fantastic.  Cant remember exa
ct name but think it is something like MB - is a french company and I g
ot it in canada and by mail order after that.  It is much better to my
taste.  Never dreamed there would be this much variance among fennel se
eds as only ingredient.
==================================================
If you are a peanut lover, these are for you. Much larger than cocktail
peanuts. Six people on my Christmas gift list ask for these every yea
r!!
==================================================
```

In [21]:

```python
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
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 [22]:

```python
# 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 Love these chips for its unique taste and incredible crispy texture.
Used to get them at Henry's in San Diego, CA before we moved out of the
re and have been ordering them from Amazon since. Running out of them c
onstantly!
==================================================
I dont like the taste of this at all.  I have some other fennel tea fro
m another company not on amazon and it is fantastic.  Cant remember exa
ct name but think it is something like MB - is a french company and I g
ot it in canada and by mail order after that.  It is much better to my
taste.  Never dreamed there would be this much variance among fennel se
eds as only ingredient.
==================================================
If you are a peanut lover, these are for you. Much larger than cocktail
peanuts. Six people on my Christmas gift list ask for these every yea
r!!
```

In [23]:

```
# 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 [24]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
I dont like the taste of this at all.  I have some other fennel tea fro
m another company not on amazon and it is fantastic.  Cant remember exa
ct name but think it is something like MB - is a french company and I g
ot it in canada and by mail order after that.  It is much better to my
taste.  Never dreamed there would be this much variance among fennel se
eds as only ingredient.
==================================================
```

In [25]:
```
#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 [26]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
I dont like the taste of this at all I have some other fennel tea from
another company not on amazon and it is fantastic Cant remember exact n
ame but think it is something like MB is a french company and I got it
in canada and by mail order after that It is much better to my taste Ne
ver dreamed there would be this much variance among fennel seeds as onl
y ingredient
```

In [27]:

```
# 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 [28]:

```
# Combining all the above stundents
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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 5979/5979 [00:03<00:00, 1766.75it/s]
```

In [29]:

```
preprocessed_reviews[1500]
```

Out[29]:

```
'dont like taste fennel tea another company not amazon fantastic cant r
emember exact name think something like mb french company got canada ma
il order much better taste never dreamed would much variance among fenn
el seeds ingredient'
```

[3.2] Preprocess Summary

In [30]:

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

[4] Featurization

[4.1] BAG OF WORDS

In [183]:

```
#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  (5979, 14318)
the number of unique words  14318
```

[4.2] Bi-Grams and n-Grams.

In [33]:

```
#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  (5979, 3711)
the number of unique words including both unigrams and bigrams  3711
```

[4.3] TF-IDF

In [34]:
```
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 buy', 'able find', 'able get', 'absolute', 'absolute best', 'absolu
te favorite', 'absolutely', 'absolutely delicious']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (5979, 3711)
the number of unique words including both unigrams and bigrams  3711
```

[4.4] Word2Vec

In [35]:
```
# 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 [36]:
```
# 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 ")
```

```
[('excellent', 0.9887293577194214), ('think', 0.9823833703994751), ('su
mmary', 0.9823787212371826), ('alternative', 0.9811113476753235), ('rig
ht', 0.9804012179374695), ('hurt', 0.9803661108016968), ('especially',
0.9803148508071899), ('overall', 0.9802097082138062), ('either', 0.9800
5211353302), ('bad', 0.9796010255813599)]
==================================================
[('teas', 0.9987434148788452), ('community', 0.9985976219177246), ('tru
e', 0.9983398914337158), ('mustard', 0.9982709884643555), ('cafe', 0.99
82611536979675), ('prefer', 0.9982181787490845), ('disappointing', 0.99
81682896614075), ('french', 0.998084545135498), ('miss', 0.998080193996
4294), ('thus', 0.9980640411376953)]
```

In [37]:

```
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  4278
sample words  ['product', 'available', 'course', 'total', 'fly', 'prett
y', 'stinky', 'right', 'nearby', 'used', 'seasons', 'ca', 'not', 'bea
t', 'great', 'really', 'good', 'idea', 'final', 'outstanding', 'use',
'car', 'window', 'everybody', 'asks', 'bought', 'made', 'two', 'thumb
s', 'received', 'shipment', 'could', 'hardly', 'wait', 'try', 'love',
'call', 'instead', 'removed', 'easily', 'daughter', 'designed', 'printe
d', 'windows', 'beautifully', 'print', 'shop', 'program', 'going', 'lo
t']
```

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

[4.4.1.1] Avg W2v

In [38]:
```
# 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, yo
u 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/re
view
    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%|██████████| 5979/5979 [00:10<00:00, 596.14it/s]
```

```
5979
50
```

[4.4.1.2] TFIDF weighted W2v

In [39]:
```
# 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 [40]:
```
# 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%|██████████| 5979/5979 [00:53<00:00, 111.66it/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

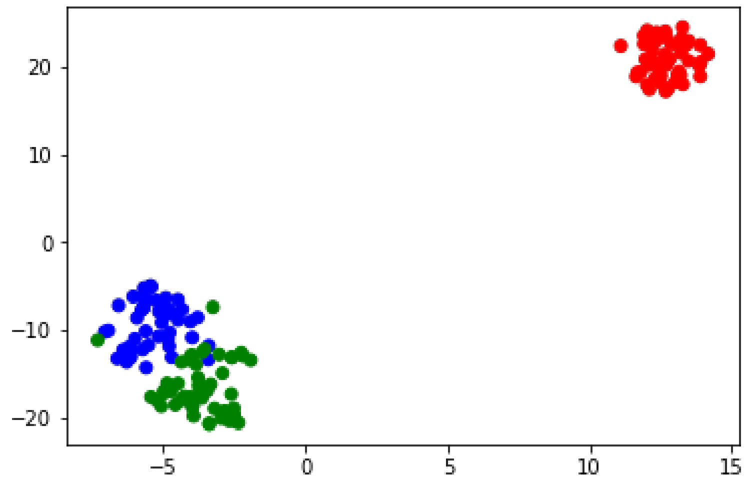
In [41]:
```
# https://github.com/pavlin-policar/fastTSNE you can try this also, thi
s version is little faster than sklearn
import numpy as np
from sklearn.manifold import TSNE
from sklearn import datasets
import pandas as pd
import matplotlib.pyplot as plt

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 TSNE on Text BOW vectors

The variable that contains the BOW implementation is "final_counts" which has been obtained after all the text preprocessing steps performed and after applying the BOW implementation.

In [59]:
```
type(final_counts)
```

Out[59]:
```
scipy.sparse.csr.csr_matrix
```

This is basically a sparse matrix representation with majority of the elements being 0 and only a few elements being non-zero.

In [62]:
```
print(final_counts.shape)

#I have taken 6k points for TSNE.
```

```
(5979, 14318)
```

The BOW representation matrix has a total of 5979 rows (each row for each review) and a total of 14318 columns representing the total number of unique words present in the Corpus.

Therefore the first step over here would be to convert this sparse matrix representation into a dense matrix representation, since TSNE only inputs dense matrices.

In [67]:
```
#todense() is a function used in scipy to convert a sparse matrix to a
 dense matrix.
BOW = final_counts.todense()
BOW.shape
```

Out[67]:
```
(5979, 14318)
```

The dimensionality of the dense matrix representation is also the same as the sparse matrix. However, the difference lies in the fact that for the dense matrix representation, the non-zero elements are stored as a dictionary which considerably reduces the time and space complexity.

Now I will also need to apply column standardization first before I can work on TSNE.

In [84]:
```
from sklearn.preprocessing import StandardScaler
standardized_bow = StandardScaler().fit_transform(BOW)
print(standardized_bow.shape)

#Now all the columns would have mean = 0 and standard deviation =1.
```

```
(5979, 14318)
```

Now I can finally work on T-SNE with a considerably large value of step-size being fixed and varying values of perplexity.

In [91]:
```
final.head(5)
final['Score'].value_counts()
```

Out[91]:
```
1    5014
0     965
```

```
Name: Score, dtype: int64
```

TSNE on BOW : Perplexity=5, Number of Iterations=1000

First I will have a look at TSNE on BOW using a small value of perplexity, such as 5 and set the number of iterations to be equal to the default value of 1000.

In [154]:
```
from sklearn.manifold import TSNE

BOW_model1 = TSNE(n_components=2, perplexity=5,n_iter=1000,random_state=0)
BOW_TSNE1 = BOW_model1.fit_transform(standardized_bow)
```

In [155]:
```
print(BOW_TSNE1.shape)
```

```
(5979, 2)
```

Therefore, here I have successfully carried out the dimensionality reduction from 14,318 to 2 dimensions. Now I need to add 'Score' as a column to this dataset in order to plot the same using "Seaborn".

In [156]:
```
labels = final['Score'].map({1:"Positive",0:"Negative"}).astype(str)
```

In [157]:
```
print(BOW_TSNE1.shape)
```

```
(5979, 2)
```

In [158]:
```
print(labels.shape)
```

```
(5979,)
```

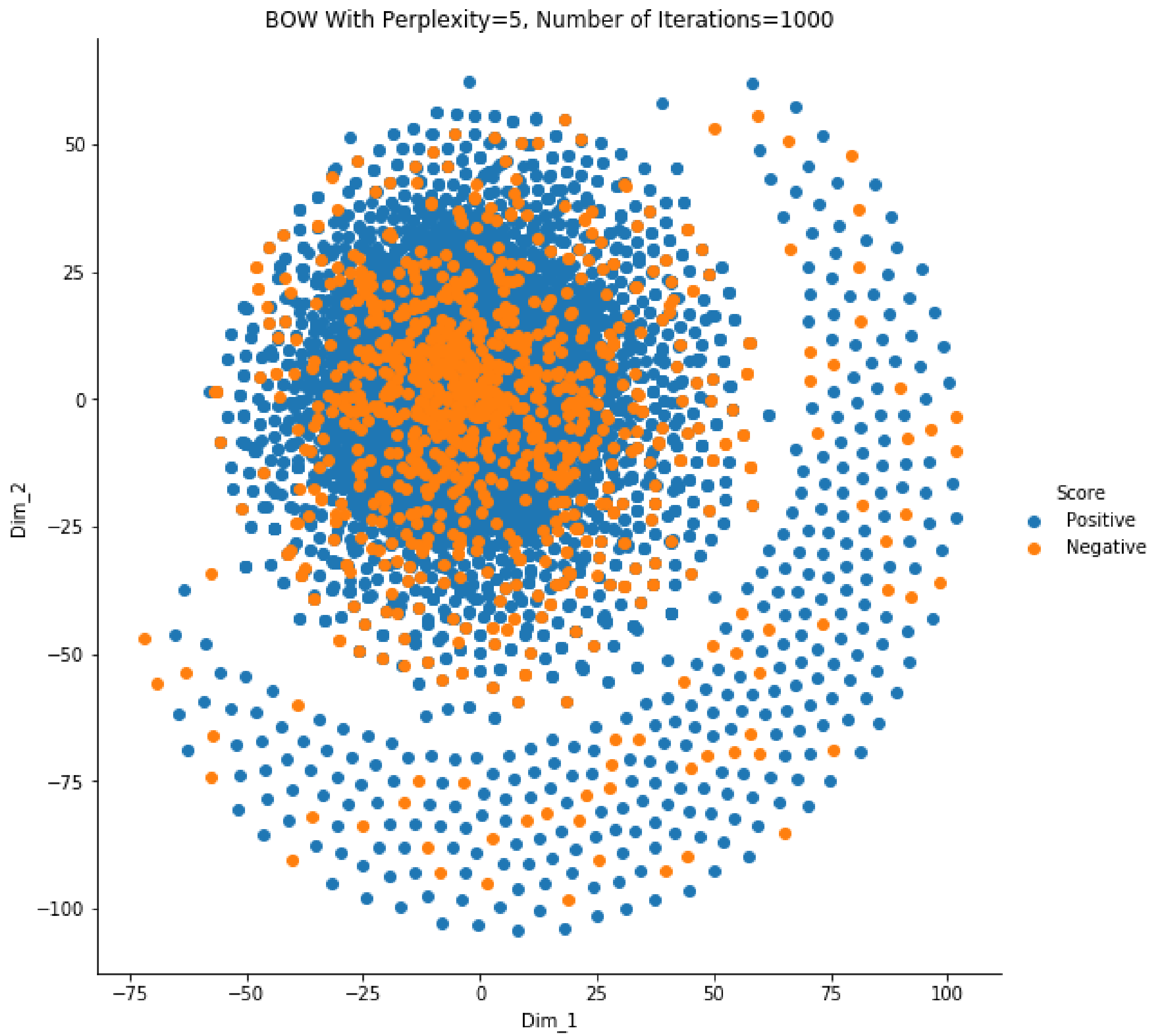
In [159]:
```
BOW_TSNE1 = np.vstack((BOW_TSNE1.T,labels)).T
```

In [160]:
```
BOW_DF1 = pd.DataFrame(data=BOW_TSNE1,columns=("Dim_1","Dim_2","Score"
))
print(BOW_DF1.head(5))
print(BOW_DF1.shape)
```

```
      Dim_1    Dim_2     Score
0   2.84063  55.5353  Positive
1   2.83988  55.5245  Positive
2   69.9908 -34.0653  Positive
3 -12.5035 -16.5918  Positive
4   82.3461  -58.677  Positive
(5979, 3)
```

This is the final dataset that I have obtained for this particular perplexity value on which I will plot the graph.

In [337]:
```
import seaborn as sns
sns.FacetGrid(data=BOW_DF1,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("BOW With Perplexity=5, Number of Iterations=1000")
plt.show()
```



TSNE on BOW : Perplexity=30, Number of Iterations=1000

In [162]:
```
BOW_model2 = TSNE(n_components=2, perplexity=30,n_iter=1000,random_stat
```

```
e=0)
BOW_TSNE2 = BOW_model2.fit_transform(standardized_bow)
```

In [163]:
```
print(BOW_TSNE2.shape)
```

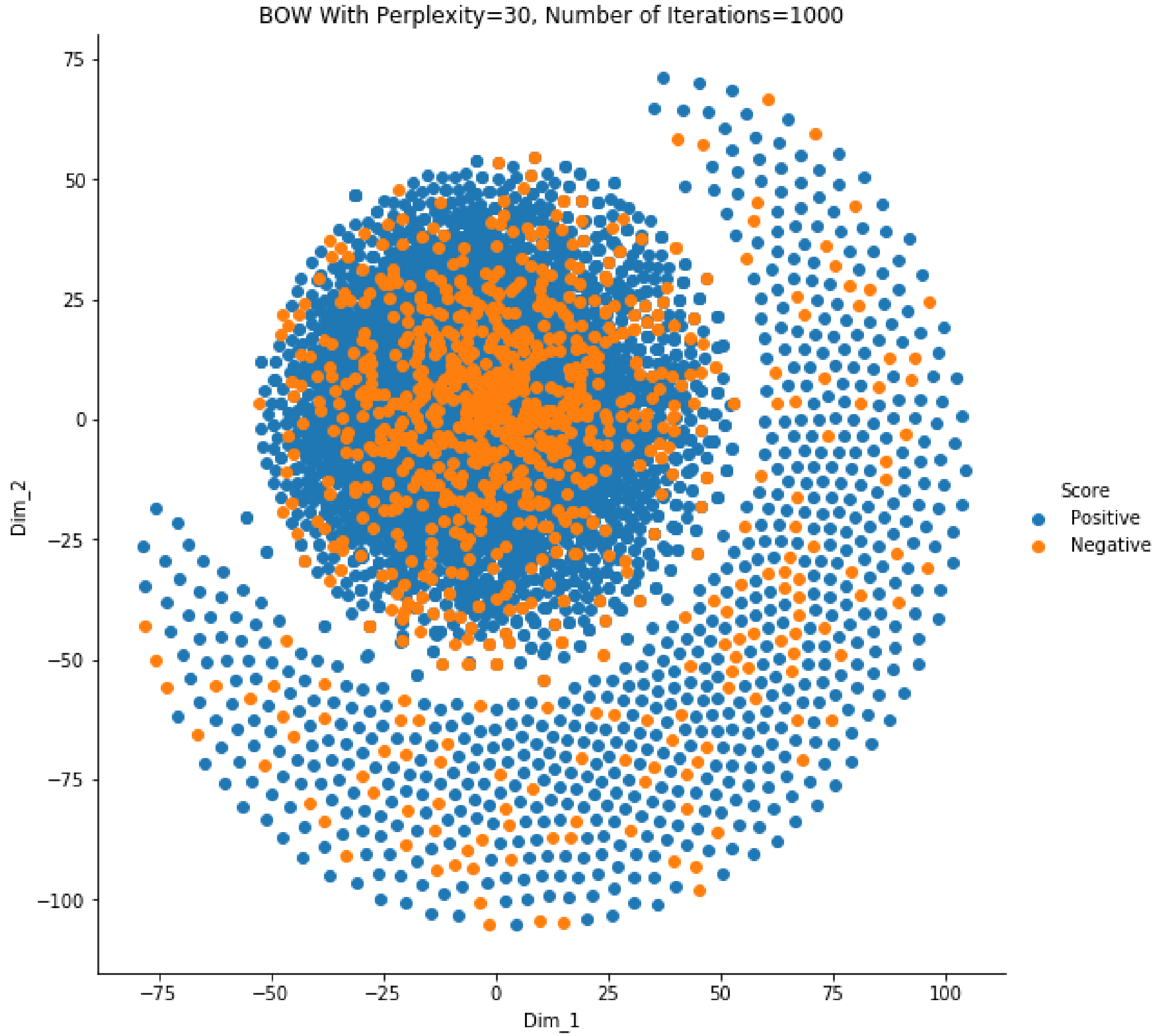
```
(5979, 2)
```

In [164]:
```
BOW_TSNE2 = np.vstack((BOW_TSNE2.T,labels)).T
```

In [165]:
```
BOW_DF2 = pd.DataFrame(data=BOW_TSNE2,columns=("Dim_1","Dim_2","Score"
))
print(BOW_DF2.head(5))
print(BOW_DF2.shape)
```

```
     Dim_1    Dim_2     Score
0  11.0247 -25.6975  Positive
1  11.0167 -25.6788  Positive
2  50.5197 -94.4213  Positive
3  4.37154 -15.5062  Positive
4    84.45 -48.3507  Positive
(5979, 3)
```

In [336]:
```
import seaborn as sns
sns.FacetGrid(data=BOW_DF2,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("BOW With Perplexity=30, Number of Iterations=1000")
plt.show()
```



TSNE on BOW : Perplexity=30, Number of Iterations=5500

In [167]:
```
from sklearn.manifold import TSNE
```

```
BOW_model3 = TSNE(n_components=2, perplexity=30,n_iter=5500,random_stat
e=0)
BOW_TSNE3 = BOW_model3.fit_transform(standardized_bow)
```

In [168]:
```
print(BOW_TSNE3.shape)
```

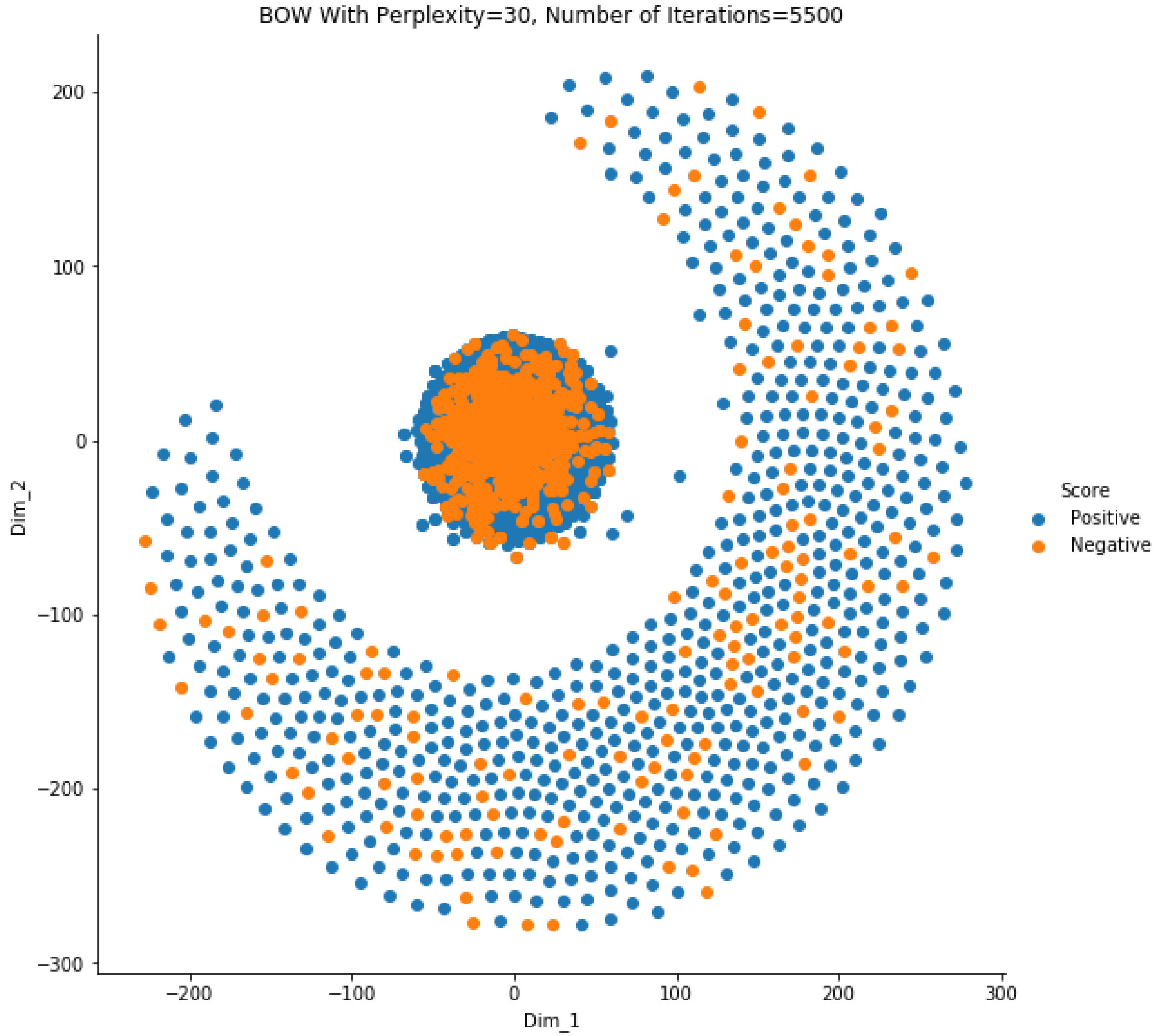
```
(5979, 2)
```

In [169]:
```
BOW_TSNE3 = np.vstack((BOW_TSNE3.T,labels)).T
```

In [170]:
```
BOW_DF3 = pd.DataFrame(data=BOW_TSNE3,columns=("Dim_1","Dim_2","Score"
))
print(BOW_DF3.head(5))
print(BOW_DF3.shape)
```

```
      Dim_1    Dim_2     Score
0  16.2351 -37.8208  Positive
1  16.2284 -37.8068  Positive
2  131.028 -248.347  Positive
3  9.38089 -17.3108  Positive
4  225.029 -117.119  Positive
(5979, 3)
```

In [335]:
```
import seaborn as sns
sns.FacetGrid(data=BOW_DF3,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("BOW With Perplexity=30, Number of Iterations=5500")
plt.show()
```



TSNE on BOW : Perplexity=50, Number of Iterations=10,000

Here, alongwith the other parameters, I have also made n_iter_without_progress = 500, which means anytime before the 10,000 iterations are completed, if 500 iterations are resulting in the plot not changing at all, the loop will be exited.

In [172]:
```
from sklearn.manifold import TSNE

BOW_model4 = TSNE(n_components=2, perplexity=50,n_iter=10000,n_iter_wit
hout_progress=500,random_state=0)
BOW_TSNE4 = BOW_model4.fit_transform(standardized_bow)
```

In [173]:
```
print(BOW_TSNE4.shape)
```

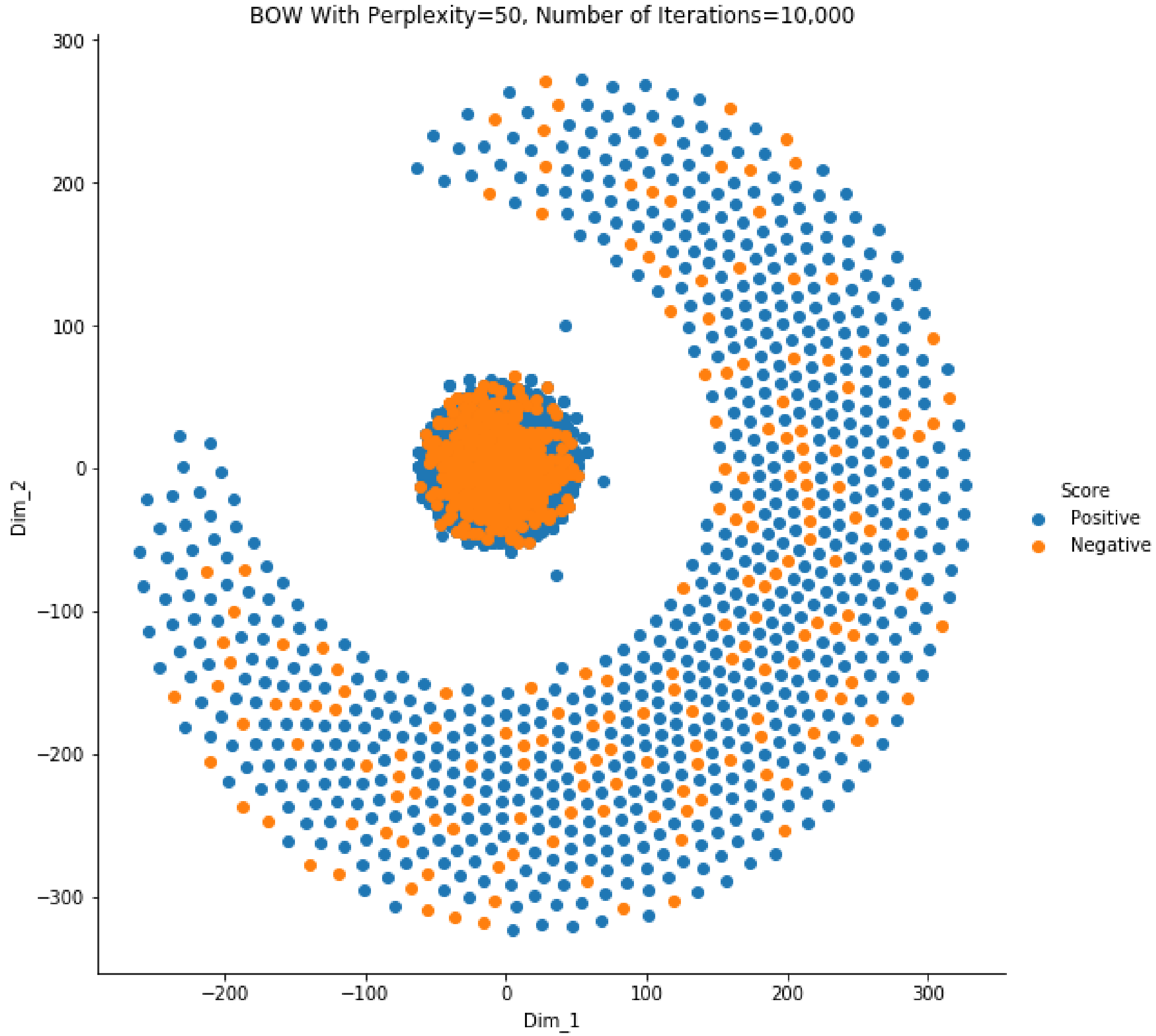
```
(5979, 2)
```

In [174]:
```
BOW_TSNE4 = np.vstack((BOW_TSNE4.T,labels)).T
```

In [175]:
```
BOW_DF4 = pd.DataFrame(data=BOW_TSNE4,columns=("Dim_1","Dim_2","Score"
))
print(BOW_DF4.head(5))
print(BOW_DF4.shape)
```

```
     Dim_1    Dim_2     Score
0  34.9715 -31.2913  Positive
1  34.9598  -31.282  Positive
2  275.248 -145.279  Positive
3  281.797  68.1296  Positive
4  283.961 -17.6504  Positive
(5979, 3)
```

In [334]:
```
import seaborn as sns
sns.FacetGrid(data=BOW_DF4,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("BOW With Perplexity=50, Number of Iterations=10,000")
plt.show()
```



TSNE on BOW : Perplexity=300, Number of Iterations=10,000

Therefore no matter how many different values of perplexity and iterations I have tried so far for t-SNE on the BOW approach, I have not obtained a plot that even remotely separates the Positive and Negative points.

Finally, I read that on average people set the value of perplexity = 5 % of the data size. {Source: [https://stats.stackexchange.com/questions/245168/choosing-the-hyperparameters-using-t-sne-for-classification}](https://stats.stackexchange.com/questions/245168/choosing-the-hyperparameters-using-t-sne-for-classification)

Here, the data size in my case = 5979.

5% of 5979 = approx. 298

Therefore, finally for the BOW approach, I will try with a much higher value of perplexity and see if it helps my case although since BOW is the most basic approach, it seems rather unlikely.

In [177]:
```
from sklearn.manifold import TSNE

BOW_model5 = TSNE(n_components=2, perplexity=300,n_iter=10000,n_iter_wi
thout_progress=500,random_state=0)
BOW_TSNE5 = BOW_model5.fit_transform(standardized_bow)
```

In [178]:
```
print(BOW_TSNE5.shape)
```

```
(5979, 2)
```

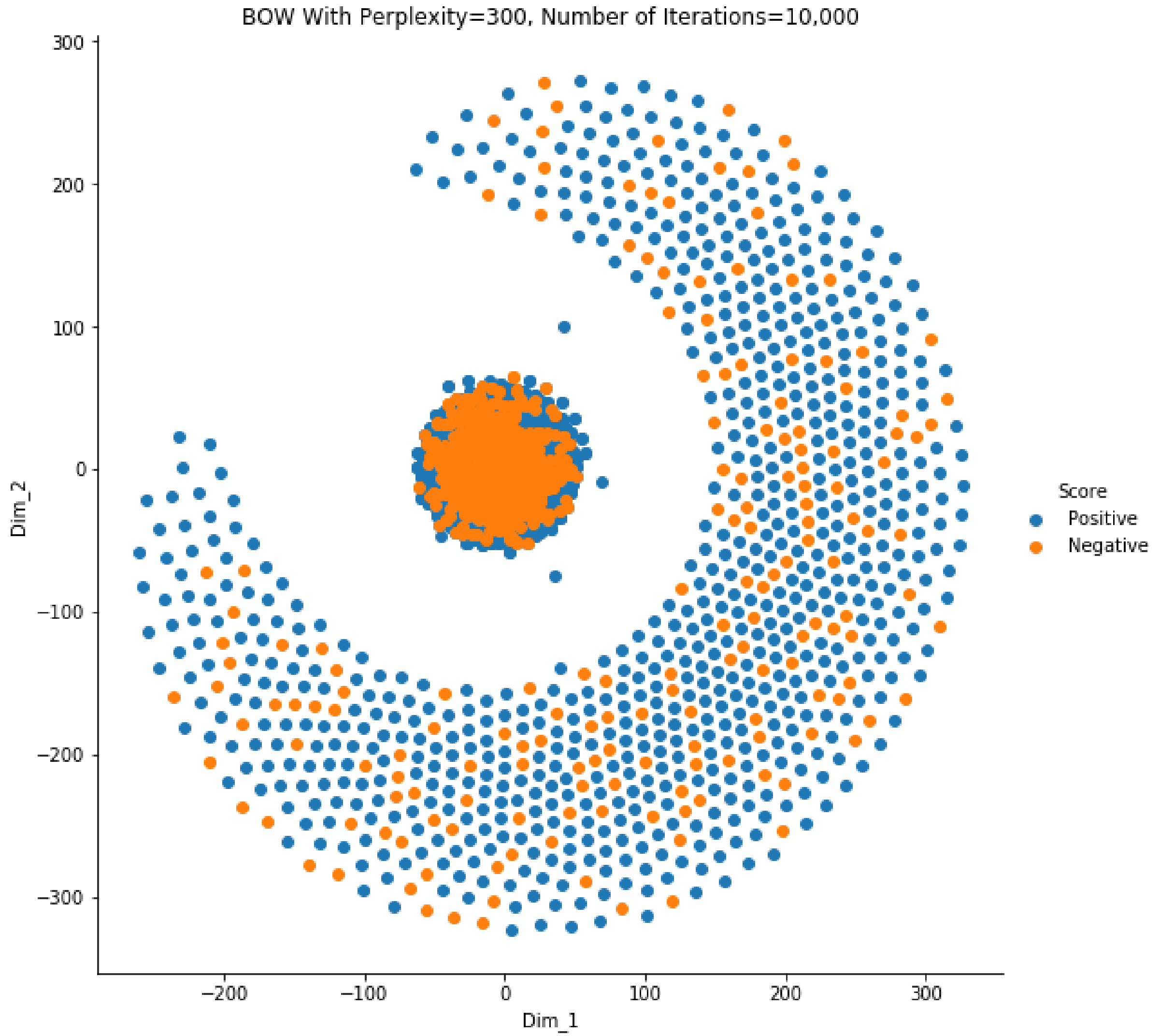
In [179]:
```
BOW_TSNE5 = np.vstack((BOW_TSNE5.T,labels)).T
```

In [180]:
```
BOW_DF5 = pd.DataFrame(data=BOW_TSNE5,columns=("Dim_1","Dim_2","Score"
))
print(BOW_DF5.head(5))
print(BOW_DF5.shape)
```

```
     Dim_1    Dim_2     Score
0  33.2727 -24.3021  Positive
1  33.2546 -24.2896  Positive
2 -17.6789 -9.47198  Positive
3 -112.977  166.435  Positive
4   18.512  12.8943  Positive
(5979, 3)
```

(3979, 3)

In [333]:
```
import seaborn as sns
sns.FacetGrid(data=BOW_DF4,hue='Score',height=8).map(plt.scatter,'Dim_1','Dim_2').add_legend()
plt.title("BOW With Perplexity=300, Number of Iterations=10,000")
plt.show()
```



So, as expected for all varying values of Perplexity as well as step size, BOW Approach does a terrible job in separating the 2 class labels.

[5.1] Applying TSNE on Text TFIDF vectors

The variable that contains the Text TFIDF implementation is "final_tf_idf" which has been obtained after all the text preprocessing steps have been performed and after applying the TFIDF implementation.

In [185]:
```
type(final_tf_idf)
```

Out[185]:
```
scipy.sparse.csr.csr_matrix
```

Again, just like the BOW approach, TFIDF is also a sparse matrix representation with most of the elements in the matrix being equal to zero. Again it needs to be converted into a dense matrix before I proceed with applying TSNE on the same.

In [189]:
```
print(final_tf_idf.shape)
```

```
(5979, 3711)
```

In [190]:
```
#Converting into a dense matrix representation
#todense() is the function used in scipy to convert a sparse matrix int
o a dense matrix.

TFIDF = final_tf_idf.todense()
TFIDF.shape
```

Out[190]:
```
(5979, 3711)
```

The dimensionality of the dense matrix representation is also the same as the sparse matrix. However, the difference lies in the fact that for the dense matrix representation, the non-zero elements are stored as a dictionary which considerably reduces the time and space complexity.

Now I will first implement Column Standardization before I work on TSNE.

In [191]:
```
#Performing Column Standardization

from sklearn.preprocessing import StandardScaler
standardized_tfidf = StandardScaler().fit_transform(TFIDF)
print(standardized_tfidf.shape)

#Now, mean=0 and standard deviation =1.
```

```
(5979, 3711)
```

Now I can work on TSNE for TFIDF Implementation with various values of Perplexity as well as step size.

TSNE on TFIDF : Perplexity = 5, Number of Iterations = 1000

In [194]:
```
from sklearn.manifold import TSNE

tfidf_model1 = TSNE(n_components=2,perplexity=5,n_iter=1000,random_stat
e=0)
tfidf_TSNE1 = tfidf_model1.fit_transform(standardized_tfidf)
```

In [195]:
```
print(tfidf_TSNE1.shape)
```

```
(5979, 2)
```

In [196]:
```
tfidf_TSNE1 = np.vstack((tfidf_TSNE1.T,labels)).T
```

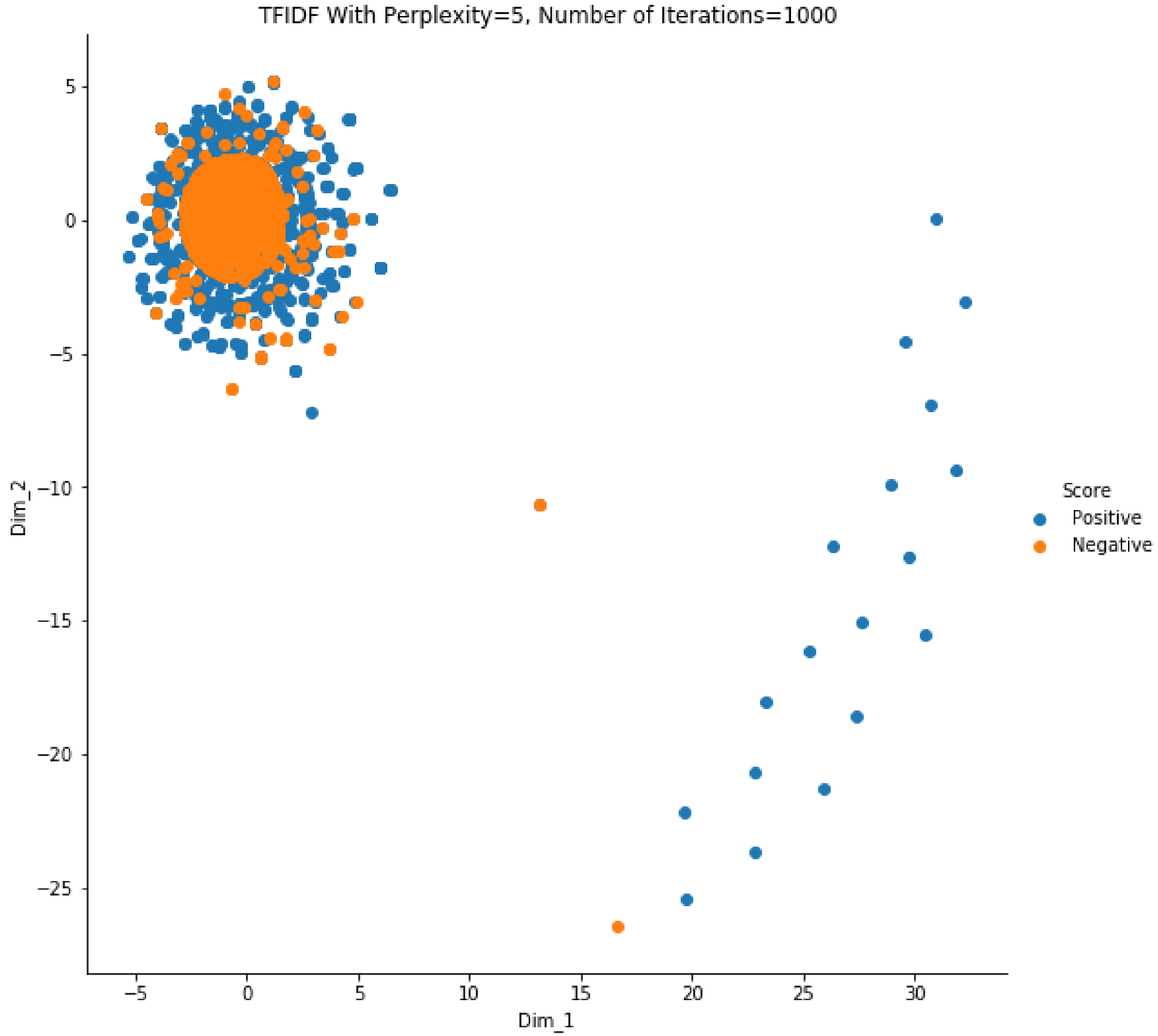
In [197]:
```
tfidf_DF1 = pd.DataFrame(data=tfidf_TSNE1,columns=("Dim_1","Dim_2","Sco
re"))
```

```
print(tfidf_DF1.head(5))
print(tfidf_DF1.shape)
```

```
      Dim_1     Dim_2     Score
0   1.16009   1.12661  Positive
1  -3.90861   2.00684  Positive
2 -0.618516   0.59965  Positive
3 -0.371132  -1.66792  Positive
4  0.912841  0.807863  Positive
(5979, 3)
```

In [332]:

```
import seaborn as sns
sns.FacetGrid(data=tfidf_DF1,hue='Score',height=8).map(plt.scatter,'Dim_1','Dim_2').add_legend()
plt.title("TFIDF With Perplexity=5, Number of Iterations=1000")
plt.show()
```



TSNE on TFIDF : Perplexity = 30, Number of Iterations = 5500

In [199]:
```
tfidf_model2 = TSNE(n_components=2,perplexity=30,n_iter=5500,random_sta
```

```
te=0)
tfidf_TSNE2 = tfidf_model2.fit_transform(standardized_tfidf)
```

In [200]:
```
print(tfidf_TSNE2.shape)
```

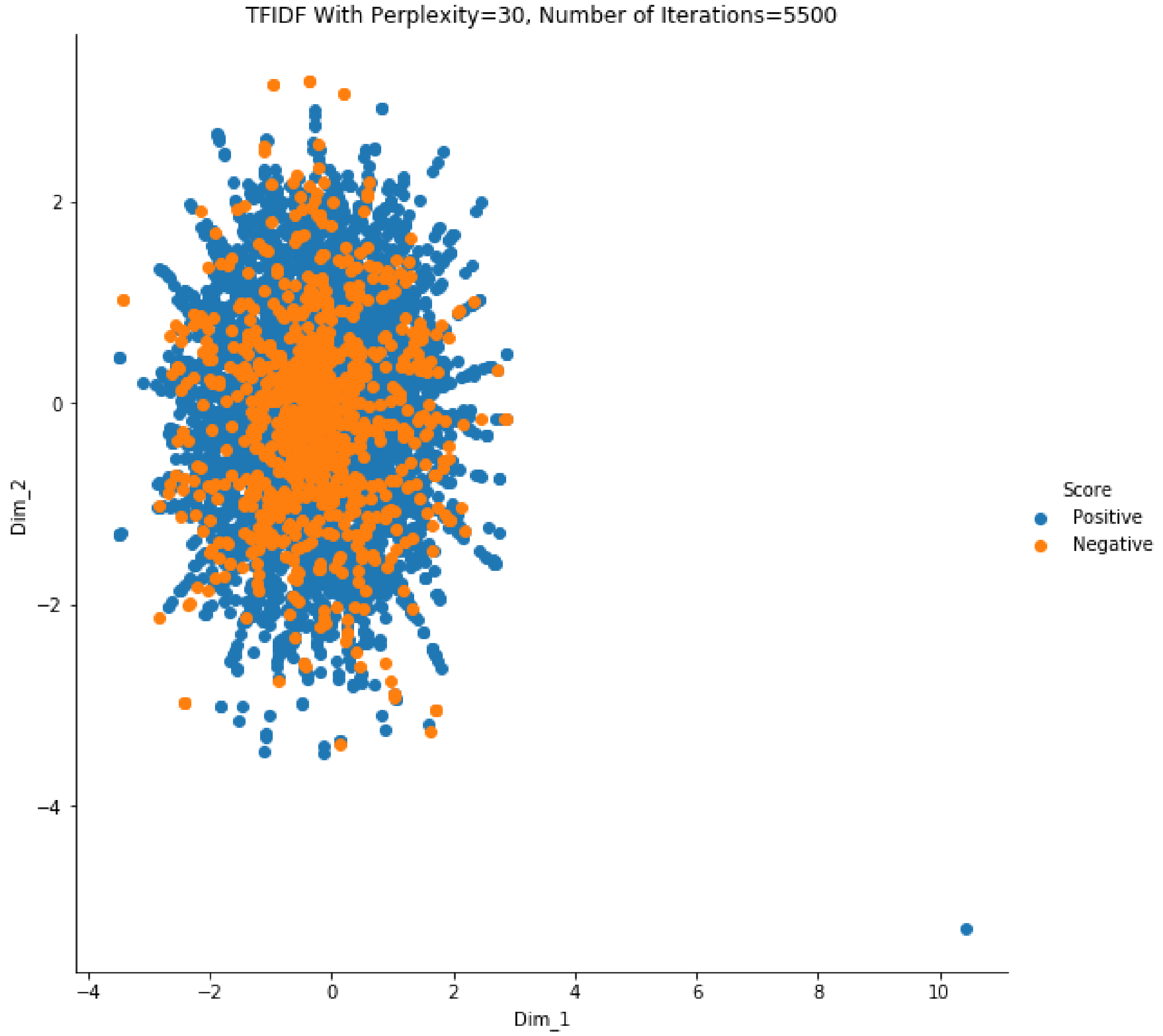
```
(5979, 2)
```

In [201]:
```
tfidf_TSNE2 = np.vstack((tfidf_TSNE2.T,labels)).T
```

In [202]:
```
tfidf_DF2 = pd.DataFrame(data=tfidf_TSNE2,columns=("Dim_1","Dim_2","Score"))
print(tfidf_DF2.head(5))
print(tfidf_DF2.shape)
```

```
      Dim_1     Dim_2     Score
0  -2.10457  0.643815  Positive
1   1.72791  0.650412  Positive
2  0.376476   1.81288  Positive
3 -0.316581 -0.218711  Positive
4  0.109447   0.75033  Positive
(5979, 3)
```

In [331]:
```
import seaborn as sns
sns.FacetGrid(data=tfidf_DF2,hue='Score',height=8).map(plt.scatter,'Dim_1','Dim_2').add_legend()
plt.title("TFIDF With Perplexity=30, Number of Iterations=5500")
plt.show()
```



TSNE on TFIDF : Perplexity = 50, Number of Iterations = 2000

In [211]:
```
tfidf_model3 = TSNE(n_components=2,perplexity=50,n_iter=2000,random_sta
```

```
te=0)
tfidf_TSNE3 = tfidf_model3.fit_transform(standardized_tfidf)
```

In [212]:
```
print(tfidf_TSNE3.shape)
```

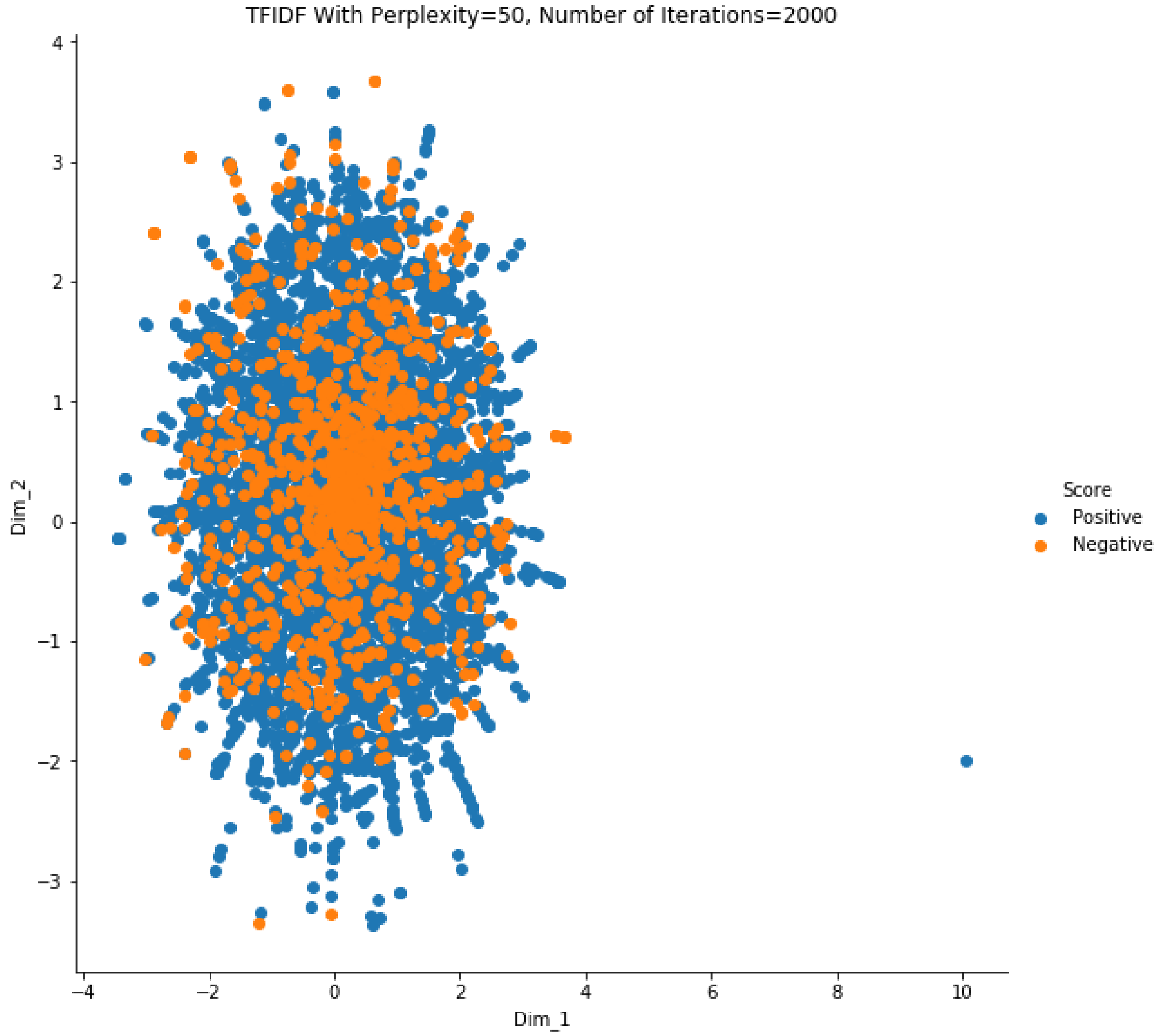
```
(5979, 2)
```

In [213]:
```
tfidf_TSNE3 = np.vstack((tfidf_TSNE3.T,labels)).T
```

In [214]:
```
tfidf_DF3 = pd.DataFrame(data=tfidf_TSNE3,columns=("Dim_1","Dim_2","Sco
re"))
print(tfidf_DF3.head(5))
print(tfidf_DF3.shape)
```

```
      Dim_1     Dim_2     Score
0  -2.07402  0.166656  Positive
1   2.43256  0.380792  Positive
2  0.670709   2.49109  Positive
3    1.1638  0.458991  Positive
4  0.284242  0.461556  Positive
(5979, 3)
```

In [330]:
```
import seaborn as sns
sns.FacetGrid(data=tfidf_DF3,hue='Score',height=8).map(plt.scatter,'Dim
_1','Dim_2').add_legend()
plt.title("TFIDF With Perplexity=50, Number of Iterations=2000")
plt.show()
```



TSNE on TFIDF : Perplexity = 50, Number of Iterations = 10,000

In [216]:
```
tfidf_model4 = TSNE(n_components=2,perplexity=50,n_iter=10000,n_iter_wi
```

```
thout_progress=1000,random_state=0)
tfidf_TSNE4 = tfidf_model4.fit_transform(standardized_tfidf)
```

In [217]:
```
print(tfidf_TSNE4.shape)
```

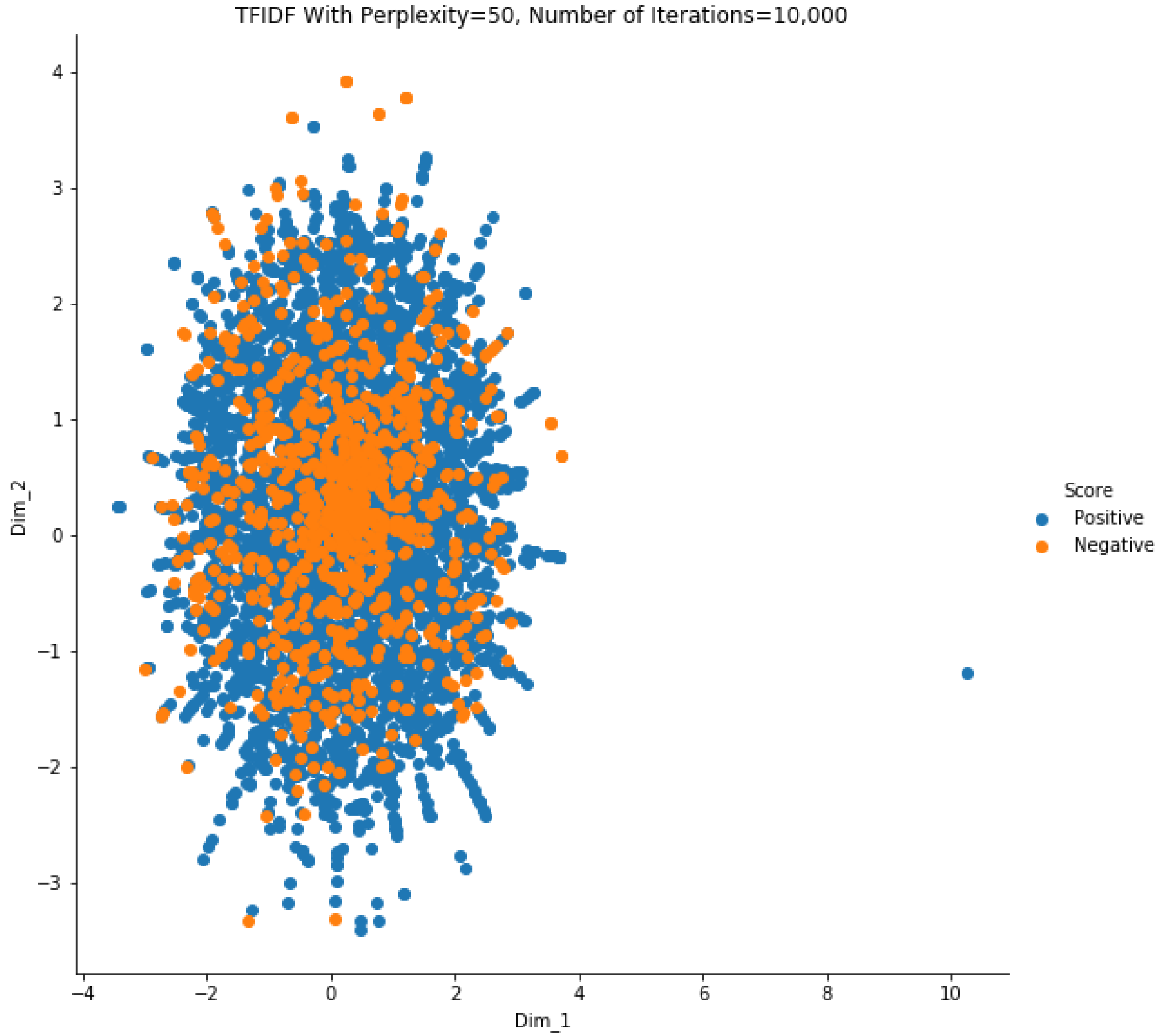
```
(5979, 2)
```

In [218]:
```
tfidf_TSNE4 = np.vstack((tfidf_TSNE4.T,labels)).T
```

In [219]:
```
tfidf_DF4 = pd.DataFrame(data=tfidf_TSNE4,columns=("Dim_1","Dim_2","Score"))
print(tfidf_DF4.head(5))
print(tfidf_DF4.shape)
```

```
      Dim_1     Dim_2     Score
0   -1.6449 -0.330043  Positive
1   2.34184  0.785406  Positive
2  0.567642    2.5694  Positive
3   1.14944  0.327963  Positive
4  0.229775  0.373214  Positive
(5979, 3)
```

In [329]:
```
import seaborn as sns
sns.FacetGrid(data=tfidf_DF4,hue='Score',height=8).map(plt.scatter,'Dim_1','Dim_2').add_legend()
plt.title("TFIDF With Perplexity=50, Number of Iterations=10,000")
plt.show()
```



TSNE on TFIDF : Perplexity = 300, Number of Iterations = 10,000

In [221]:
```
tfidf_model5 = TSNE(n_components=2,perplexity=300,n_iter=10000,n_iter_w
```

```
ithout_progress=1000,random_state=0)
tfidf_TSNE5 = tfidf_model5.fit_transform(standardized_tfidf)
```

In [222]:
```
print(tfidf_TSNE5.shape)
```

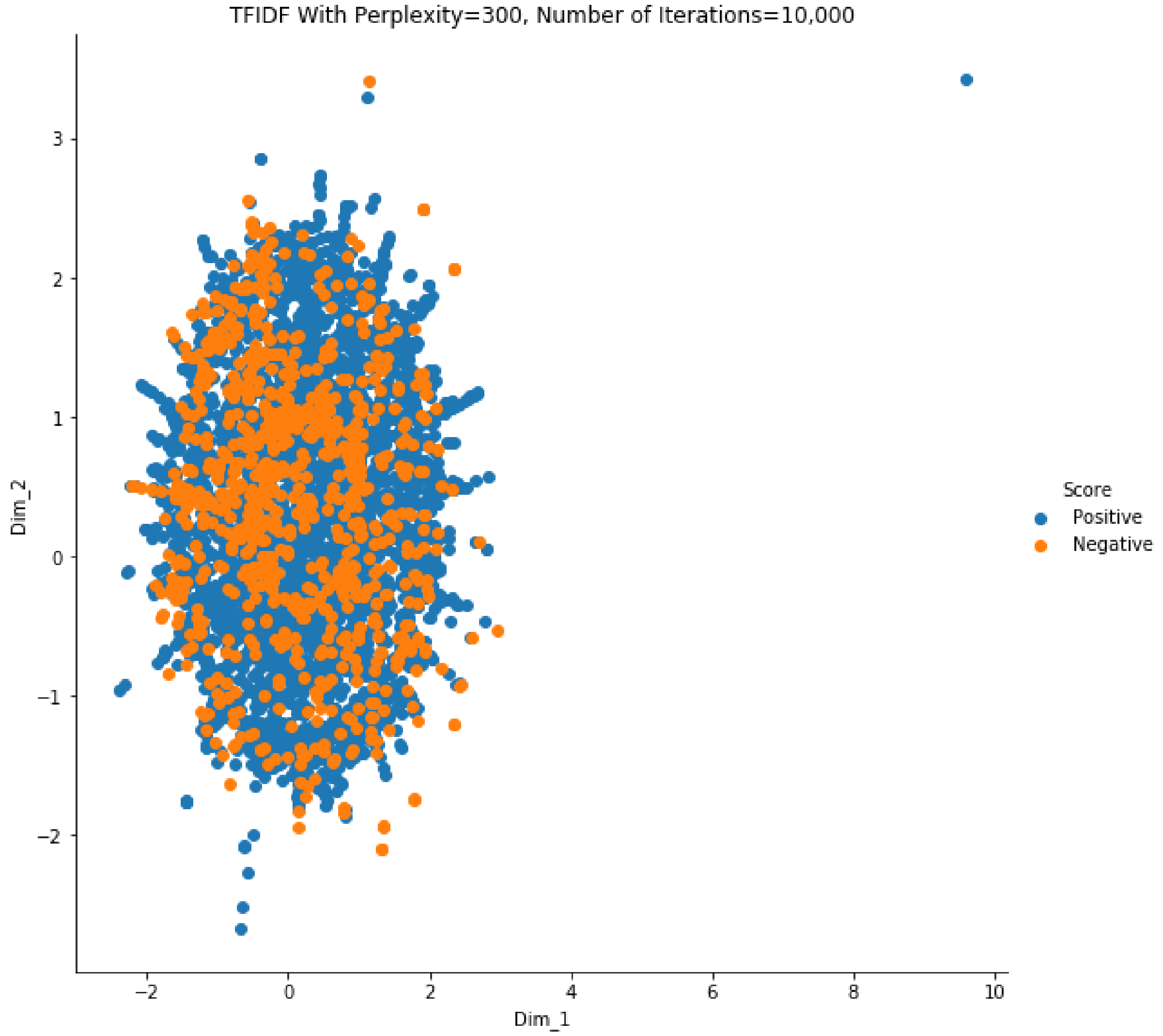
```
(5979, 2)
```

In [223]:
```
tfidf_TSNE5 = np.vstack((tfidf_TSNE5.T,labels)).T
```

In [224]:
```
tfidf_DF5 = pd.DataFrame(data=tfidf_TSNE5,columns=("Dim_1","Dim_2","Sco
re"))
print(tfidf_DF5.head(5))
print(tfidf_DF5.shape)
```

```
      Dim_1      Dim_2     Score
0 -0.631012    1.00695  Positive
1    0.3011   0.247731  Positive
2 -0.839741    1.87856  Positive
3   1.54711  -0.750114  Positive
4  -1.23732  0.0922088  Positive
(5979, 3)
```

In [328]:
```
import seaborn as sns
sns.FacetGrid(data=tfidf_DF5,hue='Score',height=8).map(plt.scatter,'Dim
_1','Dim_2').add_legend()
plt.title("TFIDF With Perplexity=300, Number of Iterations=10,000")
plt.show()
```



[5.3] Applying TNSE on Text Avg W2V vectors

The variable that contains the Text Avg W2V Representation is "sent_vectors" obtained after the completion of all the text preprocessing steps and after the Avg W2V implementation.

In [254]:
```
type(sent_vectors)
```
Out[254]:
```
list
```
In [229]:
```
len(sent_vectors)
```
Out[229]:
```
5979
```
Differing from the BOW as well as TFIDF representations which returned sparse matrices, Avg W2V is different as it returns me a list of length 5979.

In [258]:
```
sent_vectors[0]
```
Out[258]:
```
array([-0.05703185, -0.23206568,  0.14502353, -0.14157635, -0.51046246,
        0.55688779,  0.32838685,  0.13991607, -0.06681669,  0.29854992,
        0.47267885, -0.00370017, -0.25690637, -0.41701833,  0.23187369,
       -0.07570032,  0.37882946,  0.24361327,  0.13271049, -0.06462379,
       -0.33017787, -0.51655979,  0.81253935,  0.03329916, -0.019831  ,
        0.8039234 , -0.01478703,  0.18513408,  0.54002838,  0.07111467,
       -0.16202081,  0.18642075,  0.46631762,  0.34668125, -0.26345999,
       -0.297436  ,  0.02300675,  0.06880932,  0.43467439,  0.13271848,
       -0.28843465, -0.27869822,  0.08921298, -0.00908919,  0.03986808,
        0.02769456,  0.05354961, -0.18772326,  0.21384773,  0.4561420
8])
```
Word2Vec anyway returns us a dense matrix representation, and therefore there is no need to convert the same into a dense matrix representation.

However, column standardization is still important so that TSNE works smoothly. This has been performed as follows:

In [259]:
```
from sklearn.preprocessing import StandardScaler
standardized_AW2V = StandardScaler().fit_transform(sent_vectors)
```
In [246]:
```
print(standardized_AW2V.shape)
```

```
(5979, 50)
```

Now I basically have a 50 dimensional numpy array which needs to be embedded to a 2-dimensional space using TSNE. (50 was the count of the number of dimensions that were specified for Word2Vec given the size of our data corpus)

TSNE on Avg W2V : Perplexity = 5, Number of Iterations = 2000

In [269]:
```
from sklearn.manifold import TSNE

AW2V_model1 = TSNE(n_components=2,perplexity=5,n_iter=2000,random_state
=0)
AW2V_TSNE1 = AW2V_model1.fit_transform(standardized_AW2V)
```

In [270]:
```
print(AW2V_TSNE1.shape)
```

```
(5979, 2)
```

Again, the dimensionality reduction has been successful from 50 dimensions to 2 dimensions, exactly what I needed.

In [271]:
```
AW2V_TSNE1 = np.vstack((AW2V_TSNE1.T,labels)).T
```

In [272]:
```
AW2V_DF1 = pd.DataFrame(data=AW2V_TSNE1,columns=("Dim_1","Dim_2","Scor
e"))
print(AW2V_DF1.head(5))
print(AW2V_DF1.shape)
```

```
     Dim_1    Dim_2     Score
0 -122.916  26.7931  Positive
1 -124.541  26.0195  Positive
2 -140.089  7.08192  Positive
3  -119.95  21.3468  Positive
```

```
4 -128.142  3.74857  Positive
(5979, 3)
```

In [327]:

```
import seaborn as sns
sns.FacetGrid(data=AW2V_DF1,hue='Score',height=8).map(plt.scatter,'Dim_1','Dim_2').add_legend()
plt.title("Average W2V With Perplexity=5, Number of Iterations=2000")
plt.show()
```

TSNE on Avg W2V : Perplexity = 30, Number of Iterations = 10,000

In [291]:
```
AW2V_model2 = TSNE(n_components=2,perplexity=30,n_iter=10000,n_iter_wit
```

```
hout_progress=1000,random_state=0)
AW2V_TSNE2 = AW2V_model2.fit_transform(standardized_AW2V)
```

Again, here also I have set a very high value of step size and passed the parameter that if there is no progress in the visualization for 1000 continuous iterations, then terminate the loop.

In [292]:
```
print(AW2V_TSNE2.shape)
```

```
(5979, 2)
```

In [293]:
```
AW2V_TSNE2 = np.vstack((AW2V_TSNE2.T,labels)).T
```

In [294]:
```
AW2V_DF2 = pd.DataFrame(data=AW2V_TSNE2,columns=("Dim_1","Dim_2","Scor
e"))
print(AW2V_DF2.head(5))
print(AW2V_DF2.shape)
```

```
     Dim_1    Dim_2     Score
0 -73.4158  46.4927  Positive
1 -75.5961   45.351  Positive
2  -89.321  30.7844  Positive
3  -73.489  40.7262  Positive
4 -83.8492  34.3285  Positive
(5979, 3)
```

In [326]:
```
import seaborn as sns
sns.FacetGrid(data=AW2V_DF2,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("Average W2V With Perplexity=30, Number of Iterations=10,000"
)
plt.show()
```

TSNE on Avg W2V : Perplexity = 50, Number of Iterations = 10,000

In [296]:
```
AW2V_model3 = TSNE(n_components=2,perplexity=50,n_iter=10000,n_iter_wit
hout_progress=1000,random_state=0)
AW2V_TSNE3 = AW2V_model3.fit_transform(standardized_AW2V)
```

In [297]:
```
print(AW2V_TSNE3.shape)
```

```
(5979, 2)
```

In [298]:
```
AW2V_TSNE3 = np.vstack((AW2V_TSNE3.T,labels)).T
```

In [299]:
```
AW2V_DF3 = pd.DataFrame(data=AW2V_TSNE3,columns=("Dim_1","Dim_2","Scor
e"))
print(AW2V_DF3.head(5))
print(AW2V_DF3.shape)
```

```
      Dim_1    Dim_2     Score
0 -55.2174  31.2964  Positive
1 -56.8471  30.2298  Positive
2 -64.3292  19.4085  Positive
3 -54.8874  26.6795  Positive
4 -60.6783  22.6318  Positive
(5979, 3)
```

In [325]:
```
import seaborn as sns
sns.FacetGrid(data=AW2V_DF3,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("Average W2V With Perplexity=50, Number of Iterations=10,000"
)
plt.show()
```

Now I will try a random value of perplexity to see what does that give me as a result.

TSNE on Avg W2V : Perplexity = 180, Number of

Iterations = 10,000

In [301]:
```
AW2V_model4 = TSNE(n_components=2,perplexity=180,n_iter=10000,n_iter_wi
thout_progress=1000,random_state=0)
AW2V_TSNE4 = AW2V_model4.fit_transform(standardized_AW2V)
```

In [302]:
```
print(AW2V_TSNE4.shape)
```

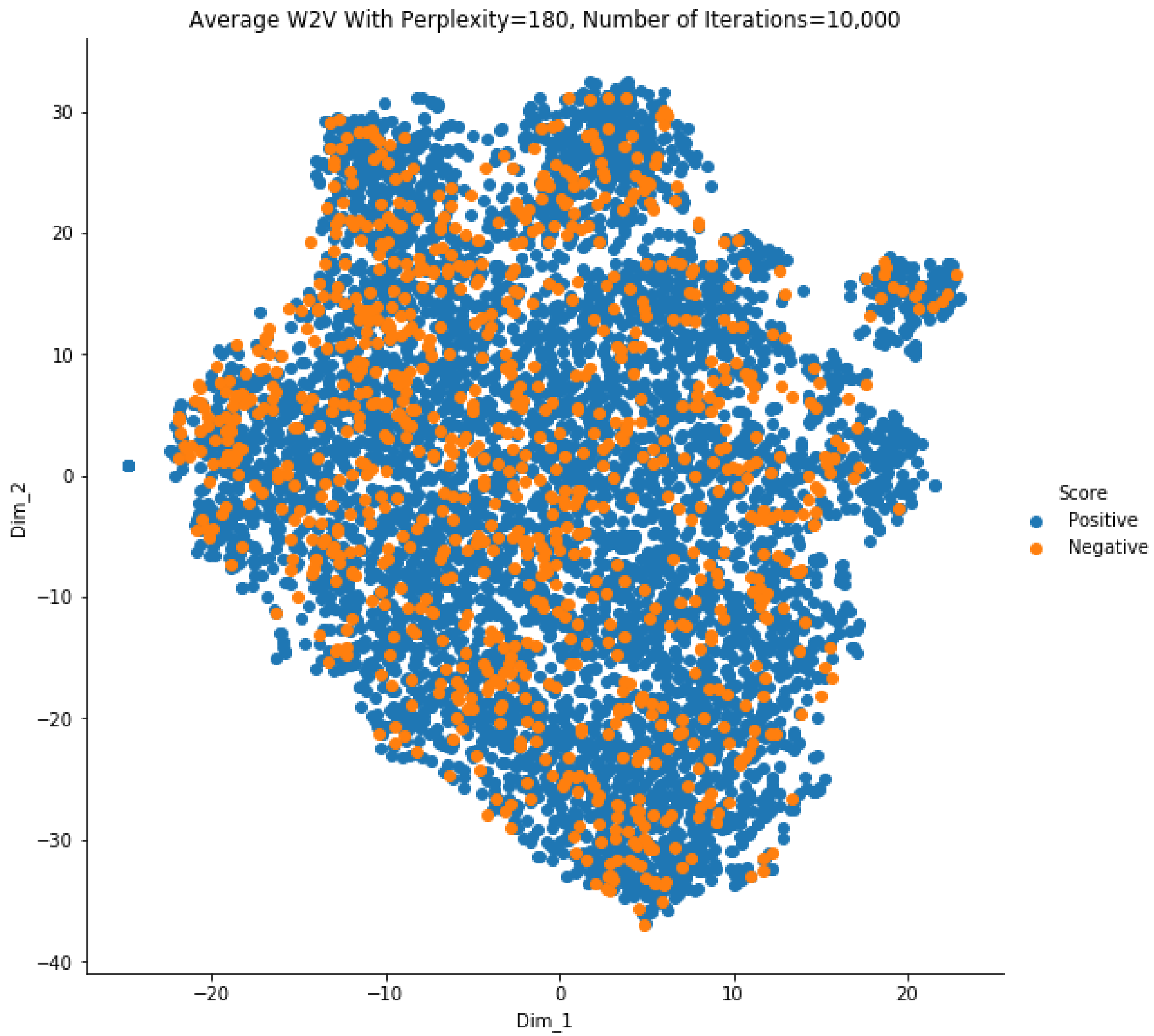
```
(5979, 2)
```

In [303]:
```
AW2V_TSNE4 = np.vstack((AW2V_TSNE4.T,labels)).T
```

In [304]:
```
AW2V_DF4 = pd.DataFrame(data=AW2V_TSNE4,columns=("Dim_1","Dim_2","Scor
e"))
print(AW2V_DF4.head(5))
print(AW2V_DF4.shape)
```

```
     Dim_1    Dim_2     Score
0 -18.5519  7.56345  Positive
1  -19.434  6.55371  Positive
2 -20.7771  2.80249  Positive
3 -18.7183  5.17442  Positive
4 -19.4862  3.93413  Positive
(5979, 3)
```

In [324]:
```
import seaborn as sns
sns.FacetGrid(data=AW2V_DF4,hue='Score',height=8).map(plt.scatter,'Dim_
1','Dim_2').add_legend()
plt.title("Average W2V With Perplexity=180, Number of Iterations=10,00
0")
plt.show()
```



Basically even for the different values of perplexity that we have tried and with a high enough value of the step size, the TSNE plot obtained is is not changing much.

[5.4] Applying TNSE on Text TFIDF weighted W2V vectors

The variable that contains the Weighted W2V implementation is "tfidf_sent_vectors" which has been obtained after the entire text preprocessing has been carried out.

In [306]:
```
type(tfidf_sent_vectors)
```

Out[306]:
```
list
```

In [307]:
```
len(tfidf_sent_vectors)
```

Out[307]:
```
5979
```

In [308]:
```
tfidf_sent_vectors[0]
```

Out[308]:
```
array([-0.07181407, -0.19929878,  0.14286958, -0.12755014, -0.42868752,
        0.48703076,  0.2771869 ,  0.11861013, -0.05463849,  0.24492784,
        0.39959753,  0.0008977 , -0.21864762, -0.36545952,  0.19043169,
       -0.05231103,  0.30488582,  0.21021077,  0.10827746, -0.06024283,
       -0.28990285, -0.43656656,  0.6980028 ,  0.01493119, -0.02633857,
        0.70044764, -0.02250358,  0.14193076,  0.45679612,  0.04595516,
       -0.13513797,  0.18521333,  0.40017933,  0.27523022, -0.23342776,
       -0.26146383,  0.00697366,  0.06690456,  0.36983069,  0.1015166 ,
       -0.25220925, -0.25548306,  0.07465367, -0.02749539,  0.04614894,
        0.01768587,  0.04439919, -0.16215477,  0.18575865,  0.3846832
8])
```

Again, in this case also there's no need to convert any of this to a dense matrix representation.

However, column standardization is performed as follows:

In [309]:
```
standardized_tfidf_W2V = StandardScaler().fit_transform(tfidf_sent_vect
ors)
```

In [310]:
```
print(standardized_tfidf_W2V.shape)
```

```
(5979, 50)
```

Now I can build TSNE models on the same to carry out dimensionality reduction.

TSNE on TFIDF W2V : Perplexity = 5, Number of Iterations = 10,000

In this scenario also, for all the models I am taking a very large step size of 10,000 and passing the parameter such that when there are 1000 iterations such that there is no progress in the visualization, the loop is terminated.

In [312]:
```
TFIDF_W2V_model1 = TSNE(n_components=2,perplexity=5,n_iter=10000,n_iter
_without_progress=1000,random_state=0)
TFIDF_W2V_TSNE1 = TFIDF_W2V_model1.fit_transform(standardized_tfidf_W2V
)
```

In [313]:
```
print(TFIDF_W2V_TSNE1.shape)
```

```
(5979, 2)
```

In [314]:
```
TFIDF_W2V_TSNE1 = np.vstack((TFIDF_W2V_TSNE1.T,labels)).T
```

In [315]:
```
TFIDF_W2V_DF1 = pd.DataFrame(data=TFIDF_W2V_TSNE1,columns=("Dim_1","Dim
_2","Score"))
print(TFIDF_W2V_DF1.head(5))
print(TFIDF_W2V_DF1.shape)
```

```
     Dim_1    Dim_2     Score
0 -184.374  69.0254  Positive
1  -219.09  55.7179  Positive
2 -235.849  35.0759  Positive
3 -186.762  70.1339  Positive
4 -160.078  47.6794  Positive
(5979, 3)
```

In [322]:

```
import seaborn as sns
sns.FacetGrid(data=TFIDF_W2V_DF1,hue='Score',height=8).map(plt.scatter,
'Dim_1','Dim_2').add_legend()
plt.title("TFIDF W2V With Perplexity=5, Number of Iterations=10,000")
plt.show()
```

TSNE on TFIDF W2V : Perplexity = 30, Number of Iterations = 10,000

In [317]:
```
TFIDF_W2V_model2 = TSNE(n_components=2,perplexity=30,n_iter=10000,n_ite
r_without_progress=1000,random_state=0)
TFIDF_W2V_TSNE2 = TFIDF_W2V_model2.fit_transform(standardized_tfidf_W2V
)
```

In [318]:
```
print(TFIDF_W2V_TSNE2.shape)
```

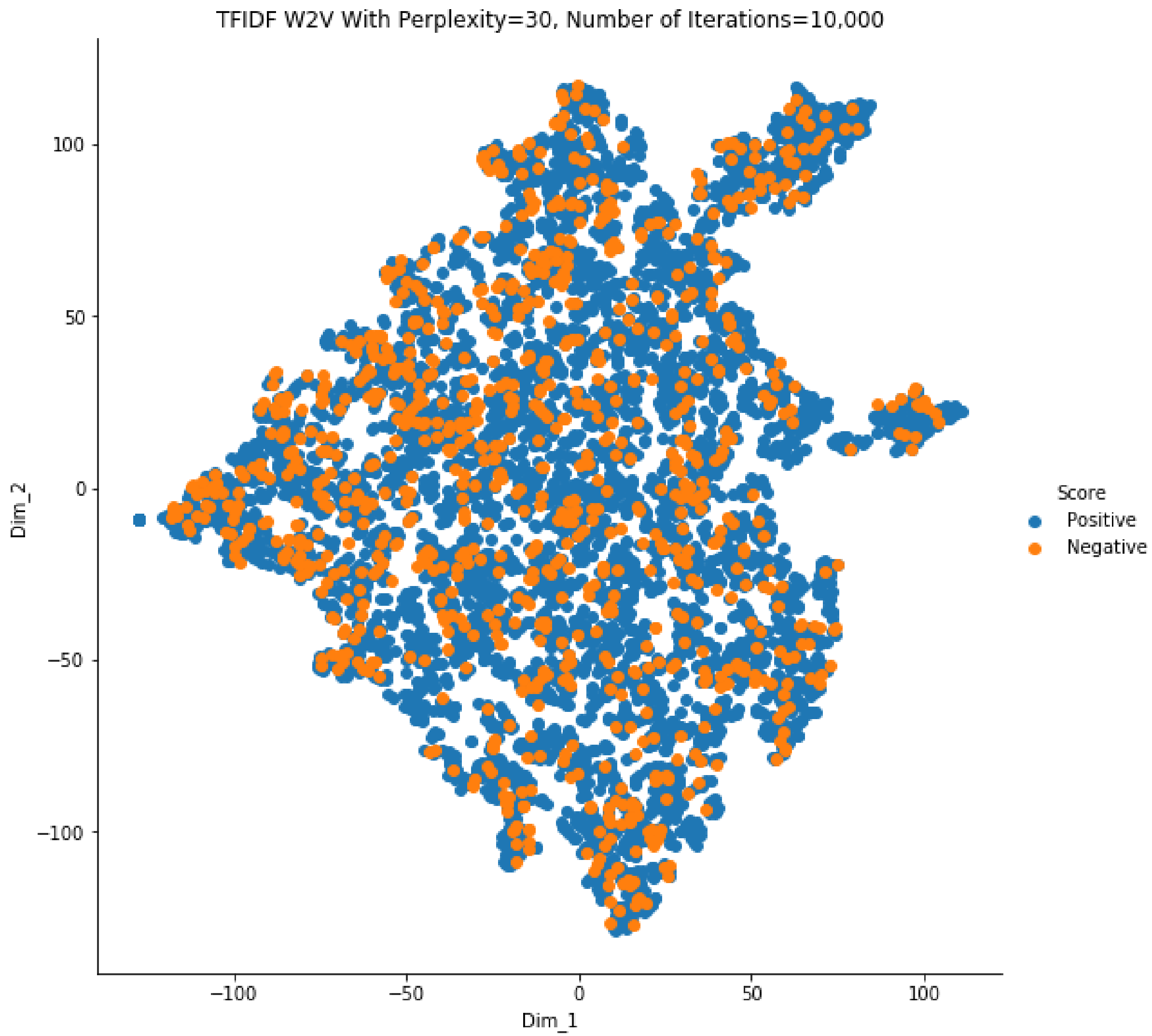
```
(5979, 2)
```

In [319]:
```
TFIDF_W2V_TSNE2 = np.vstack((TFIDF_W2V_TSNE2.T,labels)).T
```

In [320]:
```
TFIDF_W2V_DF2 = pd.DataFrame(data=TFIDF_W2V_TSNE2,columns=("Dim_1","Dim
_2","Score"))
print(TFIDF_W2V_DF2.head(5))
print(TFIDF_W2V_DF2.shape)
```

```
     Dim_1    Dim_2     Score
0 -97.3151  9.86962  Positive
1 -113.056  -1.7832  Positive
2  -113.27 -7.01147  Positive
3 -97.3651  6.45116  Positive
4 -83.1433  8.88114  Positive
(5979, 3)
```

In [321]:
```
import seaborn as sns
sns.FacetGrid(data=TFIDF_W2V_DF2,hue='Score',height=8).map(plt.scatter,
'Dim_1','Dim_2').add_legend()
plt.title("TFIDF W2V With Perplexity=30, Number of Iterations=10,000")
plt.show()
```



TSNE on TFIDF W2V : Perplexity = 50, Number of Iterations = 10,000

In [323]:
```
TFIDF_W2V_model3 = TSNE(n_components=2,perplexity=50,n_iter=10000,n_ite
```

```
r_without_progress=1000,random_state=0)
TFIDF_W2V_TSNE3 = TFIDF_W2V_model3.fit_transform(standardized_tfidf_W2V
)
```

In [338]:
```
print(TFIDF_W2V_TSNE3.shape)
```

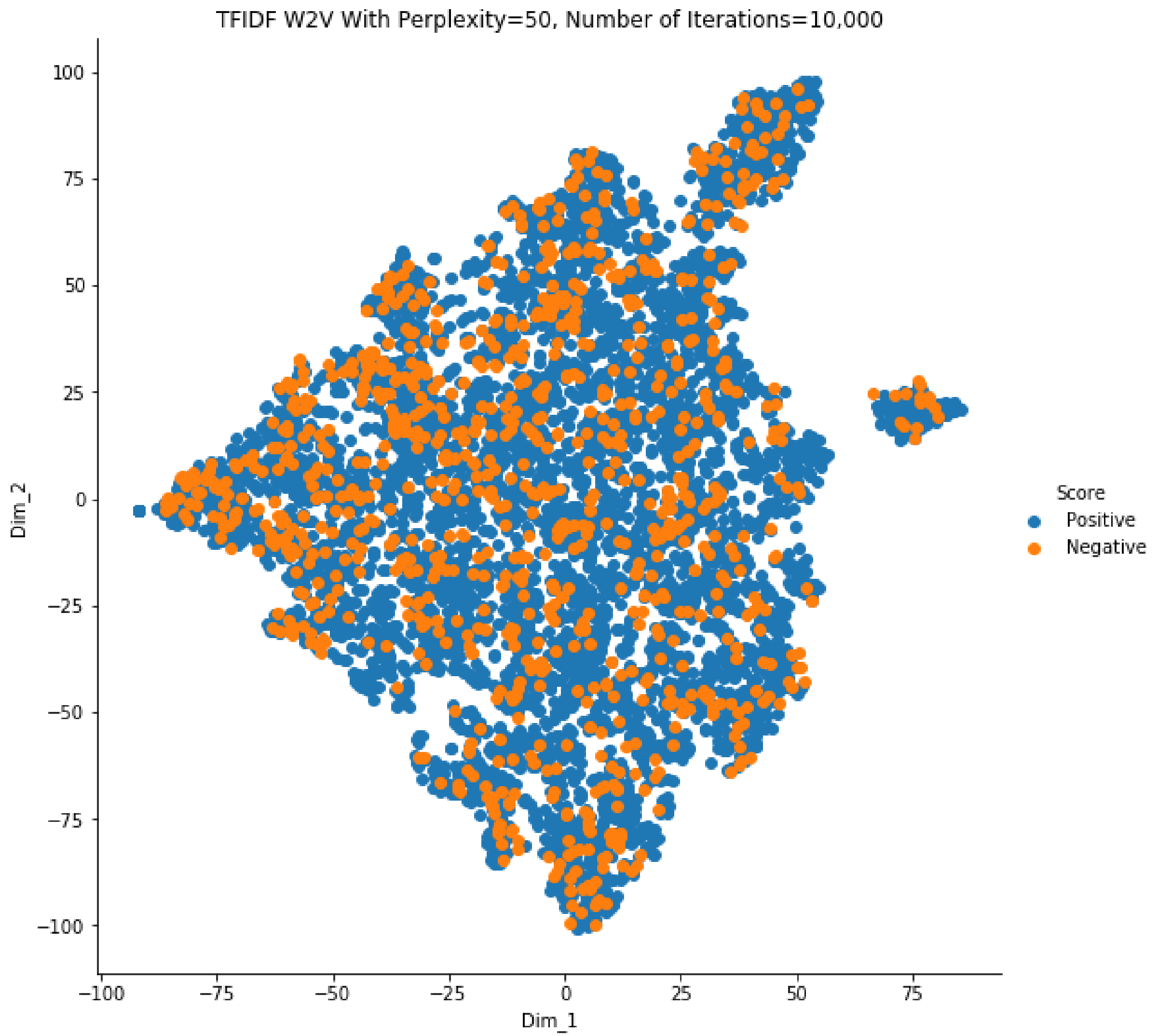
```
(5979, 2)
```

In [339]:
```
TFIDF_W2V_TSNE3 = np.vstack((TFIDF_W2V_TSNE3.T,labels)).T
```

In [340]:
```
TFIDF_W2V_DF3 = pd.DataFrame(data=TFIDF_W2V_TSNE3,columns=("Dim_1","Dim
_2","Score"))
print(TFIDF_W2V_DF3.head(5))
print(TFIDF_W2V_DF3.shape)
```

```
     Dim_1     Dim_2     Score
0 -70.4055   11.0237  Positive
1 -83.4556   3.06023  Positive
2  -82.546 -0.578869  Positive
3 -70.6545   9.26325  Positive
4 -60.8477   10.5309  Positive
(5979, 3)
```

In [341]:
```
import seaborn as sns
sns.FacetGrid(data=TFIDF_W2V_DF3,hue='Score',height=8).map(plt.scatter,
'Dim_1','Dim_2').add_legend()
plt.title("TFIDF W2V With Perplexity=50, Number of Iterations=10,000")
plt.show()
```



TSNE on TFIDF W2V : Perplexity = 300, Number of Iterations = 10,000

In [348]:
```
TFIDF_W2V_model4 = TSNE(n_components=2,perplexity=300,n_iter=10000,n_it
```

```
er_without_progress=1000,random_state=0)
TFIDF_W2V_TSNE4 = TFIDF_W2V_model4.fit_transform(standardized_tfidf_W2V
)
```

In [343]:
```
print(TFIDF_W2V_TSNE4.shape)
```

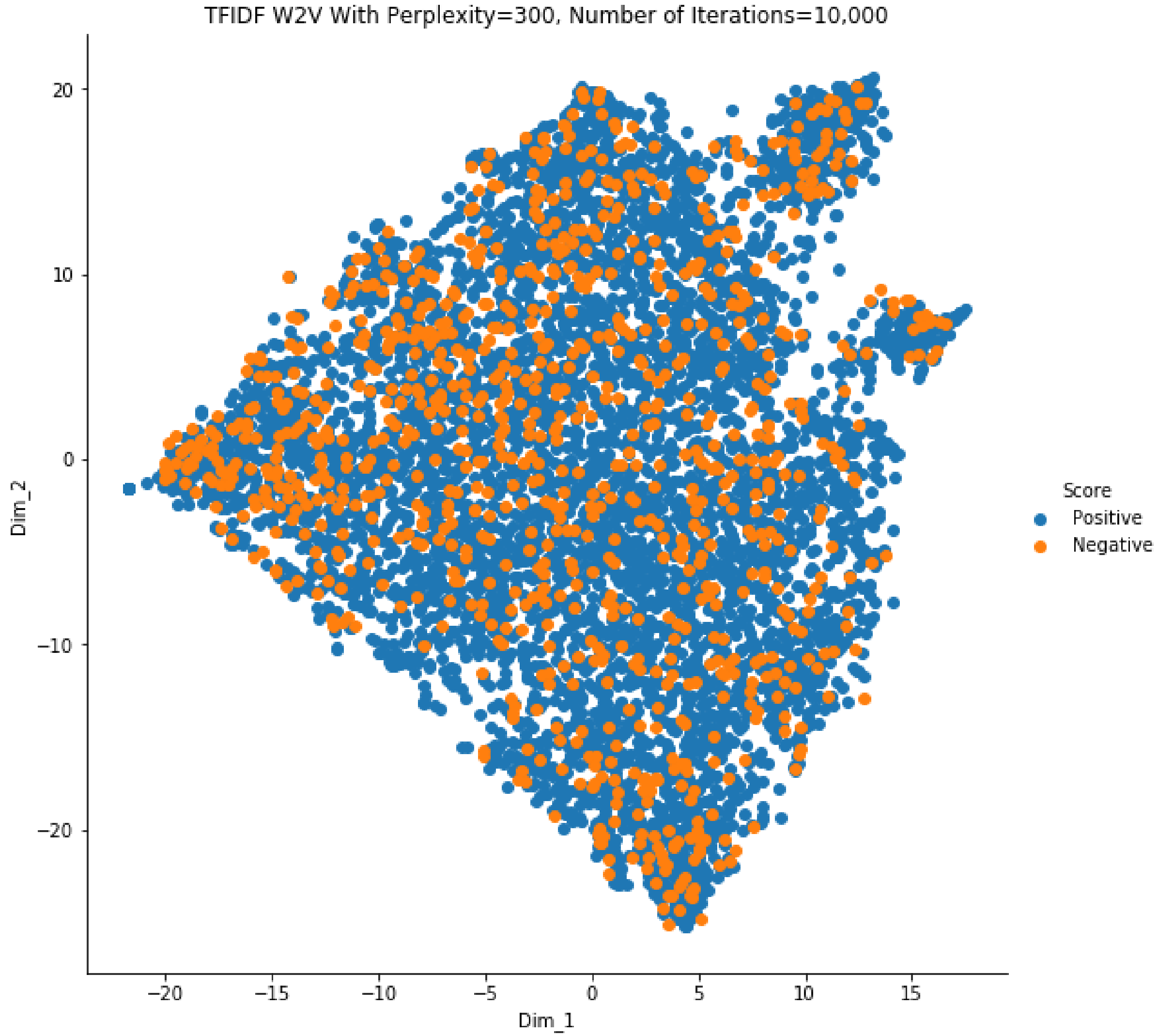
```
(5979, 2)
```

In [344]:
```
TFIDF_W2V_TSNE4 = np.vstack((TFIDF_W2V_TSNE4.T,labels)).T
```

In [345]:
```
TFIDF_W2V_DF4 = pd.DataFrame(data=TFIDF_W2V_TSNE4,columns=("Dim_1","Dim
_2","Score"))
print(TFIDF_W2V_DF4.head(5))
print(TFIDF_W2V_DF4.shape)
```

```
      Dim_1     Dim_2     Score
0 -16.5302   2.70335  Positive
1 -19.7045  0.443693  Positive
2 -19.2921 -0.301393  Positive
3 -16.7848   1.91259  Positive
4 -14.7718   1.92484  Positive
(5979, 3)
```

In [346]:
```
import seaborn as sns
sns.FacetGrid(data=TFIDF_W2V_DF4,hue='Score',height=8).map(plt.scatter,
'Dim_1','Dim_2').add_legend()
plt.title("TFIDF W2V With Perplexity=300, Number of Iterations=10,000")
plt.show()
```



[6] Conclusions

*We always need to apply TSNE more than once for multiple values of perplexity as well as step size. There's no way to ascertain the best value for perplexity but the plots are generally tried with perplexity values between 5 and 50. However, a perplexity value = 5 % of datasize could also be tried out.

*You should almost never look at small perplexity values such as 5 because TSNE tries to prserve the 5 Nearest Neighbours for each point which may show some pattern in data which may not be present in the higher dimensional dataset.

*We can fix a large value of step size and then exit from the iterative loop in case for a particular value that we specify, there's no change in the visualization for that many iterations. In TSNE, this is carried out with the help of n_iter_without_progress parameter.

1. In the BOW Representation, for all the different values of perplexity that I have tried out, both the positive as well as the negative datapoints are present throughout with no pattern present for the separation between the 2 classes. Both the negative as well as positive reviews can have the same words but the issue lies because the semantic meaning of words is not taken into consideration.
2. For the TFIDF representation, there is some circular pattern obtained for the various values of perplexity ie. perplexity = 30, 50 or 300. This means that these values of perplexity basically make sense for these many number of iterations. Here also, the issue is that the semantic meaning of words isn't taken into consideration.
3. For the Avg Word2Vec Representation, the pattern obtained is roughly the same for various values of perplexity ie perplexity = 30, 50 as well as 300. This means that these values of perplexity as defined in the TSNE model make sense for these many iterations.
4. Similarly for the TFIDF Word2Vec Representation we obtain an overalapping pattern which is because I have only taken 6k datapoints for my analysis. If I had taken the entire dataset, the datapoints of the 2 classes would have been that much separated.
5. Both Avg Word2Vec as well as TFIDF weighted Word2Vec take the semantic meaning of words into consideration. If the data size was huge, like the Google News Dataset, the relationships would have been that much more evident if the specified dimensionality was much higher, such as 300, instead of 50 in our case.
6. Word2Vec is the best model out of all these followed by Text TFIDF and lastly BOW representation.