KNN_AmazonFineFoodReviewsPreProcessing

February 3, 2019

1 Amazon Fine Food Reviews Preprocessing

This IPython notebook consists code for preprocessing of text, conversion of text into vectors and saving that information for further use.

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

1.1 Public Information -

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon. 1. Number of reviews: 568,454 2. Number of users: 256,059 3. Number of products: 74,258 4. Timespan: Oct 1999 - Oct 2012 5. Number of Attributes/Columns in data: 10

1.1.1 Attribute Information -

- 1. Id
- 2. ProductId unique identifier for the product
- 3. UserId unque 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

1.1.2 Current Objective -

Go through the reviews and perform preprocessing, convert them into vectors and save them for future use.

2 [1] Reading Data

2.1 [1.1] Loading data and libraries

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-
Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/gdrive
In [0]: !pip install numba
Requirement already satisfied: numba in /usr/local/lib/python3.6/dist-packages (0.40.1)
Requirement already satisfied: llvmlite>=0.25.0dev0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from numba) (1
In [0]: #importing necessary libraries
       %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import missingno as msno
        from nltk.stem.wordnet import WordNetLemmatizer
        import re
        from nltk.corpus import stopwords
        from nltk import pos_tag, word_tokenize
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        import nltk
        import pickle
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from gensim.models import Word2Vec
        from concurrent.futures import ThreadPoolExecutor, ProcessPoolExecutor
        from concurrent import futures
        from numba import jit
In [0]: !python -m nltk.downloader stopwords
/usr/lib/python3.6/runpy.py:125: RuntimeWarning: 'nltk.downloader' found in sys.modules after
 warn(RuntimeWarning(msg))
```

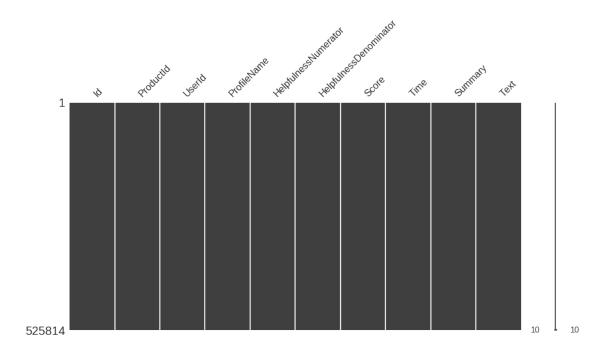
```
[nltk_data] Downloading package stopwords to /root/nltk_data...
              Unzipping corpora/stopwords.zip.
[nltk_data]
In [0]: !python -m nltk.downloader punkt averaged_perceptron_tagger wordnet
/usr/lib/python3.6/runpy.py:125: RuntimeWarning: 'nltk.downloader' found in sys.modules after
  warn(RuntimeWarning(msg))
[nltk_data] Downloading package punkt to /root/nltk_data...
             Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
                /root/nltk_data...
[nltk_data]
[nltk_data]
              Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
              Unzipping corpora/wordnet.zip.
[nltk_data]
In [0]: #connecting to sqlite db
        con = sqlite3.connect('/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_revi-
        #filtering only positive and negative reviews
        data = pd.read_sql_query("SELECT * FROM Reviews WHERE Score != 3", con)
        print("Shape of data:", data.shape)
        #scores < 3 are considered to be negative reviews and > 3 are considered to be positiv
        data.head()
Shape of data: (525814, 10)
Out [0]:
                                                               ProfileName \
           Td
               ProductId
                                   UserId
           1 B001E4KFG0 A3SGXH7AUHU8GW
                                                                delmartian
        1
           2 B00813GRG4 A1D87F6ZCVE5NK
                                                                    dll pa
           3 BOOOLQOCHO ABXLMWJIXXAIN Natalia Corres "Natalia Corres"
        3
           4 BOOOUAOQIQ A395BORC6FGVXV
           5 B006K2ZZ7K A1UQRSCLF8GW1T
                                             Michael D. Bigham "M. Wassir"
           HelpfulnessNumerator HelpfulnessDenominator Score
                                                                      Time
        0
                                                      1
                                                             5 1303862400
                              1
                              0
                                                      0
        1
                                                             1 1346976000
        2
                              1
                                                      1
                                                             4 1219017600
        3
                              3
                                                      3
                                                             2 1307923200
        4
                              0
                                                             5 1350777600
                                                                               Text
                         Summary
        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...
          "Delight" says it all This is a confection that has been around a fe...
```

```
Cough Medicine If you are looking for the secret ingredient i...
Great taffy Great taffy at a great price. There was a wid...
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Missing values

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f35bf4505f8>



3.2 [2.2] Data cleaning: Multiple reviews for the same product by same person

157871	171183	7310172001	AE9ZBY7WW3LIQ
157912	1711228	7310172001	AJD41FBJD9010
157841	171152	7310172001	AJD41FBJD9010
157842	171153	7310172001	AJD41FBJD9010
157843	171154	7310172001	AJD41FBJD9010
157876	171134	7310172001	AJD41FBJD9010
157908	171109	7310172001	AJD41FBJD9010
200626	217414	7310172001	
200626	217414	7310172101	AE9ZBY7WW3LIQ
200518	217405	7310172101	AE9ZBY7WW3LIQ AJD41FBJD9010
200631	217304	7310172101	AJD41FBJD9010
200598	217385	7310172101	AJD41FBJD9010
200663	217454	7310172101	AJD41FBJD9010
200667	217459	7310172101	AJD41FBJD9010
200596	217383	7310172101	AJD41FBJD9010
346048	374351	B00004CI84	A1K94LXX833JTT
346106	374412	B00004CI84	A1K94LXX833JTT
346119	374425	B00004CI84	A1K94LXX833JTT
417917	451939	B00004CXX9	A1K94LXX833JTT
417853	451871	B00004CXX9	A1K94LXX833JTT
417930	451952	B00004CXX9	A1K94LXX833JTT
212523	230338	B00004RYGX	A1K94LXX833JTT
212465	230277	B00004RYGX	A1K94LXX833JTT
212536	230351	B00004RYGX	A1K94LXX833JTT
341832	369818	B000084DWM	A25C5MVVCIYT5D
341815	369799	B000084DWM	A25C5MVVCIYT5D
341817	369801	B000084DWM	A36JDIN9RAAIEC
341818	369802	B000084DWM	A36JDIN9RAAIEC
341806	369790	B000084DWM	A36JDIN9RAAIEC
411612	445161	B009GHI5Q4	A3TVZM3ZIXG8YW
411671	445223	B009GHI5Q4	A3TVZM3ZIXG8YW
411611	445160	B009GHI5Q4	A3TVZM3ZIXG8YW
411608	445157	B009GHI5Q4	A3TVZM3ZIXG8YW
411603	445152	B009GHI5Q4	A3TVZM3ZIXG8YW
411599	445147	B009GHI5Q4	A3TVZM3ZIXG8YW
411621	445170	B009GHI5Q4	A3TVZM3ZIXG8YW
411659	445211	B009GHI5Q4	A3TVZM3ZIXG8YW
411670	445222	B009GHI5Q4	A3TVZM3ZIXG8YW
411613	445162	B009GHI5Q4	A3TVZM3ZIXG8YW
411631	445181	B009GHI5Q4	A966L65JSN8XN
411651	445203	B009GHI5Q4	A966L65JSN8XN
62140	67512	B009GHI6I6	A2ISKAWUPGGOLZ
62142	67515	B009GHI6I6	A2ISKAWUPGGOLZ
62138	67510	B009GHI6I6	A3TVZM3ZIXG8YW
62143	67516	B009GHI6I6	A3TVZM3ZIXG8YW
463853	501546	B009M2LUEW	A2AY7WODO4JYMY
463852	501545	B009M2LUEW	A2AY7WOD04JYMY

```
A1FQSVI2WVV5W5
        417991
                B009RB4G04
386528
386522
        417984
                B009RB4G04
                             A1FQSVI2WVV5W5
        417988
                B009RB4G04
386525
                              A1NO6XIVTDQMP
        417911
386455
                B009RB4G04
                              A1N06XIVTDQMP
386483
        417942
                B009RB4G04
                             A21GDMT9JN2A5Y
386431
        417884
                B009RB4G04
                             A21GDMT9JN2A5Y
386530
        417993
                B009RB4G04
                             A353Y7VBQHHWOT
386486
        417946
                B009RB4G04
                             A353Y7VBQHHW0T
       417952
386492
                B009RB4G04
                             A3QVP3B2VVJ9T0
386356
        417800
                B009RB4G04
                             A3QVP3B2VVJ9T0
        417917
                B009RB4G04
                              ANMGYT60QP4CM
386460
386458
       417914
                B009RB4G04
                              ANMGYT60QP4CM
                                           ProfileName
                                                         HelpfulnessNumerator
157863
                                             W. K. Ota
                                                                             0
157871
                                             W. K. Ota
                                                                             5
157912
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             5
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             0
157841
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             0
157842
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             0
157843
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
157876
                                                                            39
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
157908
                                                                             1
200626
                                             W. K. Ota
                                                                             5
200618
                                             W. K. Ota
                                                                             0
200597
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             0
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                            39
200631
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             0
200598
200663
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             1
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             5
200667
        N. Ferguson "Two, Daisy, Hannah, and Kitten"
                                                                             0
200596
346048
                                                                             1
                                               Sanpete
346106
                                                                             8
                                               Sanpete
346119
                                               Sanpete
                                                                            10
                                                                             8
417917
                                               Sanpete
                                                                             1
                                               Sanpete
417853
417930
                                               Sanpete
                                                                            10
                                                                             8
212523
                                               Sanpete
212465
                                               Sanpete
                                                                             1
212536
                                                                            10
                                               Sanpete
341832
                                          Natalie Dawn
                                                                             1
341815
                                          Natalie Dawn
                                                                             2
                                                                             2
341817
                                                   Jon
                                                                             2
341818
                                                   Jon
                                                                             3
341806
                                                   Jon
. . .
                                                                           . . .
411612
                                    christopher hayes
                                                                            11
411671
                                     christopher hayes
                                                                             6
411611
                                     christopher hayes
                                                                             7
```

411608		chr	istopher hay	res	3
411603		chr	istopher hay	res	18
411599		chr	istopher hay	res	19
411621		chr	istopher hay	res	33
411659		chr	istopher hay	res	2
411670		chr	istopher hay	res	6
411613			istopher hay		11
411631	N.		if "night ow		1
411651			if "night ow		0
62140			M. S. Handl		2
62142			M. S. Handl	*	0
62138		chr	istopher hay	•	7
62143			istopher hay		0
463853			J. Nord		1
463852			J. Nord	len	1
386528			J	ILF	3
386522				ILF	1
386525			LadyRae		1
386455			LadyRae		0
386483	Wavward 1	Travel	ler "Wayward		0
386431	•		ler "Wayward		5
386530	•		rl "wackygir		3
386486			rl "wackygir		5
386492			atrick "BAFX		2
386356		_	atrick "BAFX		0
386460		_	Patricia Kag		0
386458			Patricia Kag		0
	HelpfulnessDenominator	Score	Time	\	
157863	0	4	1182902400		
157871	13	1	1219363200		
157912	7	5	1233360000		
157841	0	5	1233360000		
157842	0	5	1233360000		
157843	0	5	1233360000		
157876	51	5	1233360000		
157908	1	5	1233360000		
200626	13	1	1219363200		
200618	0	4	1182902400		
200597	0	5	1233360000		
200631	51	5	1233360000		
200598	0	5	1233360000		
200663	1	5	1233360000		
200667	7	5	1233360000		
200596	0	5	1233360000		
346048	2	5	1211760000		
346106	10	4	1213747200		
346119	14	4	1213747200		

```
417917
                              10
                                         1213747200
                               2
                                         1211760000
417853
                                      5
417930
                              14
                                      4
                                         1213747200
212523
                                      4
                                         1213747200
                              10
                               2
212465
                                       5
                                         1211760000
212536
                              14
                                       4
                                          1213747200
341832
                               1
                                       5
                                          1304726400
341815
                               2
                                      5
                                          1304726400
                               2
                                      5
                                         1292976000
341817
                               2
341818
                                      5
                                         1292976000
                               3
                                      5
                                         1292976000
341806
                             . . .
                                     . . .
411612
                                      1
                                         1291420800
                              15
411671
                              15
                                      1
                                          1291420800
411611
                               9
                                          1291420800
411608
                               3
                                         1291420800
411603
                              24
                                       1
                                          1291420800
411599
                                      1
                                         1291420800
                              21
                              48
                                       1
                                         1291420800
411621
411659
                               4
                                       1
                                         1291420800
411670
                              14
                                       1
                                         1291420800
411613
                              15
                                       1
                                         1291420800
411631
                               1
                                       5
                                         1319241600
411651
                               0
                                      5
                                         1323820800
62140
                               4
                                      1
                                         1310774400
62142
                               1
                                       1
                                          1310774400
62138
                              11
                                       1
                                          1291420800
                               2
62143
                                       1
                                          1291420800
                                      5
463853
                                          1252195200
463852
                               1
                                         1252713600
386528
                               4
                                      1
                                          1319760000
386522
                               1
                                      1
                                          1319760000
                                      5
386525
                               1
                                         1316563200
                               0
                                       4
                                         1316563200
386455
                               1
                                       1
                                          1309910400
386483
                                          1309910400
386431
                               5
                                       1
386530
                               4
                                         1318896000
386486
                              10
                                      5
                                         1303776000
                               2
                                      1
                                         1327017600
386492
386356
                               0
                                      1
                                         1332633600
                               0
                                      5
                                         1311120000
386460
                               0
                                      5
                                         1315785600
386458
                                                      Summary \
157863
                                Best snack item for my dog.
157871
                                    Why should I get crums?
157912
        NO waste at all--- all dogs love liver treats-...
        dogs LOVE it-- best treat for rewards and tra...
157841
```

```
157842 best dog treat-- great for training--- all do...
157843 best dog treat-- great for training--- all do...
       NO waste at all ---- great for training ----...
157876
       best dog treat-- great for training--- all do...
157908
200626
                                  Why should I get crums?
200618
                              Best snack item for my dog.
200597
       best dog treat-- great for training--- all do...
200631
       NO waste at all ---- great for training ----...
200598
       best dog treat-- great for training--- all do...
200663
       best dog treat-- great for training--- all do...
200667
        NO waste at all--- all dogs love liver treats-...
        dogs LOVE it-- best treat for rewards and tra...
200596
346048
       Heads off, I mean up, Beetlejuice fans! New D...
346106
        Some early details about the new 20th Annivers...
346119
        Some early details about the new Blu-ray DVD d...
417917
        Some early details about the new 20th Annivers...
417853
       Heads off, I mean up, Beetlejuice fans! New D...
417930
        Some early details about the new Blu-ray DVD d...
212523
        Some early details about the new 20th Annivers...
212465
       Heads off, I mean up, Beetlejuice fans! New D...
212536
        Some early details about the new Blu-ray DVD d...
341832
                               The only thing that worked
341815
                                       Nothing else works
          Great product, but trust your vet not the hype
341817
341818
           Don't fall prey to fads and anecdotal reviews
341806
          Great product, but trust your vet not the hype
411612 Filler food is empty, leaves your cat always n...
411671 Filler food is empty, leaves your cat always n...
411611 Filler food is empty, leaves your cat always n...
411608 Filler food is empty, leaves your cat always n...
411603 Filler food is empty, leaves your cat always n...
411599 Filler food is empty, leaves your cat always n...
411621 Filler food is empty, leaves your cat always n...
       Filler food is empty, leaves your cat always n...
411659
411670 Filler food is empty, leaves your cat always n...
411613 Filler food is empty, leaves your cat always n...
411631
                    The only thing all my cats will eat!
411651
                           Only food my cats can agree on
62140
                                          Kitty Junk Food
62142
                                          Kitty Junk Food
62138
        Filler food is empty, leaves your cat always n...
62143
        Filler food is empty, leaves your cat always n...
463853
                       Can't believe it's not REAL sugar!
463852
                                           Perfect taste!
386528
                                                Too Sweet
386522
                                           Way too sweet!
386525
                                                Yummmm...
```

```
386455
                                              Pretty Good
386483
         Does not taste at all like I thought I would :)
386431
                 The worst tasting thing out of my Keurig
                   Tried it loved it...subscribing to it.
386530
386486
                              This Apple Cider is Awesome
386492
                                          Unspeakably bad
386356
                                    Tastes Like Chemicals
386460
                                       Grove Square Cider
386458
                                       Grove Square Cider
                                                     Text \
157863
        Otter and I are very happy with this product. ...
        I selected this company over the other even th...
157871
       Freeze dried liver has a hypnotic effect on do...
157841
       Freeze dried liver has a hypnotic effect on do...
157842
       Freeze dried liver has a hypnotic effect on do...
157843
       Freeze dried liver has a hypnotic effect on do...
       Freeze dried liver has a hypnotic effect on do...
157876
       Freeze dried liver has a hypnotic effect on do...
157908
200626
       I selected this company over the other even th...
200618
       Otter and I are very happy with this product. ...
200597
       Freeze dried liver has a hypnotic effect on do...
200631
       Freeze dried liver has a hypnotic effect on do...
       Freeze dried liver has a hypnotic effect on do...
200598
200663 Freeze dried liver has a hypnotic effect on do...
200667
       Freeze dried liver has a hypnotic effect on do...
200596
       Freeze dried liver has a hypnotic effect on do...
        Beetlejuice is coming back to DVD in a newly r...
346048
346106
        Beetlejuice is a very Tim Burtonesque Tim Burt...
346119
       Beetlejuice is a very Tim Burtonesque Tim Burt...
        Beetlejuice is a very Tim Burtonesque Tim Burt...
417917
417853
        Beetlejuice is coming back to DVD in a newly r...
417930
        Beetlejuice is a very Tim Burtonesque Tim Burt...
212523
       Beetlejuice is a very Tim Burtonesque Tim Burt...
212465
       Beetlejuice is coming back to DVD in a newly r...
212536
       Beetlejuice is a very Tim Burtonesque Tim Burt...
341832
       I understand all the complaints about Science ...
341815
       I understand all the complaints about Science ...
341817
        I have two cats, one 6 and one 2 years old. Bo...
341818
       I have two cats, one 6 and one 2 years old. Bo...
341806 I have two cats, one 6 and one 2 years old. Bo...
411612
       This review will make me sound really stupid, ...
411671
       This review will make me sound really stupid, ...
411611
       This review will make me sound really stupid, ...
411608
       This review will make me sound really stupid, ...
411603
       This review will make me sound really stupid, ...
       This review will make me sound really stupid, ...
411599
```

411621 This review will make me sound really stupid, ... 411659 This review will make me sound really stupid, ... 411670 This review will make me sound really stupid, ... 411613 This review will make me sound really stupid, ... 411631 I have three very different cats, with very di... 411651 This is the only flavor of Science Diet (or an... 62140 We have five cats - one an elderly cat of 15 y... 62142 We have five cats - one an elderly cat of 15 y... 62138 This review will make me sound really stupid, ... 62143 This review will make me sound really stupid, ... 463853 Tastes great! A super alternative to artifica... 463852 I will buy this product again and again. Even... Tasted way too sweet with a terrible after tas... 386528 386522 I posted a review for the Spiced Apple Cider b... 386525 So delicious for K Cup Brewers...could not ge... Tastes wonderful and is caramel-y, but could b... 386455 386483 I really had high expectations of this product... 386431 I really had high expectations of this product... This one is good. I am going to try to Carmel... 386530 386486 I have to say I was afraid to try it because o... 386492 This was unspeakably bad. Tasked like raw che... 386356 I was very disappointed. I love good cider, h... 386460 This is a great product and an added bonus is ... 386458 This is a great product for the K-cups. It tas...

ProdUser

157863 7310172001AE9ZBY7WW3LIQ 157871 7310172001AE9ZBY7WW3LIQ 157912 7310172001AJD41FBJD9010 157841 7310172001AJD41FBJD9010 157842 7310172001AJD41FBJD9010 157843 7310172001AJD41FBJD9010 157876 7310172001AJD41FBJD9010 157908 7310172001AJD41FBJD9010 200626 7310172101AE9ZBY7WW3LIQ 200618 7310172101AE9ZBY7WW3LIQ 200597 7310172101AJD41FBJD9010 200631 7310172101AJD41FBJD9010 7310172101AJD41FBJD9010 200598 200663 7310172101AJD41FBJD9010 200667 7310172101AJD41FBJD9010 7310172101AJD41FBJD9010 200596 B00004CI84A1K94LXX833JTT 346048 346106 B00004CI84A1K94LXX833JTT 346119 B00004CI84A1K94LXX833JTT 417917 B00004CXX9A1K94LXX833JTT 417853 B00004CXX9A1K94LXX833JTT 417930 B00004CXX9A1K94LXX833JTT

```
212523
        B00004RYGXA1K94LXX833JTT
212465
        B00004RYGXA1K94LXX833JTT
212536
        B00004RYGXA1K94LXX833JTT
        B000084DWMA25C5MVVCIYT5D
341832
341815
        B000084DWMA25C5MVVCIYT5D
341817
        B000084DWMA36JDIN9RAAIEC
341818
        B000084DWMA36JDIN9RAAIEC
341806
        B000084DWMA36JDIN9RAAIEC
411612
       B009GHI5Q4A3TVZM3ZIXG8YW
411671
        B009GHI5Q4A3TVZM3ZIXG8YW
411611
        B009GHI5Q4A3TVZM3ZIXG8YW
        BOO9GHI5Q4A3TVZM3ZIXG8YW
411608
411603
        B009GHI5Q4A3TVZM3ZIXG8YW
411599
        BOO9GHI5Q4A3TVZM3ZIXG8YW
411621
        B009GHI5Q4A3TVZM3ZIXG8YW
411659
        B009GHI5Q4A3TVZM3ZIXG8YW
411670
        B009GHI5Q4A3TVZM3ZIXG8YW
411613
        B009GHI5Q4A3TVZM3ZIXG8YW
411631
         B009GHI5Q4A966L65JSN8XN
411651
         B009GHI5Q4A966L65JSN8XN
62140
        B009GHI6I6A2ISKAWUPGGOLZ
62142
        B009GHI6I6A2ISKAWUPGGOLZ
62138
        B009GHI6I6A3TVZM3ZIXG8YW
62143
        B009GHI6I6A3TVZM3ZIXG8YW
463853
        BOO9M2LUEWA2AY7WODO4JYMY
        BOO9M2LUEWA2AY7WODO4JYMY
463852
386528
        B009RB4G04A1FQSVI2WVV5W5
386522
        B009RB4G04A1FQSVI2WVV5W5
386525
         B009RB4G04A1N06XIVTDQMP
386455
         B009RB4G04A1N06XIVTDQMP
386483
        BOO9RB4GO4A21GDMT9JN2A5Y
386431
        BOO9RB4GO4A21GDMT9JN2A5Y
       BOO9RB4GO4A353Y7VBQHHWOT
386530
386486
        BOO9RB4GO4A353Y7VBQHHWOT
386492
        B009RB4G04A3QVP3B2VVJ9T0
386356
       B009RB4G04A3QVP3B2VVJ9T0
386460
         B009RB4G04ANMGYT60QP4CM
386458
        BOO9RB4GO4ANMGYT6OQP4CM
```

[11988 rows x 11 columns]

3.2.1 Obeservations

- 1. There are some instances where a user has written more than one review for the same product.
- 2. We can remove the one which has less Helpfulness but lets keep all and treat it as review from a different user.

3. Will definitely have to remove same reviews because it is just redundant data.

In [0]: #Sorting data according to ProductId in ascending order

```
data = data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quic
   [2.3] Data cleaning: Deduplication - 1
In [0]: #Deduplication of entries
        data=data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first',
        data.shape
Out[0]: (364173, 10)
In [0]: data.head(2)
Out [0]:
                    Ιd
                         ProductId
                                            UserId
                                                        ProfileName
        138706
                150524
                        0006641040
                                     ACITT7DI6IDDL
                                                   shari zychinski
        138688
               150506 0006641040 A2IW4PEEKO2ROU
                                                               Tracy
                HelpfulnessNumerator HelpfulnessDenominator
                                                               Score
                                                                            Time \
        138706
                                                            0
                                                                       939340800
                                   0
                                                                   5
        138688
                                   1
                                                            1
                                                                   4 1194739200
                                                   Summary \
        138706
                                 EVERY book is educational
        138688 Love the book, miss the hard cover version
        138706 this witty little book makes my son laugh at 1...
        138688 I grew up reading these Sendak books, and watc...
```

3.4 [2.4] Data cleaning: Deduplication - 2

Same reviews on multiple products with different timestamps

349975 378572 B0001GSPC8 A1YUL9PCJR3JTY

```
In [0]: data[data['Text'].duplicated(keep=False)].sort_values('Text', axis=0, ascending=True, )
Out [0]:
                   Ιd
                        ProductId
                                          UserId \
       67574
                73444 B0046IISFG A30XHLG6DIBRW8
       287090 311004 B001E06FPU A30XHLG6DIBRW8
       302818 327982 B0000CEQ6H A281NPSIMI1C2R
       494235 534333 B0000CEQ72 A281NPSIMI1C2R
       387315
              418839 BOOOFZYSVC A1YUL9PCJR3JTY
       164025
              177904 B000PSFW9Q A1YUL9PCJR3JTY
       267899 290387 B000S85AVI A1YUL9PCJR3JTY
       443822 479891 B000Z91YTC A1YUL9PCJR3JTY
       442191 478132 B0001GSP9G A1YUL9PCJR3JTY
       177373 192340 BOOOM70WLE A1YUL9PCJR3JTY
```

308770	334367	BOOOM70WMS	A 1 VIII ODG ID 2 ITV
432171	467365	BOOOM/OWNS BOOO2WORX6	A1YUL9PCJR3JTY A1YUL9PCJR3JTY
306132	331530	B004JJ6ZN4	A1YUL9PCJR3JTY
68214	74193	BOOOE4AHAK	A1YUL9PCJR3JTY
36692	39874	BOOOCMIZOI	A1YUL9PCJR3JTY
204048	221073	B0000111201	A1YUL9PCJR3JTY
61803	67142	B0000CGFSC	A1YUL9PCJR3JTY
524984	567556	B003ULEOTS	A1YUL9PCJR3JTY
378979	409774	BOOOQVDP6Y	A1YUL9PCJR3JTY
438391	474076	B000CQC08C	A1YUL9PCJR3JTY
442055	477988	B000B0Z6K4	A1YUL9PCJR3JTY
410856	444343	BOOO1MOZTI	A1YUL9PCJR3JTY
113563	123178	BOOOCQBZOW	A1YUL9PCJR3JTY
360276	389666	B000Q61HH8	A1YUL9PCJR3JTY
488311	528026	B000EUCKF4	A1YUL9PCJR3JTY
367930	397829	BOOOPIMWGM	A1YUL9PCJR3JTY
367928	397826	BOOOPIMWGM	A1YUL9PCJR3JTY
227146	246294	B0009F3SB4	A1YUL9PCJR3JTY
443856	479926	B000VV0512	A1YUL9PCJR3JTY
484592	523982	B004JGQ15Y	A1KEKO9ZA6J9P8
156517	169743	B004JGQ16I	A1KEKO9ZA6J9P8
59565	64702	B0002ERVTM	A281NPSIMI1C2R
401926	434586	B000F9BCLW	A281NPSIMI1C2R
146793	159233	B002IYDXVE	A3R7Q2RWQ8K2S7
357423	386592	BOO3TN6ZN6	A3R7Q2RWQ8K2S7
503424	544379	B002BCE97K	A3BTL4FV60DKAT
246458	267240	B000E123IC	A3BTL4FV60DKAT
505442	546536	B000E148MG	A3BTL4FV60DKAT
200791	217587	B000N8OLCC	A3BTL4FV60DKAT
314550	340574	B0018CJYCO	A2AHTUMQC103M8
140727	152726	B0018CIPS8	A2AHTUMQC103M8
469169	507321	B000EEDJGE	A20EEWWSFMZ1PN
35905	39033	B002PXEQCS	A20EEWWSFMZ1PN
479858	518889	BOO3BXOAKE	A3QZ6JTOR1OWEC
514622	556404	B000IBILV6	A3QZ6JTOR1OWEC
138146	149927	B0028C44IM	AC8C9PT59CDW1
447742	484120	B001IZ9ME6	AC8C9PT59CDW1
485560	525050	B0010B6IFY	A21B8AV7E3MPXE
38078	41352	B0096EZHM2	A21B8AV7E3MPXE
54700	59365	BOOOFBM3RC	A1CVN6FWUCZOMD
151003	163798	BOOOFBKFRW	A1CVN6FWUCZOMD
37746	40992	B001T5GHUM	A3PS4V0JQ2003X
118574	128597	B0026A2BS6	A3PS4V0JQ2003X
76868	83624	B005ZBZLT4	A3LLOU6E3QK34A
167105	181178	B007Y59HVM	A3LLOU6E3QK34A
242532	263029	B006N3HYYS	A3RFWQMLYSAKIO
99008	107540	B007TJGY4Q	A3RFWQMLYSAKIO

	JOJOOT DOOTSTINION RZ400Q3TXRNO3Z	
	563808 B007JFMH8M A3IMUU0I31XF33	521496
\	ProfileName	
	C. F. Hill "CFH"	67574
	C. F. Hill "CFH"	287090
	Rebecca of Amazon "The Rebecca Review"	302818
	Rebecca of Amazon "The Rebecca Review"	494235
	O. Brown "Ms. O. Khannah-Brown"	387315
	O. Brown "Ms. O. Khannah-Brown"	164025
	O. Brown "Ms. O. Khannah-Brown"	267899
	O. Brown "Ms. O. Khannah-Brown"	443822
	O. Brown "Ms. O. Khannah-Brown"	442191
	O. Brown "Ms. O. Khannah-Brown"	177373
	O. Brown "Ms. O. Khannah-Brown"	349975
	O. Brown "Ms. O. Khannah-Brown"	308770
	O. Brown "Ms. O. Khannah-Brown"	432171
	O. Brown "Ms. O. Khannah-Brown"	306132
	O. Brown "Ms. O. Khannah-Brown"	68214
	O. Brown "Ms. O. Khannah-Brown"	36692
	O. Brown "Ms. O. Khannah-Brown"	204048
	O. Brown "Ms. O. Khannah-Brown"	61803
	O. Brown "Ms. O. Khannah-Brown"	524984
	O. Brown "Ms. O. Khannah-Brown"	378979
	O. Brown "Ms. O. Khannah-Brown"	438391
	O. Brown "Ms. O. Khannah-Brown"	442055
	O. Brown "Ms. O. Khannah-Brown"	410856
	O. Brown "Ms. O. Khannah-Brown"	113563
	O. Brown "Ms. O. Khannah-Brown"	360276
	O. Brown "Ms. O. Khannah-Brown"	488311
	O. Brown "Ms. O. Khannah-Brown"	367930
	O. Brown "Ms. O. Khannah-Brown"	367928
	O. Brown "Ms. O. Khannah-Brown"	227146
	O. Brown "Ms. O. Khannah-Brown"	443856
	•••	
	Colleen M. Schneider	484592
	Colleen M. Schneider	156517
	Rebecca of Amazon "The Rebecca Review"	59565
	Rebecca of Amazon "The Rebecca Review"	401926
	MamaCito	146793
	MamaCito	357423
	fredtownward "The Analytical Mind; Have Brain	503424
	fredtownward "The Analytical Mind; Have Brain	246458
	fredtownward "The Analytical Mind; Have Brain	505442
	fredtownward "The Analytical Mind; Have Brain	200791
	Glenn Wagstaff "GBW"	314550
	Glenn Wagstaff "GBW"	140727
	hernie "webwister"	160160

521495 563807 B007JFMH8M A248UQ9YXAM09Z

bernie "webviator"

469169

35905 479858		bernie "webviat M. Goldman "M_gol	.d~"				
514622		M. Goldman "M_gol					
138146		M.A.R.					
447742		M.A.R.					
485560		Natalie V. Gala Natalie V. Gala					
38078 54700		Natalle V. Gala A Custo					
151003							
37746		his_billyn PookieThePir					
118574		PookieThePir					
76868		A Custo					
167105		K. Bid					
242532	Mic	hael Burkett "reader rid					
99008	FIIC	A Custo					
521495			cky				
521495			cky				
321430		De	CKy				
	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	\		
67574	1	1	5	1342915200			
287090	9	9	5	1297036800			
302818	3	3	5	1084492800			
494235	1	1	5	1093651200			
387315	1	1	5	1173052800			
164025	1	1	5	1156723200			
267899	2	2	5	1173052800			
443822	6	6	5	1156723200			
442191	1	1	5	1156723200			
177373	1	1	5	1173052800			
349975	1	1	5	1156896000			
308770	3	3	5	1173052800			
432171	2	2	5	1157241600			
306132	0	0	5	1156723200			
68214	4	4	5	1181952000			
36692	13	13	5	1181692800			
204048	0	0	5	1170460800			
61803	1	1	5	1170374400			
524984	2	2	5	1296000000			
378979	2	2	5	1156723200			
438391	2	2	5	1281916800			
442055	2	2	5	1191628800			
410856	1	1	5	1191628800			
113563	2	2	5	1282003200			
360276	1	1	5	1189987200			
488311	15	15	5	1217030400			
367930	1	2	5	1187654400			
367928	10	11	5	1187740800			
227146	22	24	5	1189468800			

443856	0 0	5	1190764800
		• •	• • •
484592	0 0	5	1301529600
156517	0 0	5	1300752000
59565	1 1	5	1230249600
401926	0 0	5	1169078400
146793	0 0	4	1300406400
357423	9 9	4	1300492800
503424	1 1	5	1329609600
246458	0 0	5	1329350400
505442	1 2	5	1329091200
200791	0 0	5	1329177600
314550	1 1	5	1297382400
140727	1 2	5	1297123200
469169	1 1	5	1316908800
35905	1 1	5	1344643200
479858	0 0	1	1349481600
514622	0 0	1	1324080000
138146	0 0	5	1333756800
447742	0 0	5	1330732800
485560	2 2	5	1304121600
38078	3 3	4	1304467200
54700	2 2	5	1169596800
151003	2 2	5	1169596800
37746	8 9	5	1313452800
118574	9 10	5	1314144000
76868	0 1	4	1341619200
167105	0 1	4	1341619200
242532	0 8	4	1298592000
99008	0 8	4	1298592000
521495	0 0	5	1341792000
521496	0 0	5	1341792000
	Summary	\	
67574	Great Diabetic Friendly Sweetwner - Highly Rec	`	
287090	Great Diabetic Friendly Sweetener - Highly Rec		
302818	Superior for Bread Baking		
494235	Bob's Red Mill Whole Wheat Flour		

387315 Perfect Morning Tea (Caffeinated) 164025 Perfect Morning Tea (Caffeinated) 267899 Golden Chai Must Be Experienced! Golden Chai Must Be Experienced! 443822 442191 Superb Black Tea Blend (Caffeinated) Superb Black Tea Blend (Caffeinated) 177373 349975 Wonderful Rooibos---The "Miracle Tea"! Wonderful Rooibos---The "Miracle Tea"! 308770 A Low-Caffeine, Hand-Rolled Fine Green Tea 432171 306132 A Low-Caffeine, Hand-Rolled Fine Green Tea

```
68214
        Original Idea---Kombucha from a Tea! And Decaf...
36692
        Original Idea---Kombucha from a Tea! And Decaf...
204048
                 Distinctive, great-flavored Japanese tea
                 Distinctive, great-flavored Japanese tea
61803
524984
                     Beautiful Morning Tea, With Caffeine
378979
                                     Very Nice Morning Tea
438391
                                          Soft, Lovely Tea
442055
                                        Soft, Subtle Blend
410856
                                       Sweet and Delicious
113563
                                      Sweet and Lovely Tea
                  Great Green Tea Experience, Tazo's Best
360276
                    Fantastic Green Tea, the Best of Tazo
488311
                      Healthy Tea Supports Weight Control
367930
367928
                      Healthy Tea Supports Weight Control
227146
                      Healthy Tea Supports Weight Control
                 Romantic, Natural, Unique Tea Experience
443856
        For when the girl scouts (and your stash) are ...
484592
        for when the girl scouts and your stash are go...
156517
59565
                                          Instant Chai Tea
401926
                   Chai Tea with Whipped Cream and Nutmeg
146793
                                                 Lifesaver
357423
                                                 Lifesaver
               The Best Instant Noodle Meals You Can Buy!
503424
246458
               The Best Instant Noodle Meals You Can Buy!
               The Best Instant Noodle Meals You Can Buy!
505442
               The Best Instant Noodle Meals You Can Buy!
200791
314550
                                Great food at a good price
140727
                                Great food at a good price
469169
                             Get them free in your SP Pack
                             Get them free in your SP Pack
35905
479858
        Made in China treats still KILLING dogs - ABC ...
514622
        Made in China treats still KILLING dogs - ABC ...
                                          Love these mints
138146
447742
                                          Love these mints
485560
                                         Cheaper on Amazom
38078
                                   Better prices on Amazom
54700
                                   unusual chocolate treat
                                   unusual chocolate treat
151003
37746
        CHECK YOUR LOCAL ASIAN STORE FIRST! CHEAP IN S...
               CHECK STORE PRICE FIRST! CHEAPER IN STORE!
118574
76868
                                                   love it
167105
                                                   love it
242532
        great tasting bold coffee.
                                     make sure you're g...
99008
        great tasting bold coffee.
                                     make sure you're g...
521495
                                                     yummy
521496
                                        yummy great cookie
```

Text 67574 "Erythritol" has become one of our favorite su... 287090 "Erythritol" has become one of our favorite su... 302818 "We use and believe in stone milling because n... 494235 "We use and believe in stone milling because n... ***** Chinese Breakfast ... 387315 164025 ***** /> /> Numi Tea's Chinese Breakfast ... 267899 *****Cbr />Cbr />Numi Tea's Golden Chai Spiced... 443822 *****Cbr />Cbr />Numi Tea's Golden Chai Spiced... 442191 *****

Numi Tea's Morning Rise Break... 177373 *****

Numi Tea's Morning Rise Break... 349975 ***** />
Red Mellow Bush is a premium ... 308770 *****

Red Mellow Bush is a premium ... 432171 ***** />
Temple of Heaven Gunpowder Gr... 306132 *****Cbr />Temple of Heaven Gunpowder Gr... ***** />
This Organic Green Tea Kombuc... 68214 36692 *****Cbr />Chr />This Organic Green Tea Kombuc... *****
Ashby's Japanese Green Tea is a dis... 204048 *****
Ashby's Japanese Green Tea is a dis... 61803 524984 *****
Numi Tea's Chinese Breakfast Yunnan... 378979 ***** /> Numi Tea's Chinese Breakfast Yunnan... 438391 ***** />Stash's Fusion Red & White Tea has ... 442055 ***** />Stash's Fusion Red & White Tea has ... ***** /> Stash's Licorice Spice Caffeine Fre... 410856 ***** /> Stash's Licorice Spice Caffeine Fre... 113563 360276 ***** />Tazo's China Green Tips Green Tea i... 488311 ***** />Tazo's China Green Tips Green Tea i... *****
This Fasting Tea from Yogi Tea for ... 367930 367928 ***** />This Fasting Tea from Yogi Tea for ... 227146 *****
This Fasting Tea from Yogi Tea for ... 443856 *****
White Rose Velvet Garden White Tea ... 484592 When the girl scouts are gone and your thin mi... When the girl scouts are gone and your thin mi... 156517 59565 While you can make your own chai tea, it does ... 401926 While you can make your own chai tea, it does ... 146793 Whoever came up with this is a genius and a li... 357423 Whoever came up with this is a genius and a li... 503424 Why? Because the noodles come SOFT, sealed in... 246458 Why? Because the noodles come SOFT, sealed in... 505442 Why? Because the noodles come SOFT, sealed in... 200791 Why? Because the noodles come SOFT, sealed in... With five cats, buying premium cat food can ge... 314550 140727 With five cats, buying premium cat food can ge... 469169 Yep I used to get them for free. All you had t... 35905 Yep I used to get them for free. All you had t... 479858 Yes, dogs love these treats but educate yourse... 514622 Yes, dogs love these treats but educate yourse...

```
138146 You can't find these mints in the stores, and ...
       447742 You can't find these mints in the stores, and ...
       485560 You get a better deal for these if you order a...
               You get a better deal for these if you order a...
       38078
               i tried bahlsen chocolates in europe, but you ...
       54700
       151003 i tried bahlsen chocolates in europe, but you ...
               lol, I read that this item was cheaper in stor...
       118574 lol, I read that this item was cheaper in stor...
       76868 they are not contained in the keurig plastic c...
       167105 they are not contained in the keurig plastic c...
       242532 thought i was getting a great deal - wrong. o...
               thought i was getting a great deal - wrong. o...
       99008
        521495 yummy great cookie just like my momma makes th...
        521496 yummy great cookie just like my momma makes th...
        [630 rows x 10 columns]
In [0]: #removing duplicate reviews
       data=data.drop_duplicates(subset={"Text"}, keep='first', inplace=False)
       data.shape
Out[0]: (363836, 10)
```

3.4.1 Observations

- 1. There are reviews which are same on similar products (mostly different flavors).
- 2. These reviews were posted with different timestamps by the same person (weird).
- 3. Since we are interested in a review being positive or negative, having redundant reviews makes no sense, so removing them.

3.5 [2.5] Data cleaning: Removing practically impossible data

print("Positives shape:", data[data['Score']=='positive'].shape)

```
Negatives shape: (57070, 10)
Positives shape: (306764, 10)
```

4 [3] Text Preprocessing

We will be doing the following in order.

- 1. Text cleaning includes removal of special characters which are not required.
- 2. Check if the word is actually an English word.
- 3. 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)
- 4. Convert the word to lower case.

final_string=[]

- 5. Remove stop words but let's keep words like 'not' which makes the sentence negative.
- 6. POS Tagging and WordNet Lemmatizing the word.

```
In [0]: def cleanhtml(sentence): #function to clean the word of any html-tags
            cleanr = re.compile('<.*?>')
            cleantext = re.sub(cleanr, ' ', sentence)
            return cleantext
        def cleanpunc(sentence): #function to clean the word of any punctuation or special cha
            cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
            cleaned = re.sub(r'[.|,|)|(||/|,r'|,cleaned)
            return cleaned
In [0]: stop = list(set(stopwords.words('english'))) #set of stopwords
        print(stop)
        #removing words like 'not' that gives negative meaning to a sentence from stopwords
        important_stopwords = ['hadn', 'weren', 'shouldn', "needn't", 'needn', 'doesn', "shan'
                              'wouldn', "weren't", "didn", "mustn't", "wasn't", "didn't", "don
        pre_final_stops = [x for x in stop if x not in important_stopwords]
        #removing punctuation from stop words
        final_stops = list(set([cleanpunc(x) for x in pre_final_stops]))
        print("Final stopwords:", final_stops)
["it's", 'more', 'just', 'couldn', 'and', 'our', "hasn't", 'this', 've', 'off', 'needn', 'them
Final stopwords: ['more', 'just', 'couldn', 'and', 'havent', 'our', 've', 'this', 'off', 'them
In [0]: wnl = WordNetLemmatizer()
In [0]: #Code for implementing step-by-step the checks mentioned in the pre-processing phase
        # this code takes a while to run as it needs to run on 500k sentences.
        i=0
       str1=' '
```

```
s=' '
       scores = data['Score'].values
       for sent in data['Text'].values:
           filtered_sentence=[]
           #print(sent);
           sent=cleanhtml(sent) # remove HTMl tags
           tokens = pos_tag(word_tokenize(sent))
           for w in tokens:
               for cleaned_words in cleanpunc(w[0]).split():
                   if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                       if(cleaned_words.lower() not in stop):
                           #s=(sno.stem(cleaned_words.lower())).encode('utf8')
                           # lemmatization works better with POS tagging
                           tag = w[1][0].lower()
                           tag = tag if tag in ['a', 'n', 'v'] else None
                           if not tag:
                               s = cleaned_words.lower().encode('utf8')
                           else:
                               s = wnl.lemmatize(cleaned_words.lower(), tag).lower().encode("
                           filtered_sentence.append(s)
                           if scores[i] == "positive":
                               all_positive_words.append(s) #list of all words used to descri
                           if scores[i] == "negative":
                               all_negative_words.append(s) #list of all words used to descri
                       else:
                           continue
                   else:
                       continue
           #print(filtered_sentence)
           str1 = b" ".join(filtered_sentence) #final string of cleaned words
           final_string.append(str1)
           i+=1
       print("Done!")
Done!
In [0]: data['CleanedText']=final_string #adding a column of CleanedText which displays the da
       data['CleanedText'] = data['CleanedText'].str.decode("utf-8")
In [0]: # store final table into an SQLLite table for future.
       conn = sqlite3.connect('/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_rev
       c=conn.cursor()
       conn.text_factory = str
       data.to_sql('Reviews', conn, schema=None, if_exists='replace', index=True, index_labe
```

all_positive_words=[] # store words from +ve reviews here all_negative_words=[] # store words from -ve reviews here.

```
con = sqlite3.connect('/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_revi-
       data = pd.read_sql_query(""" SELECT * FROM Reviews """, con)
       del data['index']
       data.shape
Out[0]: (363834, 11)
In [0]: data.head()
Out[0]:
             Ιd
                ProductId
                                   UserId
                                                        ProfileName \
       0 150524 0006641040
                           ACITT7DI6IDDL
                                                     shari zychinski
       1 150506 0006641040 A2IW4PEEKO2ROU
                                                              Tracy
       2 150507 0006641040 A1S4A3IQ2MU7V4
                                               sally sue "sally sue"
       3 150508 0006641040
                              AZGXZ2UUK6X Catherine Hallberg "(Kate)"
       4 150509 0006641040 A3CMRKGE0P909G
                                                             Teresa
         HelpfulnessNumerator HelpfulnessDenominator
                                                     Score
                                                                 Time
       0
                                                   positive
                                                             939340800
       1
                           1
                                                1 positive 1194739200
       2
                           1
                                                   positive 1191456000
       3
                           1
                                                1 positive 1076025600
                           3
       4
                                                   positive 1018396800
                                         Summary \
       0
                         EVERY book is educational
       1
         Love the book, miss the hard cover version
                     chicken soup with rice months
       3
             a good swingy rhythm for reading aloud
       4
                   A great way to learn the months
                                                  Text \
        this witty little book makes my son laugh at 1...
        I grew up reading these Sendak books, and watc...
       2 This is a fun way for children to learn their ...
       3 This is a great little book to read aloud- it ...
       4 This is a book of poetry about the months of t...
                                            CleanedText
       0 witty little book make son laugh loud recite c...
       1 grow read sendak book watch really rosie movie...
       2 fun way child learn month year learn poem thro...
       3 great little book read nice rhythm well good r...
       4 book poetry month year go month cute little po...
In [0]: # positive reviews
       pos_df = data[data['Score'] == 'positive'].copy()
       pos_df['Time'] = pos_df['Time'].astype('int')
```

```
# sorting it based on time so that we can split based on time
        pos_df.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na
       pos_df.shape
Out[0]: (306764, 11)
In [0]: #negative reviews
       neg_df = data[data['Score'] == 'negative'].copy()
       neg_df['Time'] = neg_df['Time'].astype('int')
       neg_df.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na
       neg_df.shape
Out[0]: (57070, 11)
In [0]: pos_50k = pos_df.head(10000).copy()
       neg_50k = neg_df.head(10000).copy()
In [0]: pos_50k = pos_df.head(50000).copy()
       neg_50k = neg_df.head(50000).copy()
In [0]: # training data 60%
       pos_train = pos_50k.head(6000).copy()
       neg_train = neg_50k.head(6000).copy()
        # cross validation data 20%
       pos_cv = pos_50k[6000:8000].copy()
       neg_cv = neg_50k[6000:8000].copy()
        # test data 20%
       pos_test = pos_50k[8000:].copy()
       neg_test = neg_50k[8000:].copy()
In [0]: # training data 60%
       pos_train = pos_50k.head(30000).copy()
       neg_train = neg_50k.head(30000).copy()
        # cross validation data 20%
       pos_cv = pos_50k[30000:40000].copy()
       neg_cv = neg_50k[30000:40000].copy()
        # test data 20%
        pos_test = pos_50k[40000:].copy()
       neg_test = neg_50k[40000:].copy()
In [0]: train_df = pos_train.append(neg_train, ignore_index=True).copy()
        cv_df = pos_cv.append(neg_cv, ignore_index=True).copy()
        test_df = pos_test.append(neg_test, ignore_index=True).copy()
       train_df.shape
Out[0]: (60000, 11)
```

5 [4] Featurization

5.1 [4.1] Bag of words - unigrams and bigrams

```
In [0]: #BoW
        count_vect = CountVectorizer() #in scikit-learn
        train_final_counts = count_vect.fit_transform(train_df['CleanedText'].values)
        cv_final_counts = count_vect.transform(cv_df['CleanedText'].values)
        test_final_counts = count_vect.transform(test_df['CleanedText'].values)
        print("the type of count vectorizer ",type(train_final_counts))
        print("the shape of out text BOW vectorizer ",train_final_counts.get_shape())
        print("the number of unique words ", train_final_counts.get_shape()[1])
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (60000, 40286)
the number of unique words 40286
In [0]: freq_dist_positive=nltk.FreqDist(all_positive_words)
        freq_dist_negative=nltk.FreqDist(all_negative_words)
        print("Most Common Positive Words : ",freq_dist_positive.most_common(20))
        print("Most Common Negative Words : ",freq_dist_negative.most_common(20))
Most Common Positive Words: [(b'like', 137224), (b'taste', 122045), (b'good', 111390), (b'lo
Most Common Negative Words: [(b'taste', 33523), (b'like', 31734), (b'product', 28122), (b'bu
In [0]: #saving BoW unigrams
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_
            pickle.dump(train_final_counts, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/train_la
            pickle.dump(train_df['Score'].values, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_
            pickle.dump(cv_final_counts, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/cv_lab.p.
            pickle.dump(cv_df['Score'].values, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_
            pickle.dump(test_final_counts, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/test_lab
           pickle.dump(test_df['Score'].values, bow)
In [0]: #bi-gram, tri-gram and n-gram
        #removing stop words like "not" should be avoided before building n-grams
        count_vect = CountVectorizer(ngram_range=(1,2) ) #in scikit-learn
        train_bigram_counts = count_vect.fit_transform(train_df['CleanedText'].values)
        cv_bigram_counts = count_vect.transform(cv_df['CleanedText'].values)
```

```
print("the type of count vectorizer ",type(train_bigram_counts))
        print("the shape of out text BOW vectorizer ",train_bigram_counts.get_shape())
        print("the number of unique words including both unigrams and bigrams ", train_bigram_
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (60000, 977013)
the number of unique words including both unigrams and bigrams 977013
In [0]: #saving BoW bigrams
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_ve
           pickle.dump(train_bigram_counts, bow)
        # with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi
              pickle.dump(train_df['Score'].values, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_ve
            pickle.dump(cv_bigram_counts, bow)
        # with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi
             pickle.dump(cv_df['Score'].values, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi_ve
            pickle.dump(test_bigram_counts, bow)
        # with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_bi
             pickle.dump(test_df['Score'].values, bow)
5.2 [4.2] TF-IDF
In [0]: \#tf-idf
       tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
        train_tf_idf = tf_idf_vect.fit_transform(train_df['CleanedText'].values)
        cv_tfidf = tf_idf_vect.transform(cv_df['CleanedText'].values)
        test_tfidf = tf_idf_vect.transform(test_df['CleanedText'].values)
       print("the type of count vectorizer ",type(train_tf_idf))
        print("the shape of out text TFIDF vectorizer ",train_tf_idf.get_shape())
        print("the number of unique words including both unigrams and bigrams ", train_tf_idf.
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer (60000, 977013)
the number of unique words including both unigrams and bigrams 977013
In [0]: features = tf_idf_vect.get_feature_names()
        print("some sample features(unique words in the corpus)", features[100000:100010])
some sample features (unique words in the corpus) ['bpa originally', 'bpa packaging', 'bpa pers
In [0]: def top_tfidf_feats(row, features, top_n=25):
            ''' Get top n tfidf values in row and return them with their corresponding feature
```

test_bigram_counts = count_vect.transform(test_df['CleanedText'].values)

```
topn_ids = np.argsort(row)[::-1][:top_n]
            top_feats = [(features[i], row[i]) for i in topn_ids]
            df = pd.DataFrame(top_feats)
            df.columns = ['feature', 'tfidf']
            return df
        top_tfidf = top_tfidf_feats(train_tf_idf[1,:].toarray()[0],features,25)
In [0]: top_tfidf
Out [0]:
                      feature
                                  tfidf
        0
               paperback seem 0.182072
        1
                  rosie movie 0.182072
        2
            incorporate love 0.182072
        3
           version paperback 0.182072
        4
                cover version 0.182072
        5
                    page open 0.182072
        6
                    keep page 0.182072
        7
                  read sendak 0.182072
        8
           movie incorporate 0.182072
        9
                  hard cover 0.175544
        10
                   miss hard 0.175544
        11
                  sendak book 0.175544
        12
                    grow read 0.175544
        13
                 kind flimsy 0.175544
                 really rosie 0.175544
        14
        15
                 watch really 0.175544
                  flimsy take 0.175544
        16
        17
                 however miss 0.175544
                   book watch 0.175544
        18
        19
                     two hand 0.175544
        20
                     love son 0.167320
        21
                        rosie 0.164385
        22
                    paperback 0.164385
        23
                    seem kind 0.161903
        24
                    hand keep 0.157857
In [0]: #saving tfidf
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_ve-
            pickle.dump(train_tf_idf, bow)
        # with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_
             pickle.dump(train_df['Score'].values, bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_ve-
            pickle.dump(cv_tfidf, bow)
        # with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_
             pickle.dump(cv_df['Score'].values, bow)
```

```
with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_ve
            pickle.dump(test_tfidf, bow)
        # with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_
              pickle.dump(test_df['Score'].values, bow)
In [0]: list_of_sent=[]
        for sent in train_df['CleanedText'].values:
            list_of_sent.append(sent.split())
In [0]: list_of_sent=[]
        for sent in cv_df['CleanedText'].values:
            list_of_sent.append(sent.split())
In [0]: list_of_sent=[]
        for sent in test_df['CleanedText'].values:
            list_of_sent.append(sent.split())
5.3 [4.3] Word2Vec
In [0]: w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=7)
In [0]: #saving w2v model
        w2v model.save("/content/gdrive/My Drive/appliedAI/datasets/amzn fine food reviews/amz
In [0]: #loading model
        w2v_model = Word2Vec.load("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_;
In [0]: w2v_words = list(w2v_model.wv.vocab)
        print("number of words that occured minimum 5 times ",len(w2v_words))
        print("sample words ", w2v_words[0:50])
number of words that occured minimum 5 times 12979
sample words ['witty', 'little', 'book', 'make', 'son', 'laugh', 'loud', 'recite', 'car', 'dr
5.4 [4.3.1] Average Word2Vec
In [0]: # average Word2Vec
        # compute average word2vec for each review.
        def avg_w2vec(list_of_sent):
            sent_vectors = [] # the avg-w2v for each sentence/review is stored in this list
            for sent in list_of_sent: # for each review/sentence
                sent_vec = np.zeros(50) # as word vectors are of zero length
                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]))
            return sent_vectors
In [0]: avg_w2v_train = avg_w2vec([sent.split() for sent in train_df['CleanedText'].values])
        avg_w2v_cv = avg_w2vec([sent.split() for sent in cv_df['CleanedText'].values])
        avg_w2v_test = avg_w2vec([sent.split() for sent in test_df['CleanedText'].values])
60000
50
20000
50
20000
50
In [0]: #saving word2vec
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/avg_w2v_
            pickle.dump(avg_w2v_train, w2v_pickle)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/avg_w2v_
            pickle.dump(avg_w2v_cv, w2v_pickle)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/avg_w2v_
            pickle.dump(avg_w2v_test, w2v_pickle)
5.5 [4.3.2] TFIDF-Word2Vec
In [0]: def helper(list_of_sent, final_tf_idf):
            tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in thi
            row=0;
            for sent in tqdm(list_of_sent): # 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:
                        vec = w2v_model.wv[word]
                        # obtain the tf_idfidf of a word in a sentence/review
                        tf_idf = final_tf_idf[row, tfidf_feat.index(word)]
                        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
                #print(row, end=" ")
            return tfidf_sent_vectors
```

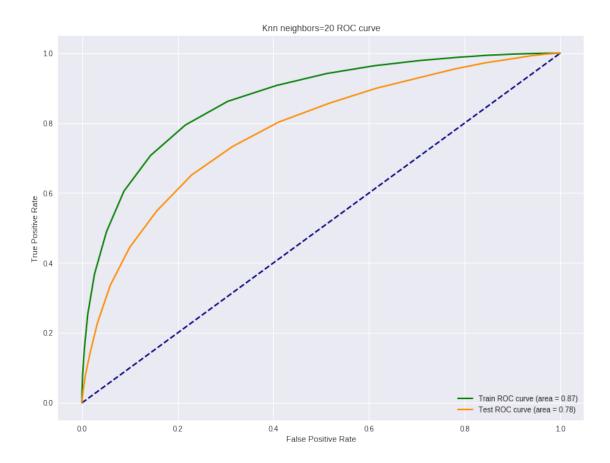
```
In [0]: from tqdm import tqdm
In [0]: helper_numba = jit()(helper)
In [0]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
       model = TfidfVectorizer()
       tf_idf_matrix = model.fit_transform(train_df['CleanedText'].values)
        # we are converting a dictionary with word as a key, and the idf as a value
        dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
In [0]: # TF-IDF weighted Word2Vec
        def tfidf_w2vec(list_of_sent):
            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 = tf
            tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in thi
            row=0;
            for sent in tqdm(list_of_sent): # 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
            return tfidf_sent_vectors
In [0]: # TF-IDF weighted Word2Vec
        tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
        # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
        #tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
        #row=0;
        #for sent in list_of_sent: # for each review/sentence
        #this was taking a lot of time
        # with ThreadPoolExecutor(max_workers=10000) as executor:
             result_futures = [executor.submit(helper_numba, sent=x, row=y) for y, x in enume
             for f in futures.as_completed(result_futures):
                  i = f.result()
```

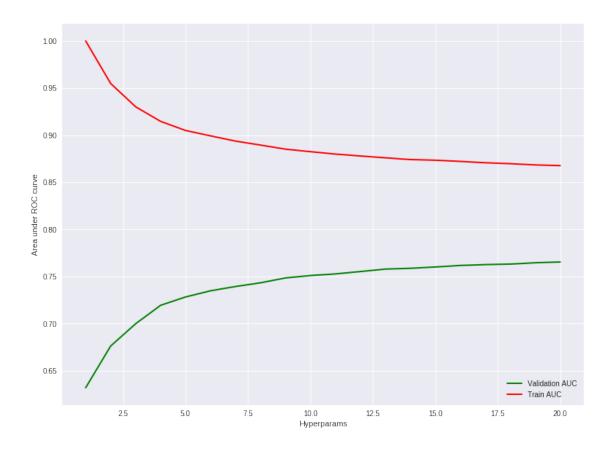
```
print(i)
        # print("Threading done!")
        # for y, x in enumerate(list_of_sent):
        # i = helper_numba(sent=x, row=y)
              print(i)
        list_of_sent = [sent.split() for sent in train_df['CleanedText'].values]
        # train_tfidf_w2v = helper(list_of_sent, train_tf_idf)
        train_tfidf_w2v = []; # the tfidf-w2v for each sentence/review is stored in this list
        row=0;
        for sent in tqdm(list_of_sent): # 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:
                     vec = w2v_model.wv[word]
                      \begin{tabular}{ll} \# \ obtain \ the \ tf\_idfidf \ of \ a \ word \ in \ a \ sentence/review \\ \end{tabular} 
                     tf_idf = train_tf_idf[row, tfidf_feat.index(word)]
                     sent_vec += (vec * tf_idf)
                     weight_sum += tf_idf
            if weight_sum != 0:
                sent_vec /= weight_sum
            train_tfidf_w2v.append(sent_vec)
            row += 1
            #print(row, end=" ")
        print("Done!")
  0%1
                | 121/60000 [03:36<33:49:49, 2.03s/it]
                                                    Traceback (most recent call last)
        KeyboardInterrupt
        <ipython-input-20-7d49c173ee40> in <module>()
                         vec = w2v_model.wv[word]
         28
         29
                         # obtain the tf_idfidf of a word in a sentence/review
                        tf_idf = train_tf_idf[row, tfidf_feat.index(word)]
    ---> 30
                         sent_vec += (vec * tf_idf)
         31
         32
                         weight_sum += tf_idf
        KeyboardInterrupt:
In [0]: #saving tfidf weighted w2v
```

with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_we

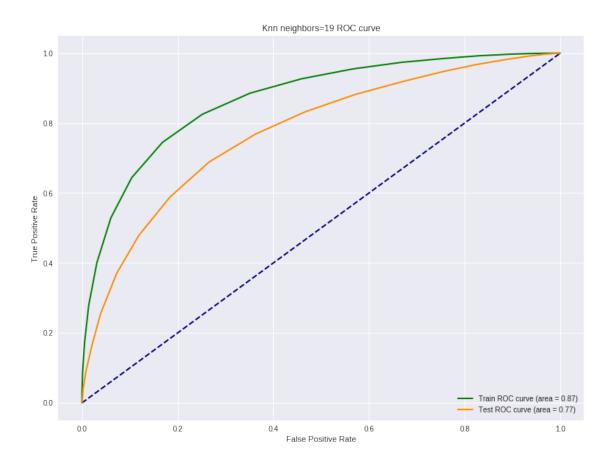
```
pickle.dump(tfidf_sent_vectors, tfidf_w2v_pickle)
       print("Done!")
Done!
In [0]: with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_we
           pickle.dump(tfidf_sent_vectors, tfidf_w2v_pickle)
In [0]: with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_we
           pickle.dump(tfidf_sent_vectors, tfidf_w2v_pickle)
   [5] KNN Assignment
6.1 [5.1] KNN Brute Force
6.1.1 [5.1.1] Bag of Words
In [0]: # loading the libraries
        from sklearn.neighbors import KNeighborsClassifier
        from tqdm import tqdm
        import matplotlib.pyplot as plt
In [0]: from sklearn.metrics import classification_report
In [0]: from sklearn.model_selection import GridSearchCV
In [0]: from sklearn.metrics import roc_curve, auc
In [0]: # loading the pickle file
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_
            bow_train = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/train_la
            bow_train_lab = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_
            bow_cv = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/cv_lab.pd
            bow_cv_lab = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/bow_uni_
            bow_test = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/test_lab
            bow_test_lab = pickle.load(bow)
In [0]: train_lab_bin = [1 if x=='positive' else 0 for x in bow_train_lab]
        test_lab_bin = [1 if x=='positive' else 0 for x in bow_test_lab]
        cv_lab_bin = [1 if x=='positive' else 0 for x in bow_cv_lab]
```

```
In [0]: # finding best k using AUC
       lw = 2
       auc_train = []
       auc_cv = []
       auc_test = []
       fpr_train = dict()
       tpr_train = dict()
       fpr_test = dict()
       tpr_test = dict()
       fpr_cv = dict()
       tpr_cv = dict()
       bow_train_lab_bin = [1 if x=='positive' else 0 for x in bow_train_lab]
       bow_test_lab_bin = [1 if x=='positive' else 0 for x in bow_test_lab]
       bow_cv_lab_bin = [1 if x=='positive' else 0 for x in bow_cv_lab]
       for idx, k in enumerate(range(1, 21)):
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
           knn_classifier.fit(bow_train, bow_train_lab_bin)
           bow_train_proba = knn_classifier.predict_proba(bow_train)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(bow_train_lab_bin, bow_train_proba[:
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           bow_test_proba = knn_classifier.predict_proba(bow_test)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(bow_test_lab_bin, bow_test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           bow_cv_proba = knn_classifier.predict_proba(bow_cv)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(bow_cv_lab_bin, bow_cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





```
In [0]: # 19-NN
        knn_classifier = KNeighborsClassifier(n_neighbors=19, algorithm='brute')
        knn_classifier.fit(bow_train, bow_train_lab)
        bow_cv_predict = knn_classifier.predict(bow_cv)
        print(classification_report(bow_cv_lab, bow_cv_predict))
        train_proba = knn_classifier.predict_proba(bow_train)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(bow_test)
        fpr_test, tpr_test, = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                           recall f1-score
                                              support
   negative
                   0.73
                             0.60
                                       0.66
                                                10000
   positive
                   0.66
                             0.78
                                       0.72
                                                10000
  micro avg
                   0.69
                             0.69
                                       0.69
                                                20000
                             0.69
  macro avg
                   0.70
                                       0.69
                                                20000
weighted avg
                             0.69
                                       0.69
                                                20000
                   0.70
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \# max_i dx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
       plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = ')
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(19) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```

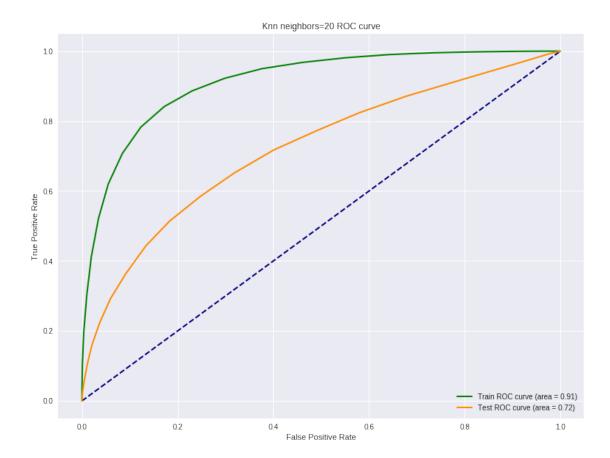


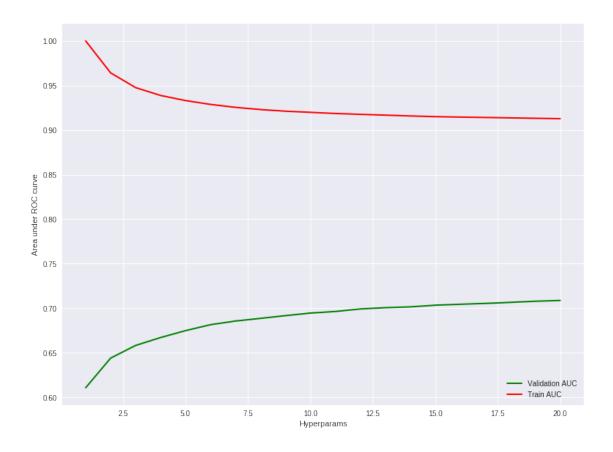
6.1.2 [5.1.2] TFIDF

tpr_cv = dict()

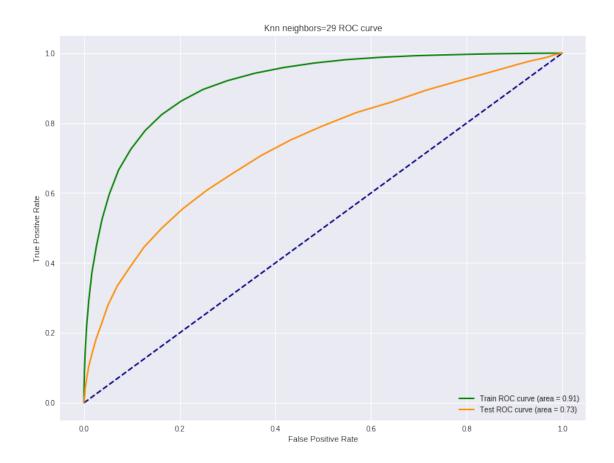
```
In [0]: # loading tfidf vectors
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_ve-
            train_data = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_ve-
            cv_data = pickle.load(bow)
        with open("/content/gdrive/My Drive/appliedAI/datasets/amzn_fine_food_reviews/tfidf_ve
            test_data = pickle.load(bow)
In [0]: # finding best k using AUC
        lw = 2
        auc_train = []
        auc_cv = []
        auc_test = []
        fpr_train = dict()
        tpr_train = dict()
        fpr_test = dict()
        tpr_test = dict()
        fpr_cv = dict()
```

```
train_lab_bin = [1 if x=='positive' else 0 for x in bow_train_lab]
       test_lab_bin = [1 if x=='positive' else 0 for x in bow_test_lab]
       cv_lab_bin = [1 if x=='positive' else 0 for x in bow_cv_lab]
       for idx, k in enumerate(range(1, 21)):
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





```
In [0]: # 29-NN
        knn_classifier = KNeighborsClassifier(n_neighbors=29, algorithm='brute')
       knn_classifier.fit(train_data, bow_train_lab)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(bow_cv_lab, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                           recall f1-score
                                              support
   negative
                   0.63
                             0.77
                                       0.70
                                                10000
                                                10000
   positive
                   0.71
                             0.56
                                       0.62
  micro avg
                   0.66
                             0.66
                                       0.66
                                                20000
                             0.66
  macro avg
                   0.67
                                       0.66
                                                20000
weighted avg
                             0.66
                                       0.66
                                                20000
                   0.67
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \#max_idx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
       plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = '
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(29) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```

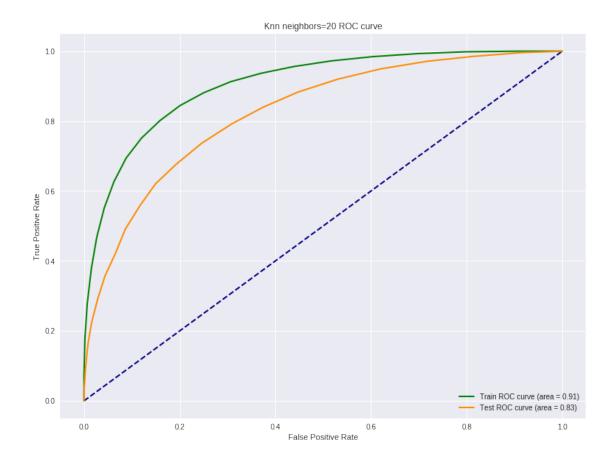


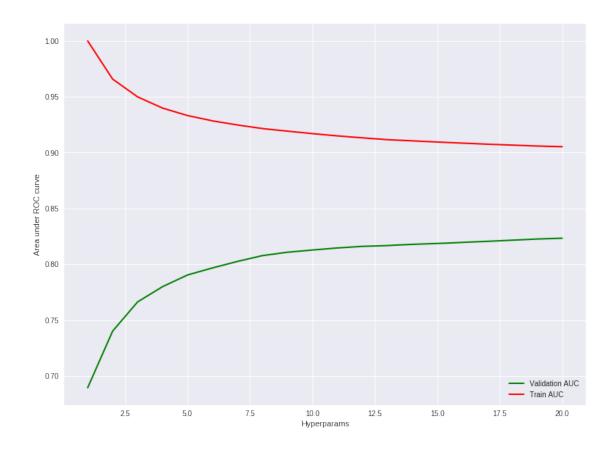
6.1.3 [5.1.3] Word2Vec

In [0]: #loading word2vec vectors

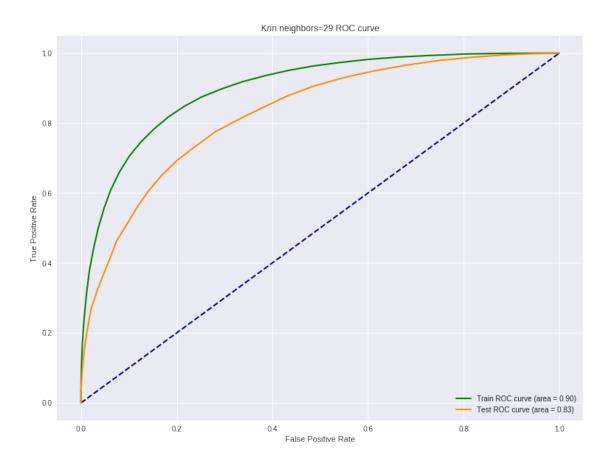
fpr_cv = dict()
tpr_cv = dict()

```
train_lab_bin = [1 if x=='positive' else 0 for x in bow_train_lab]
       test_lab_bin = [1 if x=='positive' else 0 for x in bow_test_lab]
       cv_lab_bin = [1 if x=='positive' else 0 for x in bow_cv_lab]
       for idx, k in enumerate(range(1, 21)):
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





```
In [0]: # 29-NN
        knn_classifier = KNeighborsClassifier(n_neighbors=29, algorithm='brute')
       knn_classifier.fit(train_data, bow_train_lab)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(bow_cv_lab, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                          recall f1-score
                                              support
   negative
                   0.71
                             0.82
                                       0.76
                                                10000
   positive
                   0.78
                             0.67
                                       0.72
                                                10000
  micro avg
                   0.74
                             0.74
                                       0.74
                                                20000
  macro avg
                   0.75
                             0.74
                                       0.74
                                                20000
weighted avg
                             0.74
                                       0.74
                                                20000
                   0.75
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \#max_idx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
       plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = '
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(29) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```

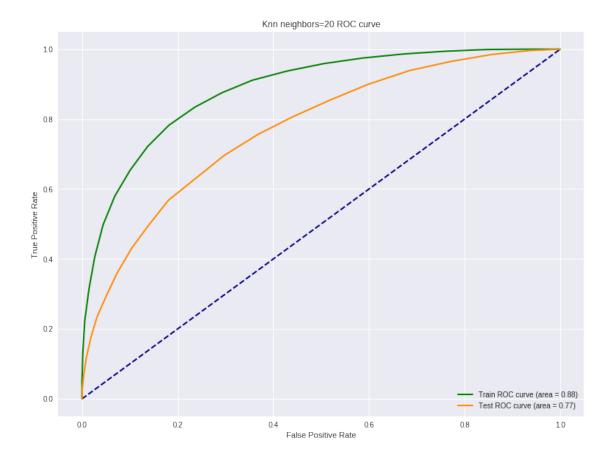


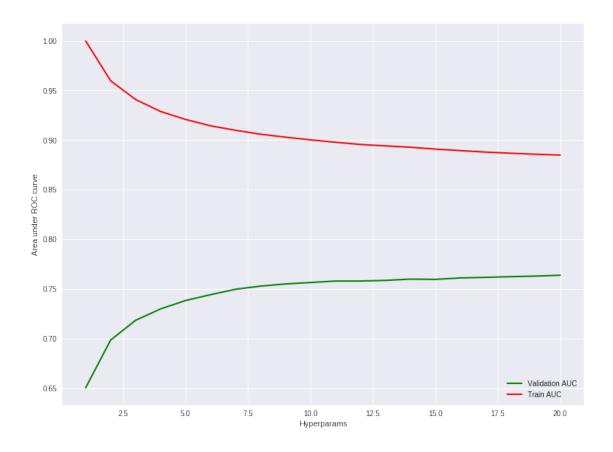
6.1.4 [5.1.4] TFIDF Word2Vec

```
In [0]: #loading tfidf word2vec
```

```
lw = 2
auc_train = []
auc_cv = []
auc_test = []
fpr_train = dict()
tpr_train = dict()
fpr_test = dict()
tpr_test = dict()
fpr_cv = dict()
```

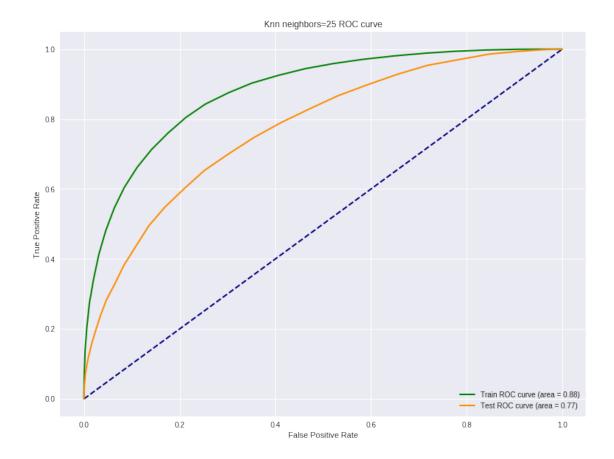
```
tpr_cv = dict()
       train_lab_bin = [1 if x=='positive' else 0 for x in bow_train_lab]
       test_lab_bin = [1 if x=='positive' else 0 for x in bow_test_lab]
       cv_lab_bin = [1 if x=='positive' else 0 for x in bow_cv_lab]
       for idx, k in enumerate(range(1, 21)):
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





```
knn_classifier = KNeighborsClassifier(n_neighbors=27, algorithm='brute')
       knn_classifier.fit(train_data, train_lab_bin)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(cv_lab_bin, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                           recall f1-score
                                              support
           0
                   0.67
                             0.77
                                       0.72
                                                10000
           1
                   0.73
                             0.62
                                                10000
                                       0.67
  micro avg
                   0.69
                             0.69
                                       0.69
                                                20000
  macro avg
                   0.70
                             0.69
                                       0.69
                                                20000
weighted avg
                             0.69
                                       0.69
                                                20000
                   0.70
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \#max_idx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
       plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = ')
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(25) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```

In [0]: # 27-NN

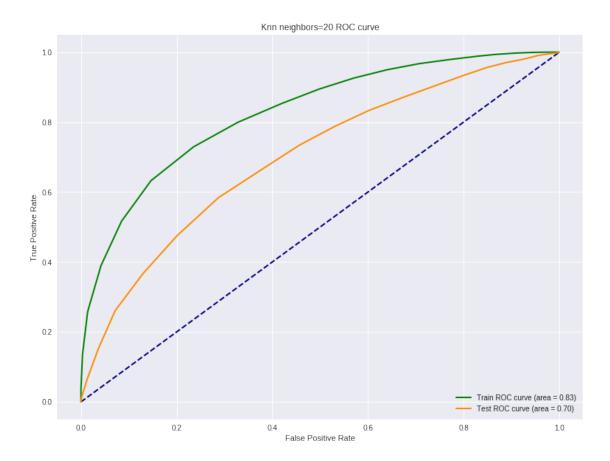


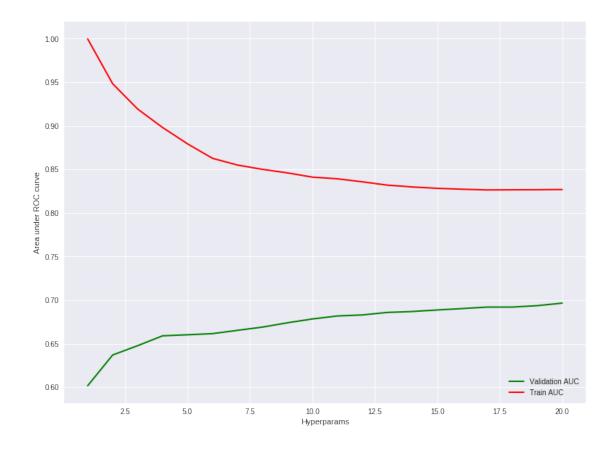
6.2 [5.2] KNN kd-tree

6.2.1 [5.2.1] Bag of words

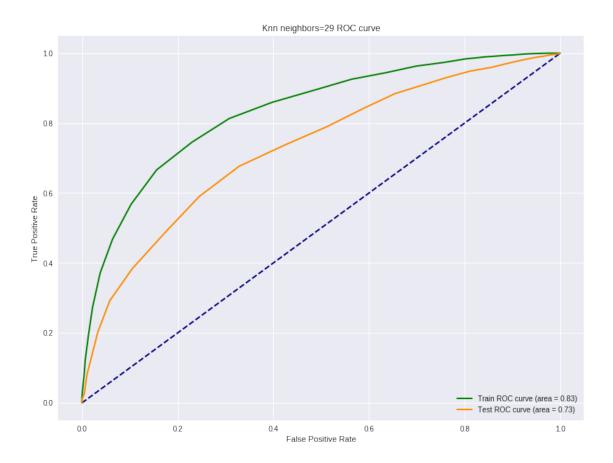
the type of count vectorizer <class 'numpy.ndarray'>

```
In [0]: # finding best k using AUC
       lw = 2
       auc_train = []
       auc_cv = []
       auc_test = []
       fpr_train = dict()
       tpr_train = dict()
       fpr_test = dict()
       tpr_test = dict()
       fpr_cv = dict()
       tpr_cv = dict()
       for idx, k in enumerate(range(1, 21)):
           print(k, end=" ")
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





```
In [0]: # 28-NN
        knn_classifier = KNeighborsClassifier(n_neighbors=28, algorithm='brute')
       knn_classifier.fit(train_data, train_lab_bin)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(cv_lab_bin, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                           recall f1-score
                                              support
           0
                   0.68
                             0.60
                                       0.64
                                                 2000
                                                 2000
           1
                   0.64
                             0.72
                                       0.68
  micro avg
                   0.66
                             0.66
                                       0.66
                                                 4000
                             0.66
  macro avg
                   0.66
                                       0.66
                                                 4000
weighted avg
                   0.66
                             0.66
                                       0.66
                                                 4000
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \#max_idx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
       plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = '
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(29) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```

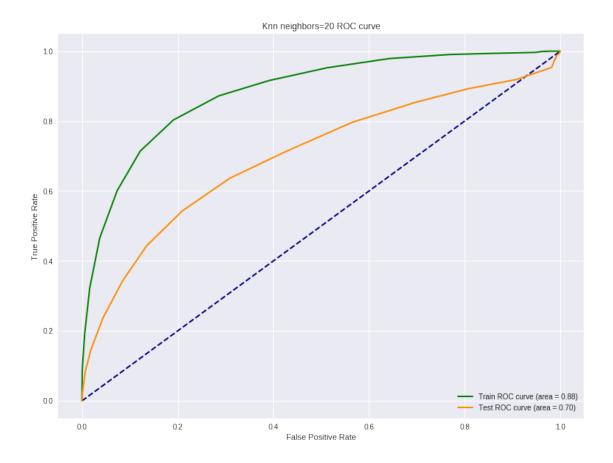


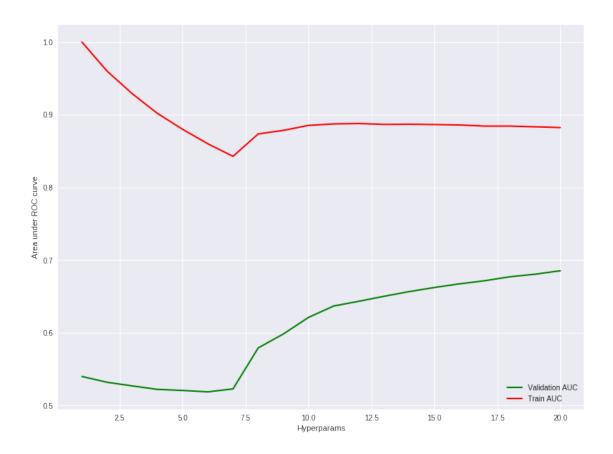
6.2.2 [5.2.2] TFIDF

```
In [0]: # finding best k using AUC
    lw = 2
    auc_train = []
    auc_cv = []
    auc_test = []
    fpr_train = dict()
    tpr_train = dict()
```

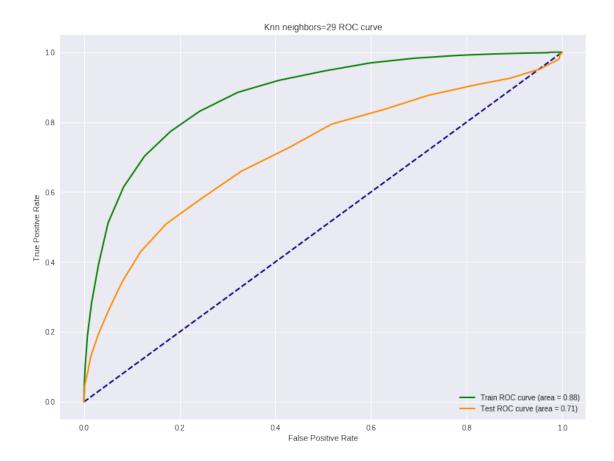
the type of count vectorizer <class 'numpy.ndarray'>

```
fpr_test = dict()
       tpr_test = dict()
       fpr_cv = dict()
       tpr_cv = dict()
       for idx, k in enumerate(range(1, 21)):
           print(k, end=" ")
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





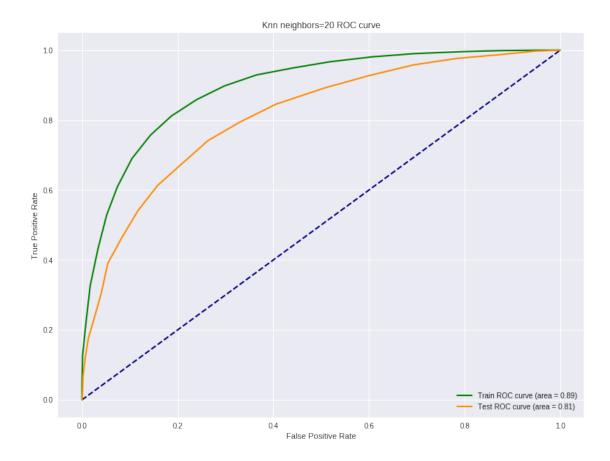
```
In [0]: # 25-NN
        knn_classifier = KNeighborsClassifier(n_neighbors=25, algorithm='kd_tree')
        knn_classifier.fit(train_data, train_lab_bin)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(cv_lab_bin, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                           recall f1-score
                                              support
           0
                   0.66
                             0.63
                                       0.64
                                                  2000
                                                  2000
           1
                   0.64
                             0.67
                                       0.66
  micro avg
                   0.65
                             0.65
                                       0.65
                                                 4000
  macro avg
                   0.65
                             0.65
                                       0.65
                                                 4000
weighted avg
                             0.65
                                       0.65
                                                  4000
                   0.65
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
        plt.figure(figsize=(12.8, 9.6))
        plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \#max_idx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
        plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = ')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('Knn neighbors=' + str(29) + ' ROC curve')
        plt.legend(loc="lower right")
        plt.show()
```

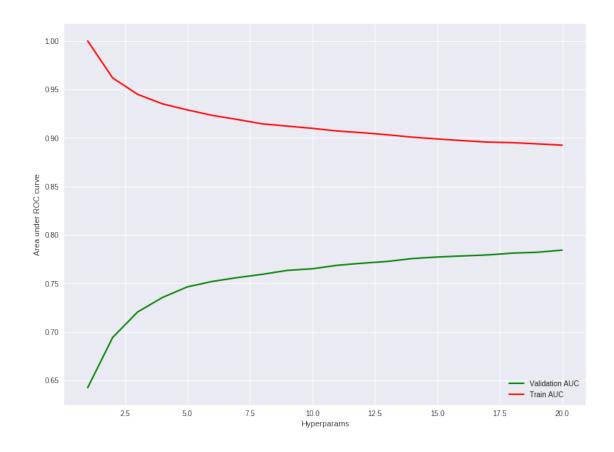


6.2.3 [5.2.3] Word2Vec

```
In [0]: # finding best k using AUC
    lw = 2
    auc_train = []
    auc_cv = []
    auc_test = []
    fpr_train = dict()
    tpr_train = dict()
```

```
fpr_test = dict()
       tpr_test = dict()
       fpr_cv = dict()
       tpr_cv = dict()
       for idx, k in enumerate(range(1, 21)):
           print(k, end=" ")
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





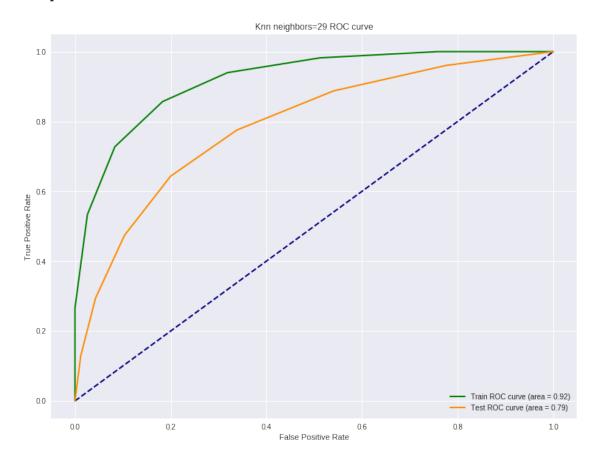
```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done 30 out of 30 | elapsed: 5.7min finished
CV Accuracy: 0.691
Best Params {'n_neighbors': 7}
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done 30 out of 30 | elapsed: 5.7min finished
CV Accuracy: 0.691
Best Params {'n_neighbors': 7}
In [0]: # 7-NN
       knn_classifier = KNeighborsClassifier(n_neighbors=7, algorithm='kd_tree')
       knn_classifier.fit(train_data, train_lab_bin)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(cv_lab_bin, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
              precision
                        recall f1-score
                                              support
           0
                   0.65
                             0.81
                                       0.72
                                                 2000
           1
                   0.75
                             0.57
                                       0.65
                                                 2000
  micro avg
                   0.69
                             0.69
                                       0.69
                                                 4000
  macro avg
                   0.70
                             0.69
                                       0.69
                                                 4000
weighted avg
                   0.70
                             0.69
                                       0.69
                                                 4000
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
        plt.figure(figsize=(12.8, 9.6))
```

```
plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = 'plt.xlabel('False Positive Rate')
```

plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')

 $\#max_idx = auc_cv.index(max(auc_cv))$

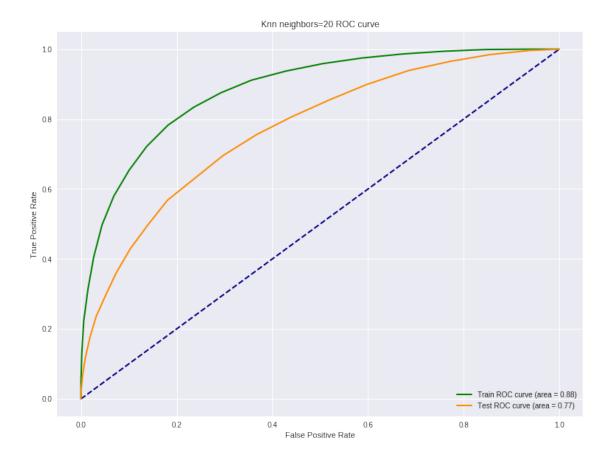
```
plt.ylabel('True Positive Rate')
plt.title('Knn neighbors=' + str(29) + ' ROC curve')
plt.legend(loc="lower right")
plt.show()
```

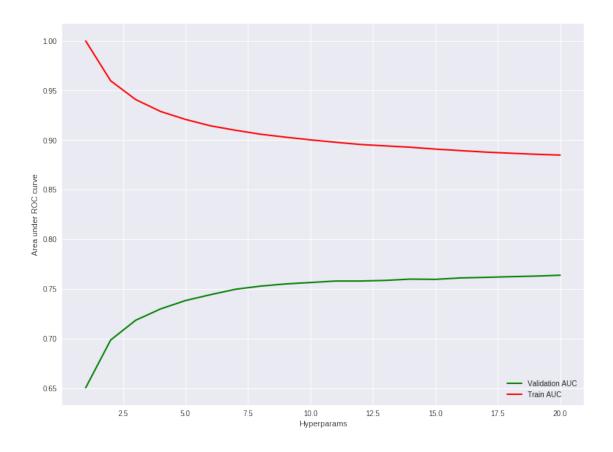


6.2.4 [5.2.4] TFIDF Word2Vec

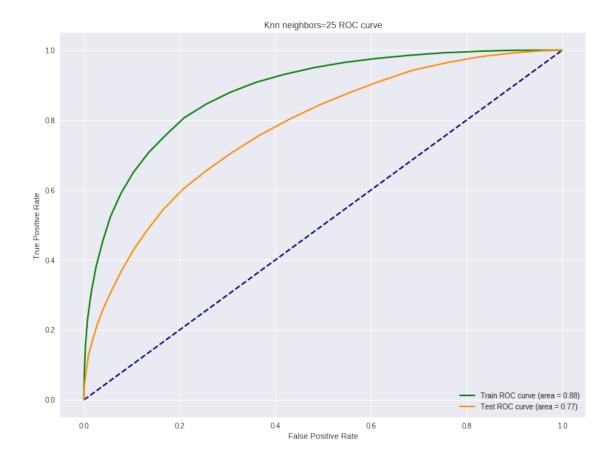
60000 60000

```
In [0]: # finding best k using AUC
       lw = 2
       auc_train = []
       auc_cv = []
       auc_test = []
       fpr_train = dict()
       tpr_train = dict()
       fpr_test = dict()
       tpr_test = dict()
       fpr_cv = dict()
       tpr_cv = dict()
       for idx, k in enumerate(range(1, 21)):
           print(k, end=" ")
           knn_classifier = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
           knn_classifier.fit(train_data, train_lab_bin)
           train_proba = knn_classifier.predict_proba(train_data)
           fpr_train[idx], tpr_train[idx], _ = roc_curve(train_lab_bin, train_proba[:,1])
           auc_train.append(auc(fpr_train[idx], tpr_train[idx]))
           test_proba = knn_classifier.predict_proba(test_data)
           fpr_test[idx], tpr_test[idx], _ = roc_curve(test_lab_bin, test_proba[:,1])
           auc_test.append(auc(fpr_test[idx], tpr_test[idx]))
           cv_proba = knn_classifier.predict_proba(cv_data)
           fpr_cv[idx], tpr_cv[idx], _ = roc_curve(cv_lab_bin, cv_proba[:,1])
           auc_cv.append(auc(fpr_cv[idx], tpr_cv[idx]))
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
In [0]: # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
       plt.figure(figsize=(12.8, 9.6))
       plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
       max_idx = auc_cv.index(max(auc_cv))
       plt.plot(fpr_train[max_idx], tpr_train[max_idx], color='green', lw=lw, label='Train RO
       plt.xlabel('False Positive Rate')
       plt.ylabel('True Positive Rate')
       plt.title('Knn neighbors=' + str(max_idx+1) + ' ROC curve')
       plt.legend(loc="lower right")
       plt.show()
```





```
knn_classifier.fit(train_data, train_lab_bin)
        cv_predict = knn_classifier.predict(cv_data)
        print(classification_report(cv_lab_bin, cv_predict))
        train_proba = knn_classifier.predict_proba(train_data)
        fpr_train, tpr_train, _ = roc_curve(train_lab_bin, train_proba[:,1])
        auc_train = auc(fpr_train, tpr_train)
        test_proba = knn_classifier.predict_proba(test_data)
        fpr_test, tpr_test, _ = roc_curve(test_lab_bin, test_proba[:,1])
        auc_test = auc(fpr_test, tpr_test)
                           recall f1-score
              precision
                                              support
           0
                   0.67
                             0.77
                                                10000
                                       0.71
           1
                   0.73
                             0.62
                                       0.67
                                                10000
                   0.69
                             0.69
                                       0.69
                                                20000
  micro avg
  macro avg
                             0.69
                                                20000
                   0.70
                                       0.69
weighted avg
                   0.70
                             0.69
                                       0.69
                                                20000
In [0]: 1w=2
        # plotting styles from https://scikit-learn.org/stable/auto_examples/model_selection/p
        plt.figure(figsize=(12.8, 9.6))
        plt.plot([0,1], [0,1], color='navy', lw=lw, linestyle='--')
        \#max_idx = auc_cv.index(max(auc_cv))
        plt.plot(fpr_train, tpr_train, color='green', lw=lw, label='Train ROC curve (area = %0
        plt.plot(fpr_test, tpr_test, color='darkorange', lw=lw, label='Test ROC curve (area = '
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('Knn neighbors=' + str(25) + ' ROC curve')
        plt.legend(loc="lower right")
        plt.show()
```



7 [6] Conclusion

+-		+-		+-		+		-+
Ī	BoW	Ī	Brute		19		0.77	1
-	TFIDF		Brute		29		0.73	
-	Word2Vec		Brute		29		0.83	
-	TFIDF Word2Vec		Brute		27		0.77	
-	BoW		kd-tree		28		0.73	
-	TFIDF		kd-tree		25		0.71	
-	Word2Vec		kd-tree		7		0.79	
-	TFIDF Word2Vec		kd-tree		27		0.77	
4.		4.		+-		 -		-+