Information about data:

```
                    ->We have the amazon reviews dataset from kaggle

                    ->Reviews are given for the product

                    ->The features of the data were:

                          Id

                          ProductId- unique identifier for the product

                          UserId- unqiue identifier for the user

                          ProfileName

                          HelpfullnessNumerator- number of users who fou
nd the review helpful

                          HelpfulnessDenominator- number of users who in
dicated whether they
                          found the review helpful or not

                          Score-rating between 1 and 5

                          Time-timestamp for the review

                          Summary- brief summary of the review

                          Text- text of the review

                    -> Based on the score of the review we review we cla
ssify them into positive
                        and negative

                    Number of reviews: 568,454
```

Objective:

```
    -> Convert the reviews to vectors by using different approaches
like Bag of Words, TFIDF,            Average Word2vec,TFIDF-Word2vec
and apply the dimensionality reduction technique
```

Importing the required libraries to process

In [1]:

```
import sqlite3
import numpy as np
import pandas as pd
import matplotlib.pyplot as mp
import nltk
import string
from sklearn.feature_extraction.text import TfidfTransformer,TfidfVectorizer,CountVectorizer
from sklearn import metrics
from sklearn.metrics import auc,roc_curve
from nltk.stem.porter import PorterStemmer
```

Using the sqlite3 to read data

In [2]:

```
con = sqlite3.connect("database.sqlite")
```

Filtering the reviews with positive and negative based on the score

In [3]:

```
filtereddata = pd.read_sql_query("SELECT * FROM Reviews WHERE Score !=3",con)
```

->function to classify reviews into positive and negative based on rating.

->Here we are considering that reviews with a rating more than 3 are as positive and reviews with rating

->less than 3 as negative. So considering 3 as the neutral rating, so neglecting the reviews which are give-n

with rating of 3

In [4]:

```
def classify(x):
    if x>3:
        return 'positive'
    return 'negative'
```

Applying the function on rating(score) in the data

In [5]:

```
rating = filtereddata['Score']
rating = rating.map(classify)
filtereddata['Score'] = rating
```

Information about the data:

```
->The shape of data
```

->dimensionality of data

->Number of features

->Sample data

In [6]:

```
print(filtereddata.shape)
print(filtereddata.ndim)
print(filtereddata.columns)
print(filtereddata.head(5))
```

```
(525814, 10)
2
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

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

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...

1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...

3         Cough Medicine  If you are looking for the secret ingredient i...

4            Great taffy  Great taffy at a great price.  There was a wid...
```

Exploratory data analysis

Deduplication:removing duplicates

In [7]:

```
dup = pd.read_sql_query("""SELECT * FROM REVIEWS WHERE Score !=3 AND UserId
="AR5J8UI46CURR" ORDER BY ProductId """,con)
dup
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD

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

->It shows that same user have 5 reviews at the same time which is not possible

->This is because if we review on product it is applied to different flavors in the product

->In order to remove the product we have to sort them and drop the duplicates

In [8]:

```
sorteddata = filtereddata.sort_values("ProductId",axis=0,ascending=True,inp
lace=False,kind='quicksort',na_position='last')
```

In [9]:

```
finaldata = sorteddata.drop_duplicates(subset=('Time','Text','ProfileName',
'UserId'),keep='first',inplace=False)
```

In [10]:

```
finaldata.shape
```

Out[10]:

```
(364173, 10)
```

Percentage reduction of data after dropping duplicates

In [11]:

```
print(filtereddata['Id'].size)
print(finaldata['Id'].size)
```

```
525814
364173
```

In [12]:

```
(364173/525814)*100
```

Out[12]:

```
69.25890143662969
```

->One more observation is that for a product the useful review(helpfullnessnumerator) is greater that the

->Total number of reviews on the product(helpfullnessdenominator) which is not possible

In [13]:

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

In [14]:

```
numden
```

Out[14]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [15]:

```
finaldata = finaldata[finaldata.HelpfulnessNumerator<=finaldata.Helpfulness
Denominator]
finaldata
```

Out[15]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1
138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg "(Kate)"	1
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3
138693	150511	0006641040	A1C9K534BCI9GO	Laura Purdie Salas	0
138694	150512	0006641040	A1DJXZA5V5FFVA	A. Conway	0
138695	150513	0006641040	ASH0DZQQF6AIZ	tessarat	0
138696	150514	0006641040	A2ONB6ZA292PA	Rosalind Matzner	0
138697	150515	0006641040	A2RTT81R6Y3R7X	Lindylu	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138687	150505	0006641040	A2PTSM496CF40Z	Jason A. Teeple "Nobody made a greater mistak...	1
138698	150516	0006641040	A3OI7ZGH6WZJ5G	Mary Jane Rogers "Maedchen"	0
138700	150518	0006641040	AK1L4EJBA23JF	L. M. Kraus	0
138701	150519	0006641040	A12HY5OZ2QNK4N	Elizabeth H. Roessner	0
138702	150520	0006641040	ADBFSA9KTQANE	James L. Hammock "Pucks Buddy"	0
138703	150521	0006641040	A3RMCRB2NDTDYP	Carol Carruthers	0
138704	150522	0006641040	A1S3C5OFU508P3	Charles Ashbacher	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11
138709	150529	0006641040	[illegible]	Matt Hetling	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138709	150529	0006641040	A25ACLV5KPB4W	"Matt"	0
138699	150517	0006641040	ABW4IC5G5G8B5	kevin clark	0
138686	150504	0006641040	AQEYF1AXARWJZ	Les Sinclair "book maven"	1
138692	150510	0006641040	AM1MNZMYMS7D8	Dr. Joshua Grossman	0
138680	150498	0006641040	A3SJWISOCP31TR	R. J. Wells	2
138677	150494	0006641040	AYZ0PR5QZROD1	Mother of 3 girls	3
138678	150496	0006641040	A3KKR87BJ0C595	Gretchen Goodfellow "Lover of children's lit"	3
138685	150503	0006641040	A3R5XMPFU8YZ4D	Her Royal Motherliness "Nana"	1
138684	150502	0006641040	AVFMJ50HNO21J	Jane Doe	1
138679	150497	0006641040	A1HKYQOFC8ZZCH	Maria Apolloni "lanarossa"	2
...	...	...	...	...	...

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
35419	38512	B009O7B1I0	A2YWHBF45M64S2	EcyMom	0
195185	211594	B009O7DGEW	A2UAKIEWZLQCUE	Cindy S.	0
494393	534495	B009OY38SY	A1H1OCLG2B4AEQ	base64	0
134853	146374	B009P4KMZA	A217L3D5UK74I6	george karlin	0
430102	465120	B009PCDDO4	A2II09GQGWOMTQ	Brian Nallick "METALMANMN"	1
264734	286941	B009PFJUF2	A2UAKIEWZLQCUE	Cindy S.	1
264735	286942	B009PFJUF2	A16HJRHRHNSUZ6	Danielle Tietz	1
241028	261429	B009PG8MVO	A2UAKIEWZLQCUE	Cindy S.	0
269822	292509	B009PIAFTE	A00489763J7YUCSN6CP7K	Andrea Llyod	0
343072	371148	B009PICJTS	A09229701Z8W88AD38877	Kristi Greene	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
427660	462501	B009PIEW3Q	A0849196AFU725N8S7RS	Brady Gibson	0
184728	200383	B009RE0Y5G	A3M2YJ76LOMNBK	turbo418	0
178140	193169	B009RSR8HO	A3M3S2NCVZ8UXF	Stephanie	0
178139	193168	B009RSR8HO	A1L130V9KINC45	mildred rosa	0
178138	193167	B009RSR8HO	A5F9OUO3F2N7C	Jan	0
178135	193164	B009RSR8HO	A2IZG2VYD476QH	CSTreviso	1
178136	193165	B009RSR8HO	A1I08MP3H92U6R	Thomas	1
178134	193163	B009RSR8HO	A1QX7TAALGCUKM	H.B. "H.B."	2
178137	193166	B009RSR8HO	AD0V42PRKCDBM	Rachelle	0
178142	193171	B009RSR8HO	AH2FVNP7Z6PZH	Marty Campbell	0
178141	193170	B009RSR8HO	A1TNEJA68OD7ZH	morgan	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
178143	193172	B009RSR8HO	A3JJTHP8T7A8LY	Joanne Eklund "Joanne"	0
178147	193176	B009RSR8HO	A76WHW051R3KV	Shawn "Shawn"	0
178146	193175	B009RSR8HO	A1A0PMN417S4V9	mamaelle "mamaelle"	0
178144	193173	B009RSR8HO	A34TVEXPHSSPBV	Beth	0
178145	193174	B009RSR8HO	A4P6AN2L435PV	romarc	0
173675	188389	B009SF0TN6	A1L0GWGRK4BYPT	Bety Robinson	0
204727	221795	B009SR4OQ2	A32A6X5KCP7ARG	sicamar	1
5259	5703	B009WSNWC4	AMP7K1O84DH1T	ESTY	0
302474	327601	B009WVB40S	A3ME78KVX31T21	K'la	0

364171 rows × 10 columns

In [16]:

```
finaldata.shape
```

Out[16]:

```
(364171, 10)
```

Text preprocessing: ->Which includes cleaning the text like

```
->Removing special characters,stemming,lemitization

->Checking a word length greater that 2

->Removing stopwords

->converting words to lowercase
```

In [17]:

```
import re
i=0
for sent in finaldata['Text'].values:
    if(len(re.findall("<.*?>",sent))):
        print(i)
        print(sent)
        break
    i =i+1
```

```
6
I set aside at least an hour each day to read to my son (3 y/o). At this po
int, I consider myself a connoisseur of children's books and this is one of
the best. Santa Clause put this under the tree. Since then, we've read it p
erpetually and he loves it.<br /><br />First, this book taught him the mont
hs of the year.<br /><br />Second, it's a pleasure to read. Well suited to
1.5 y/o old to 4+.<br /><br />Very few children's books are worth owning. M
ost should be borrowed from the library. This book, however, deserves a per
manent spot on your shelf. Sendak's best.
```

In [18]:

```
import string
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/vthumati/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[18]:

```
True
```

->Removing stop words

->Stemming the words

In [20]:

```
stop = set(stopwords.words('english'))
sno = nltk.stem.SnowballStemmer('english')
```

Function to clean html tags and special characters

In [21]:

```
def cleanhtml(sentence):
    clean = re.compile("<.*?>")
    cleantext = re.sub(clean," ",sentence)
    return cleantext
def cleanpunct(sentence):
    cleanr = re.sub(r"[?|!|\|'|#|.|,|)|(|/]",r' ',sentence)
    return cleanr
```

In [22]:

```
print(sno.stem('because'))
print(stop)
```

```
becaus
{'hasn', 'above', 'don', 'or', 'himself', 'am', "doesn't", 'his', 'themselv
es', 'any', 'through', 'be', 'an', "shouldn't", 'me', 'their', 'up', 'out',
'do', 'during', 'did', 'them', 'into', "you've", 'we', "she's", 'before', "
isn't", 'same', 'there', 'below', 'other', 'this', "it's", 'if', 'only', 'o
f', 'they', 'having', 'to', 'couldn', "weren't", 're', 'myself', "hadn't",
'yours', "you're", 'which', 'against', 'aren', 'm', 'once', 'was', 'again',
'very', 'after', 'were', 'as', 'those', 'from', 'her', 'over', 'each', 'the
n', 'all', 'further', 'should', 'mightn', 'no', 'weren', "should've", 'down
', 'about', 'o', 'and', 'by', 'what', 't', 'does', 'both', 'nor', "mightn't
", 'between', 'i', 'in', 'most', "didn't", 'needn', 'a', 'hadn', 'few', 'ma
', 'the', 'now', 'on', 'herself', 'such', 'not', 'my', 'is', 've', "you'll"
, 'has', 'theirs', 'some', 'she', 'doesn', 'than', 'with', 'wouldn', 'isn',
'you', 'more', 'just', "hasn't", "wasn't", 'too', 'your', 'have', 'own', 'o
urselves', 'wasn', "don't", 'yourself', 'shouldn', 'under', "shan't", 'why'
, 's', 'won', 'here', 'while', 'these', 'll', 'its', 'doing', "you'd", 'you
rselves', "couldn't", 'had', 'are', 'at', 'so', 'ain', 'until', "mustn't",
'whom', 'will', 'for', 'that', "aren't", 'because', 'him', 'being', 'off',
'our', 'didn', "won't", 'd', 'he', 'y', 'can', "that'll", 'been', 'ours', '
hers', 'shan', 'itself', 'where', "wouldn't", 'mustn', 'but', 'who', 'haven
', 'when', 'it', 'how', "haven't", "needn't"}
```

In [23]:

```
i=0
final_string=[]
all_positive_words=[]
all_negative_words=[]
str1=' '
s=' '
for sent in finaldata['Text'].values:
    sent = cleanhtml(sent)
    filtered_sentence=[]
    for w in sent.split():
        for word in cleanpunct(w).split():
            if((word.isalpha()) & (len(word)>2)):
                if(word.lower() not in stop):
                    s = (sno.stem(word.lower())).encode('utf8')
```

```
                        filtered_sentence.append(s)
                        if(finaldata['Score'].values)[i]=='positive':
                            all_positive_words.append(s)
                        if(finaldata['Score'].values)[i]=='negative':
                            all_negative_words.append(s)

    str1 = b" ".join(filtered_sentence)
    final_string.append(str1)
    i = i+1
```

In [24]:

```
len(final_string)
```

Out[24]:

```
364171
```

BAG OF WORDS:

```
    Using bow to convert text to vector and reducing its
dimensionality
```

In [25]:

```
count_vect = CountVectorizer()
```

In [26]:

```
final_count = count_vect.fit_transform(finaldata['Text'].values)
```

In [27]:

```
print(type(final_count))

final_count.shape
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

Out[27]:

```
(364171, 115281)
```

In [28]:

```
print(type(final_count))

final_count.shape
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

Out[28]:

```
(364171, 115281)
```

Applying TRUNCATEDSVD technique on bag of words data to reduce dimensionality

In [29]:

```
from sklearn.decomposition import TruncatedSVD
```

In [30]:

```
truncatedsvd = TruncatedSVD(n_components=2,n_iter=100,random_state=999,tol=
0.0)
```

In [31]:

```
tsvd = truncatedsvd.fit_transform(final_count)
```

In [32]:

```
print(tsvd.shape)
print(type(tsvd.shape))
```

```
(364171, 2)
<class 'tuple'>
```

In [33]:

```
score = finaldata['Score']
print(score.head(5))
```

```
138706    positive
138688    positive
138689    positive
138690    positive
138691    positive
Name: Score, dtype: object
```

In [34]:

```
score.shape
```

Out[34]:

```
(364171,)
```

In [35]:

```
tsvddata = np.vstack((tsvd.T,score)).T
```

In [36]:

```
tsvddata.shape
```

Out[36]:

```
(364171, 3)
```

In [37]:

```
tsvddatadf=pd.DataFrame(data=tsvddata,columns=('1stdim','2nddim','score'))
```

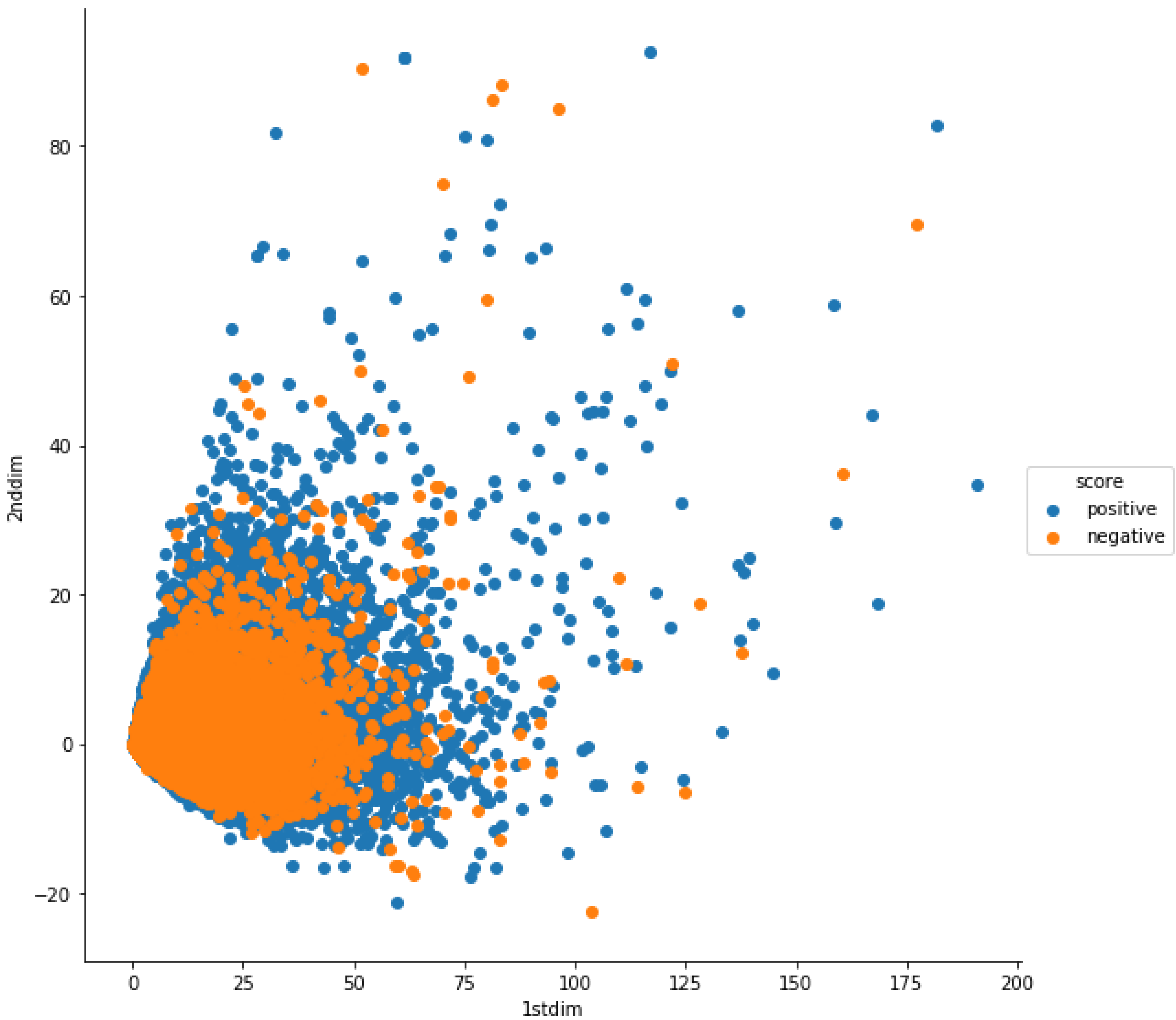
In [38]:

```
import seaborn as s
```

In [39]:

```
s.FacetGrid(tsvddatadf,hue='score',size=8).map(mp.scatter,'1stdim','2nddim'
).add_legend()
mp.show()
```

```
plt.show()
```



TF-IDF

```
Using TF-IDF to convert text to vector and reducing its dimensiona
lity
```

In [40]:

```
tf_idf = TfidfVectorizer(ngram_range=(1,2))
```

In [41]:

```
tf_idf_vector = tf_idf.fit_transform(finaldata['Text'].values)
```

In [42]:

```
print(tf_idf_vector.get_shape())
```

```
(364171, 2910192)
```

In [43]:

```
type(tf_idf_vector)
```

Out[43]:

```
scipy.sparse.csr.csr_matrix
```

->After converting the reviews to vectors using tfidf the resultant is a sparse matrix

->So i have to go with truncatedsvd method for dimensionality redcution

In [44]:

```
svd1 = TruncatedSVD(n_components=2,n_iter=100,random_state=888,tol=0.0)
```

In [45]:

```
svd1_data = svd1.fit_transform(tf_idf_vector)
```

In [46]:

```
print(svd1_data.shape)
print(type(svd1_data))
```

```
(364171, 2)
<class 'numpy.ndarray'>
```

In [47]:

```
score.shape
```

Out[47]:

```
(364171,)
```

In [48]:

```
svd1_dataframe = np.vstack((svd1_data.T,score)).T
```

In [49]:

```
svd1_dataframe.shape
```

Out[49]:

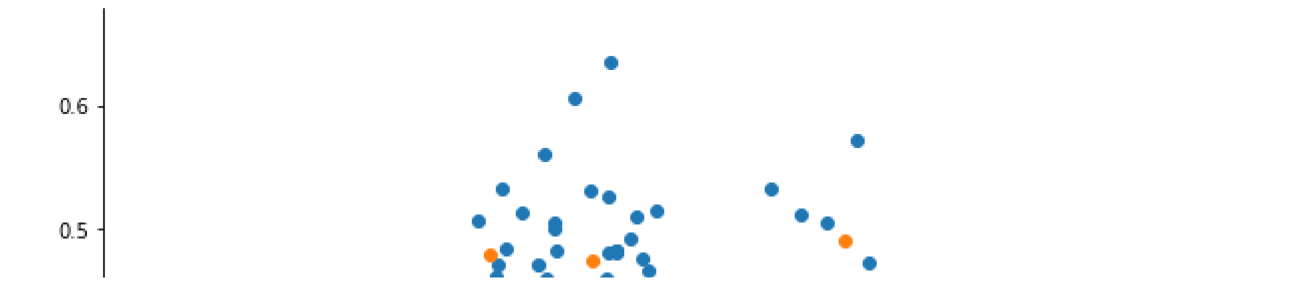
```
(364171, 3)
```

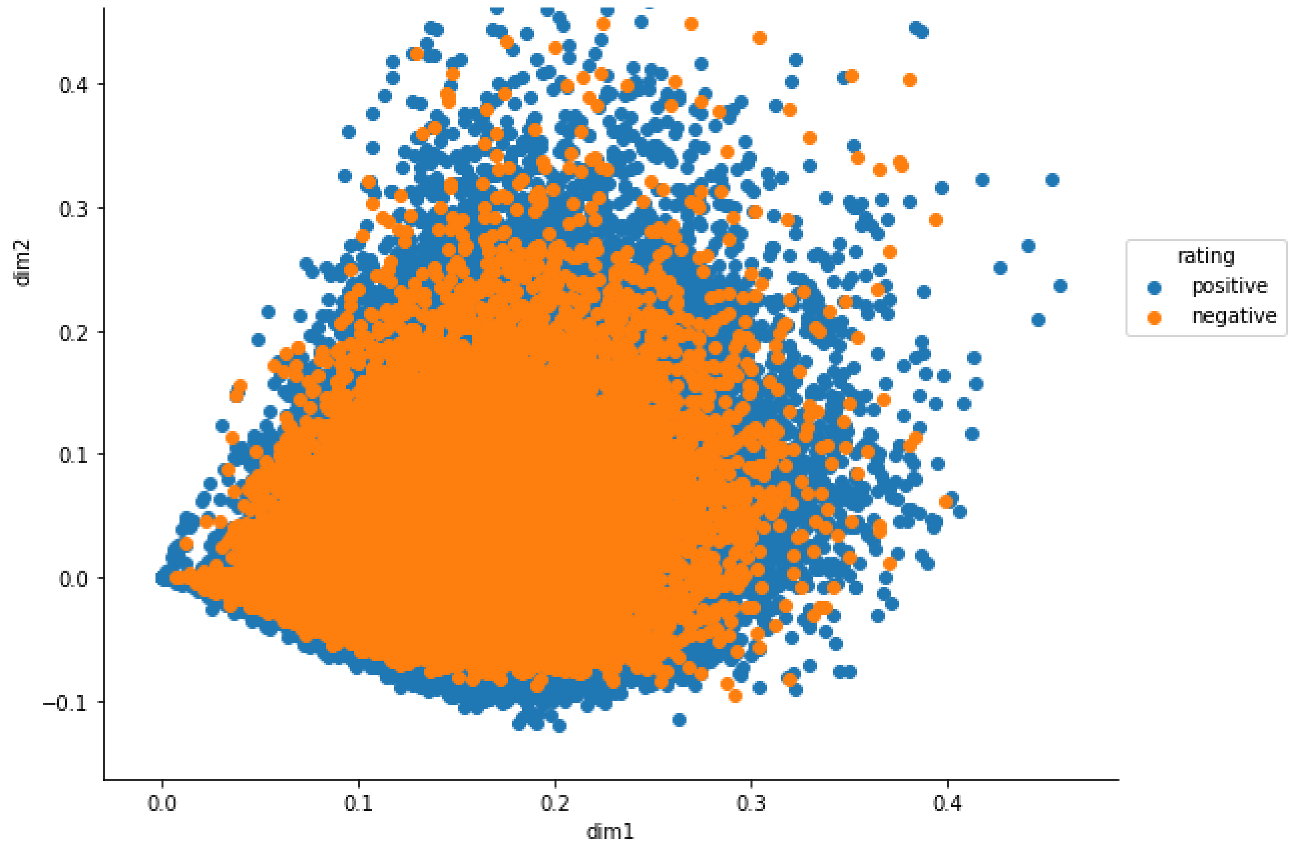
In [50]:

```
svd1_df = pd.DataFrame(svd1_dataframe,columns=('dim1','dim2','rating'))
```

In [51]:

```
s.FacetGrid(svd1_df,hue='rating',size=8).map(mp.scatter,'dim1','dim2').add_l
egend()
mp.show()
```





WORD2VEC:

```
-> Uisng word2vec approach to convert the words in sentences
```

In [52]:

```
import gensim
from gensim.models import word2vec
from gensim.models import keyedvectors
```

Constructing our own word2vec model with available data by cleaning the data

In [53]:

```
i=0
listofsent=[]
for sent in finaldata['Text'].values:
    filtered_sentences = []
    sent = cleanhtml(sent)
    for w in sent.split():
        for cleanedwords in cleanpunct(w).split():
            if(cleanedwords.isalpha()):
                filtered_sentences.append(cleanedwords.lower())
    listofsent.append(filtered_sentences)
```

In [54]:

```
print(len(listofsent))
```

364171

In [55]:

```
listofsent[364170]
```

Out[55]:

```
['i',
 'purchased',
 'this',
 'to',
 'send',
 'to',
 'my',
 'son',
 'who',
 's',
 'away',
 'at',
 'college',
 'it',
 'was',
 'delivered',
 'right',
 'to',
 'his',
 'dorm',
 'room',
 'with',
 'very',
 'fast',
 'shipping',
 'he',
 'loved',
 'it',
 'so',
 'much',
 'he',
 'called',
 'me',
 'to',
 'thank',
 'me',
 'and',
 'sadly',
 'he',
 'hardly',
 'ever',
 'calls',
 'me',
 'anymore',
 'if',
 'you',
 'want',
 'your',
 'kids',
 'to',
 'call',
 'home',
 'and',
 'have',
 'some',
 'good',
```

```
 'snack',
 'to',
 'get',
 'them',
 'through',
 'midterms',
 'then',
 'send',
 'them',
 'this']
```

In [56]:

```
finaldata['Text'][7]
```

Out[56]:

```
'This taffy is so good.  It is very soft and chewy.  The flavors are amazin
g.  I would definitely recommend you buying it.  Very satisfying!!'
```

In [57]:

```
w2vmodel = gensim.models.Word2Vec(listofsent,min_count=4,size=50,workers=4)
```

In [58]:

```
print(w2vmodel.most_similar('the'))
print(len(w2vmodel.wv.vocab))
```

```
[('which', 0.5728905200958252), ('each', 0.5433917045593262), ('their', 0.5
308894515037537), ('this', 0.5060376524925232), ('my',
0.48464125394821167), ('simply', 0.45643067359924316), ('flat', 0.452905356
8840027), ('clear', 0.45220744609832764), ('eruption', 0.4510941803455353),
('delicateness', 0.44709208607673645)]
37022
```

```
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/ipykernel_launcher.py:1: DeprecationWarning: Call to deprecated `m
ost_similar` (Method will be removed in 4.0.0, use self.wv.most_similar() i
nstead).
  """Entry point for launching an IPython kernel.
```

We can get similar words and the percentage of relationship between the words

In [59]:

```
print(w2vmodel.most_similar('care'))
```

```
[('know', 0.6655935645103455), ('understand', 0.6083115935325623), ('realiz
e', 0.6025015711784363), ('complain', 0.586801290512085), ('notice', 0.5743
852257728577), ('mind', 0.5673655271530151), ('forget',
0.5611222386360168), ('mean', 0.56031334400177), ('wonder',
0.5506972670555115), ('think', 0.5449468493461609)]
```

```
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/ipykernel_launcher.py:2: DeprecationWarning: Call to deprecated `m
ost_similar` (Method will be removed in 4.0.0, use self.wv.most_similar() i
nstead).
```

In [60]:

```
w2vmodel.similarity('care','cares')
```

```
/Users/vthumati/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: DeprecationWarning: Call to deprecated `similarity` (Method will be removed in 4.0.0, use self.wv.similarity() instead).
  """Entry point for launching an IPython kernel.
```

Out[60]:

```
0.4535463963042511
```

In [61]:

```
w2vmodel.wv['the']
```

Out[61]:

```
array([ 1.4760077 ,  0.06088085,  0.25122893,  3.8024113 , -0.7325647 ,
        0.3348562 , -1.227128  ,  1.0383446 ,  1.9653679 , -0.9013535 ,
       -3.3546283 , -2.7682312 ,  0.5758802 , -1.1963058 ,  0.10881724,
        0.01830601, -1.3414948 , -0.9830876 ,  0.05742005, -0.82297766,
       -1.5509261 , -3.6913466 ,  0.44190043, -1.0714308 , -3.6228158 ,
        0.5253932 ,  0.83740276, -0.7880022 ,  0.03580055,  4.513867  ,
       -0.81963825, -3.9849663 ,  0.4207909 ,  1.086782  ,  2.1443024 ,
       -0.9370693 , -1.7344187 ,  1.9087057 , -0.75689244,  1.077857  ,
        2.7157898 ,  1.0272412 , -0.1846602 ,  0.9406825 , -1.04837   ,
       -0.8381365 , -0.36185342,  1.3645554 ,  0.17003968,  1.6306833 ],
      dtype=float32)
```

Observation:

```
-> We can train our own model with the available data, in which we can specify the number of dimensions for each
   word

-> By using word2vec we can the similarity between the words and also most similar words for the given word

-> We get each word in the form of 45-dimension vector
representation
```

AVERAGE WORD2VEC:

```
Using word2vec model and average word2vec to convert sentences to vectors and applying dimensionality reduction technique
```

In [62]:

```
sent_vectors = []
for sent in listofsent:
    sent_vec = np.zeros(50)
    cnt=0
    for word in sent:
        try:
            vec = w2vmodel.wv[word]
            sent_vec += vec
```

```
            cnt += 1
        except:
            pass
    sent_vec /= cnt
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[8]))
```

```
/Users/vthumati/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:13: RuntimeWarning: invalid value encountered in true_divide
  del sys.path[0]
```

```
364171
50
```

In [63]:

```
print(len(sent_vectors))
print(len(sent_vectors[9999]))
```

```
364171
50
```

In [64]:

```
type(sent_vectors)
```

Out[64]:

```
list
```

In [65]:

```
sent_vectors[364170]
```

Out[65]:

```
array([ 0.36570453,  0.09334156,  0.98163805,  0.73257641,  0.27443594,
       -0.30483963,  0.25059458,  0.2841531 ,  0.6156666 ,  0.60540936,
       -0.6850321 , -0.7704277 , -0.85955792, -0.36570157, -0.9139018 ,
        0.32033311,  0.59219124, -0.99978455, -0.30295844, -0.67316759,
        0.54540802, -0.16040993, -0.29966747, -0.04598839, -0.43404739,
        0.31542922, -0.54752204,  1.77304547, -0.80832378,  0.59803742,
       -0.11124071, -1.02951697,  0.90932121,  0.23180143,  0.71062997,
        0.70429823,  1.17052499,  1.51756817,  0.07588771, -0.82052859,
        1.08738133, -0.92131361,  0.33412902, -0.24660408, -0.38576354,
        0.39805261,  0.89788988, -1.67742117, -0.45916062, -0.52337357])
```

In [66]:

```
np.isnan(sent_vectors).any()
```

Out[66]:

```
True
```

In [67]:

```
np.nansum(sent_vectors)
```

Out[67]:

```
-157262.27503916554
```

In [68]:

```
type(sent_vectors)
```

Out[68]:

```
list
```

In [69]:

```
from sklearn.decomposition import TruncatedSVD
```

In [70]:

```
tsvd = TruncatedSVD(n_components=2,tol=0.0,random_state=555)
```

In [72]:

```
sent_vectors = np.nan_to_num(sent_vectors)
```

In [73]:

```
print(sent_vectors.shape)
print(len(sent_vectors))
```

```
(364171, 50)
364171
```

In [75]:

```
np.isnan(sent_vectors).any()
```

Out[75]:

```
False
```

In [74]:

```
from sklearn.decomposition import TruncatedSVD
```

In [76]:

```
truncatedsvd = TruncatedSVD(n_components=2,tol=0.0,random_state=4)
```

In [77]:

```
tsvd_data = truncatedsvd.fit_transform(sent_vectors)
```

In [78]:

```
tsvd_data.shape
```

Out[78]:

```
(364171, 2)
```

In [79]:

```
score.shape
```

Out[79]:

```
(364171,)
```

In [80]:

```
tsne_data_avgw2vec = np.vstack((tsvd_data.T,score)).T
```

In [81]:

```
tsne_data_avgw2vec.shape
```

Out[81]:

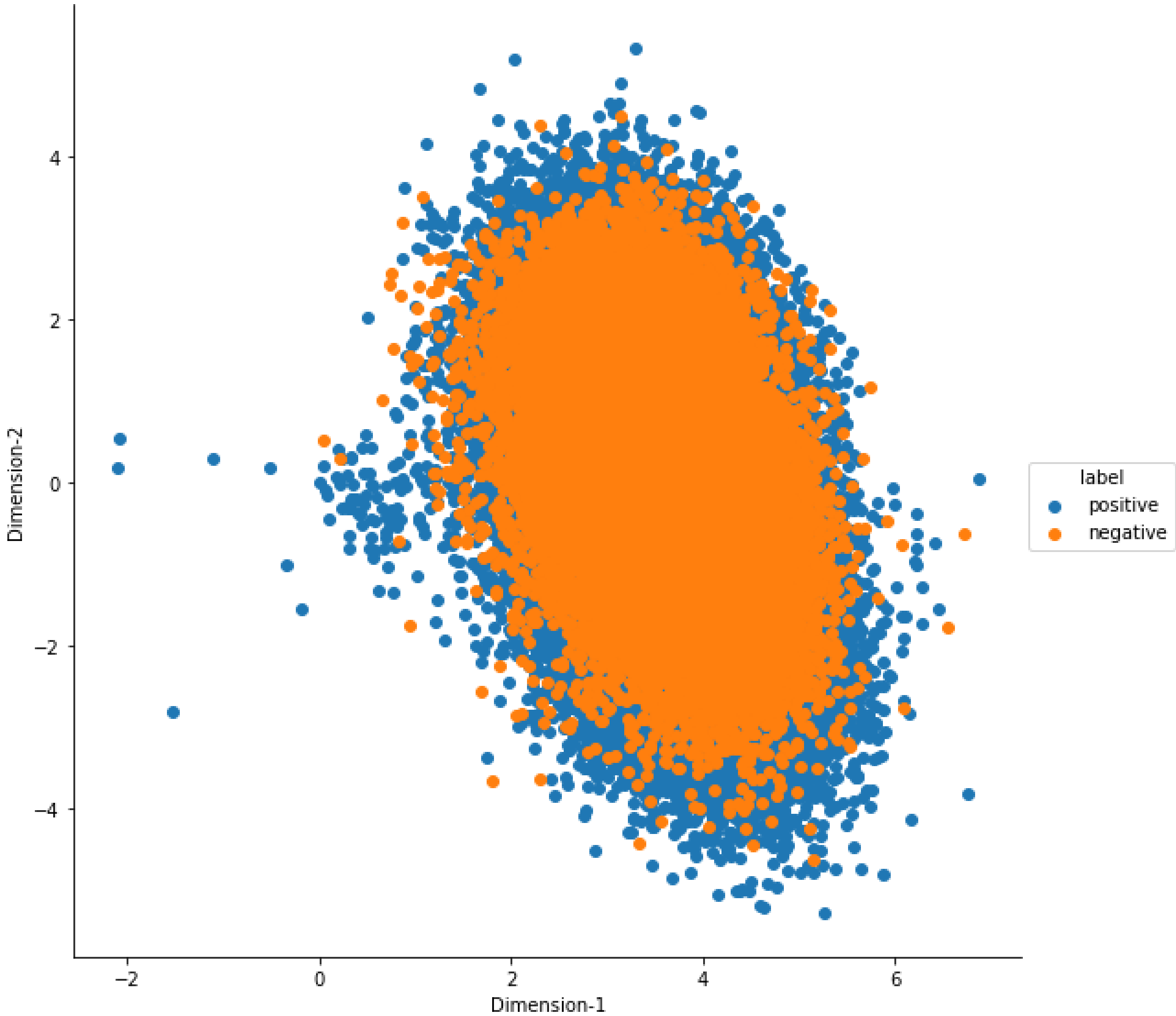
```
(364171, 3)
```

In [82]:

```
tsne_data_avgw2vec_df = pd.DataFrame(data=tsne_data_avgw2vec,columns=("Dime
nsion-1",'Dimension-2','label'))
```

In [83]:

```
s.FacetGrid(tsne_data_avgw2vec_df,hue="label",size=8).map(mp.scatter,'Dimen
sion-1','Dimension-2').add_legend()
mp.show()
```



Observation:

```
-> We have constructed the word2vec for each word with the available
data

-> Using the word2vec model for each word we have constructed the ve
ctor representation of each sentence

-> By using t-SNE dimensionality reduction technique we have reduced
it to 2-dimension representation
```

TFIDF-W2V:

```
-> This is an alternative for the average word2vec representation

-> Using this model with the help of the word2vec model we construct
the vector representation of each sentence

-> Applying dimensionality reduction technique to reduce the dimensi
ons of each sentences
```

In [84]:

```
tf_idf_features = tf_idf.get_feature_names()
print(len(tf_idf_features))
```

```
2910192
```

In [85]:

```
tfidf_sent_vec = []
row=0
for sent in listofsent:
        sent_vector = np.zeros(50)
        sum =0
        for word in sent:
            try:
                vec = w2vmodel.wv[word]
                tf_idf = tf_idf_vector[row, tfidf_features.index(word)]
                sent_vec += (vec * tf_idf)
                sum += tf_idf
            except:
                pass
        sent_vec /= sum
        tfidf_sent_vec.append(sent_vector)
        row += 1
```

```
/Users/vthumati/anaconda3/lib/python3.6/site-
packages/ipykernel_launcher.py:14: RuntimeWarning: divide by zero encounter
ed in true_divide
```

In [86]:

```
len(tfidf_sent_vec)
```

Out[86]:

```
364171
```

In [87]:

```
len(tfidf_sent_vec[99999])
```

Out[87]:

```
50
```

In [88]:

```
np.isnan(tfidf_sent_vec).any()
```

Out[88]:

```
False
```

In [89]:

```
type(tfidf_sent_vec)
```

Out[89]:

```
list
```

In [90]:

```
tfidf_sent_vec = np.nan_to_num(tfidf_sent_vec)
```

In [91]:

```
tfidf_sent_vec.shape
```

Out[91]:

```
(364171, 50)
```

In [92]:

```
len(tfidf_sent_vec)
```

Out[92]:

```
364171
```

In [93]:

```
type(tfidf_sent_vec)
```

Out[93]:

```
numpy.ndarray
```

In [94]:

```
from sklearn.decomposition import TruncatedSVD
```

In [95]:

```
tsvd_tfidf_avgw2v =
TruncatedSVD(n_components=2,n_iter=200,tol=0.0,random_state=8)
```

In [96]:

```
tsvd_tfidf_avgw2v_data = tsvd_tfidf_avgw2v.fit_transform(tfidf_sent_vec)
```

```
tsvd_tfidf_avgw2v_data = tsvd_tfidf_avgw2v.fit_transform(tfidf_sent_vec)
```

```
/Users/vthumati/anaconda3/lib/python3.6/site-packages/sklearn/decomposition/truncated_svd.py:192: RuntimeWarning: invalid value encountered in true_divide
  self.explained_variance_ratio_ = exp_var / full_var
```

In [98]:

```
print(tsvd_tfidf_avgw2v_data.shape)
print(len(tsvd_tfidf_avgw2v_data))
print(score.shape)
```

```
(364171, 2)
364171
(364171,)
```

In [100]:

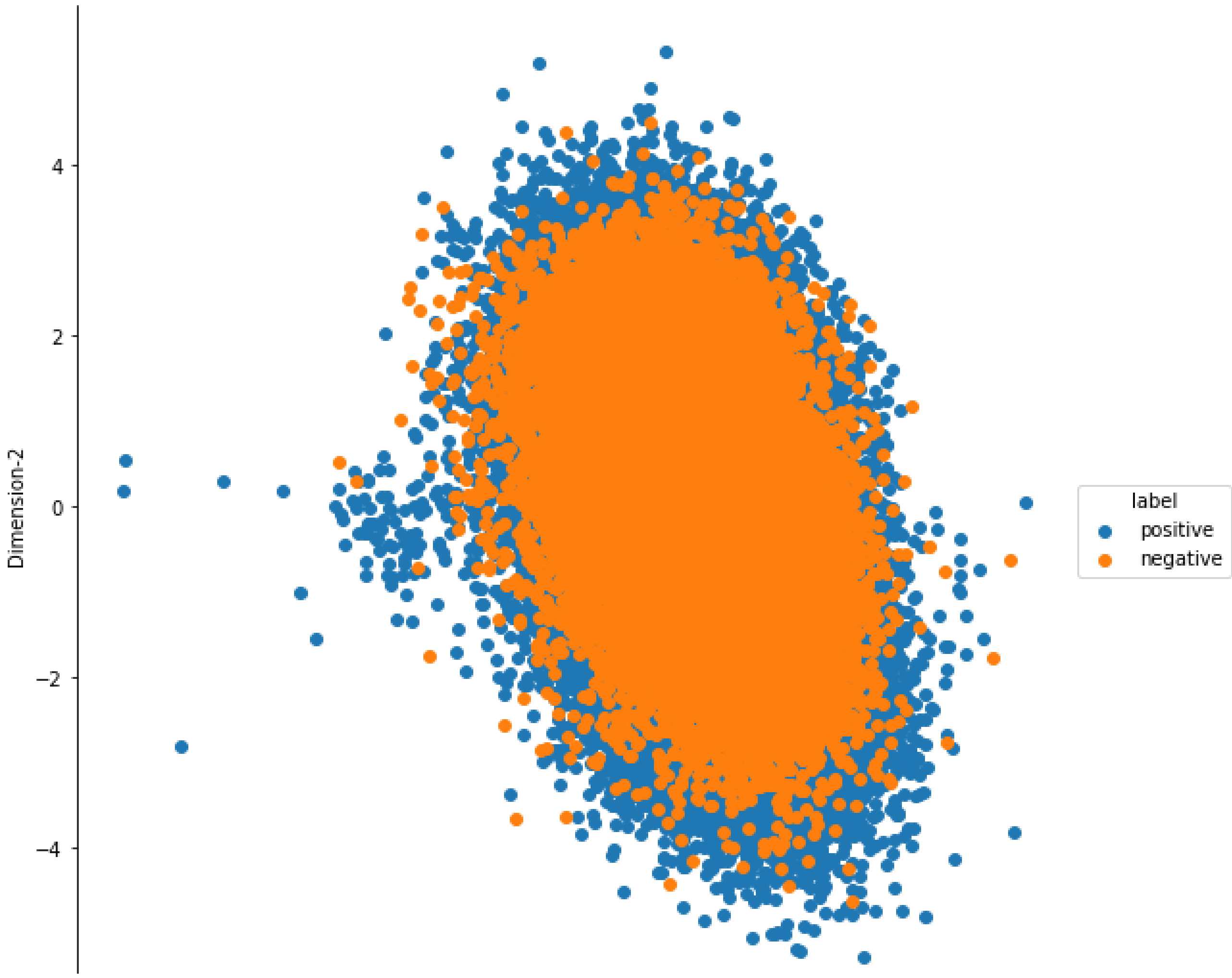
```
tsne_data_tfidf_avgw2vec = np.vstack((tsvd_tfidf_avgw2v_data.T,score)).T
```

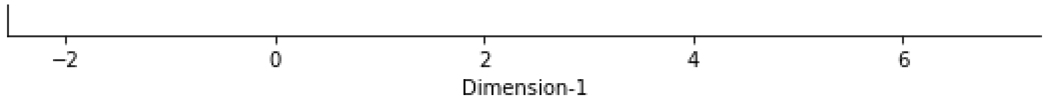
In [101]:

```
tsne_data_tfidf_avgw2vec_df = pd.DataFrame(data=tsne_data_avgw2vec,columns=("Dimension-1",'Dimension-2','label'))
```

In [102]:

```
s.FacetGrid(tsne_data_tfidf_avgw2vec_df,hue="label",size=8).map(mp.scatter,'Dimension-1','Dimension-2').add_legend()
mp.show()
```





Sample example for constructing tfidf-word2vec of a word

In [106]:

```
print(tf_idf_vector[0,tf_idf_features.index('in')])
print(w2vmodel.wv['in'])
a = tf_idf_vector[0,tf_idf_features.index('in')]
b = w2vmodel.wv['in']
c = a*b
print(c)
```

```
0.03277183177760655
[ 2.0197868   1.584507    0.5037021   0.8123775   0.22914465  0.39732596
  0.6230064  -1.964715    0.6152098   3.4045718  -1.2768095   0.684145
  1.1673226  -0.05719063  2.8159833  -2.1201591   1.2506253   1.832313
  1.1778784  -1.3166465  -3.5585659  -3.6476698  -3.0662668  -3.2881083
  0.50599736  2.845872    0.02283531  0.16117303 -0.4806304   1.9380871
  1.727675   -2.8744116  -1.0183523   0.12740374 -2.1708148   0.57003117
 -0.9761366  -0.798371   -5.5048757   2.6155515  -1.239809    0.6248961
  0.8735584  -1.6617626  -2.1666777  -0.6809082   0.8801965  -3.4966476
 -4.1194386   0.33846864]
[ 0.06619212  0.0519272   0.01650724  0.0266231   0.00750949  0.0130211
  0.02041706 -0.06438731  0.02016155  0.11157406 -0.04184339  0.02242069
  0.0382553  -0.00187424  0.09228493 -0.0694815   0.04098528  0.06004825
  0.03860123 -0.04314892 -0.11662073 -0.11954083 -0.10048718 -0.10775734
  0.01658246  0.09326444  0.00074835  0.00528194 -0.01575114  0.06351466
  0.05661907 -0.09419974 -0.03337327  0.00417525 -0.07114158  0.01868097
 -0.03198979 -0.02616408 -0.18040487  0.08571642 -0.04063081  0.02047899
  0.02862811 -0.05445901 -0.071006   -0.02231461  0.02884565 -0.11459155
 -0.13500156  0.01109224]
```

Observation:

```
-> The alternate strategy to construct sentence vectors is TFIDF-WOR
D2vec

-> It computes the tfidf vector for text and then it computes the wo
rd2vec for the text

-> The result is the average of product of tfidf vector and word2vec
vector to the tfidf vector

-> We can apply the dimensionality reduction technique on the result
```

Conclusion:

```
-> For the given dataset we have constructed the vector
representation by using techniques
   like Bag of words,TFIDF, Average word2vec, TFIDF-Word2vec

-> Dimensionality reduction technique is applied on each of these te
```

```
chniques.

-> Based on the polarity of the class labels.

-> By applying the dimensionality reduction technique on each of the
se representations to
   reduce the dimensions from n to 2-dimensions
```