## PresidentSpeeches

## August 31, 2016

```
In [2]: # import required libraries to scrape presidential transcripts
       from bs4 import BeautifulSoup
       import pandas as pd
       import pickle
       import urllib2
       import re
In [35]: import urllib2,sys,os
        from bs4 import BeautifulSoup, NavigableString
        from string import punctuation as p
        from multiprocessing import Pool
        import re, nltk
        import requests
        reload(sys)
        sys.setdefaultencoding('utf8')
        # Scraping and cleaning one speech from Obama to show the method works
        #-----
        obama_4427_url = 'http://www.millercenter.org/president/obama/speeches/speech-4427'
        obama_4427 = urllib2.urlopen(obama_4427_url).read()
        obama_4427 = BeautifulSoup(obama_4427)
        # find the speech itself within the HTML
        obama_4427 = obama_4427.find('div', {'id': 'transcript'}, {'class': 'displaytext'})
        # obama_4427_div.text removes extraneous characters (e.g. '<br/>')
        obama_4427 = obama_4427.text.lower()
        # for further text analysis, remove punctuation
        punctuation = re.compile('[{}]+'.format(re.escape(p)))
        \# obama_4427_nopunct = [line.decode('utf-8').strip() for line in obama_4427_html.readlines()]
        obama_4427 = punctuation.sub('', obama_4427)
        obama_4427 = obama_4427.replace(',',',')
        obama_4427 = obama_4427.replace('transcript','')
        \# divide obama_4427_str_processed into individual words
        words = obama_4427.split(' ')
```

```
# Cleaning links begins below, so that we can process all 911 speeches through processURL()
url = 'http://www.millercenter.org/president/speeches'
url2 = 'http://www.millercenter.org'
conn = urllib2.urlopen(url)
html = conn.read()
miller_center_soup = BeautifulSoup(html)
links = miller_center_soup.find_all('a')
linklist = [tag.get('href') for tag in links if tag.get('href') is not None]
# remove all items in list that don't contain 'speeches'
linkslist = [_ for _ in linklist if re.search('speeches',_)]
del linkslist[0:2]
# concatenate 'http://www.millercenter.org' with end of speech links
every_link_dups = [url2 + end_link for end_link in linkslist]
# remove duplicates
seen = set()
every_link = [] # no duplicates array
for l in every_link_dups:
   if 1 not in seen:
       every_link.append(1)
       seen.add(1)
# list of presidents (print(len(set(presidents))) = 43 total)
presidents_dups = [l[l.find('president/')+len('president/'):] for l in every_link if 'presiden
presidents_dups = [1[0:1.find(',')] for 1 in presidents_dups]
set2 = set()
presidents = []
for 1 in presidents_dups:
   if 1 not in set2:
       presidents.append(1)
       seen.add(1)
presidents = sorted(presidents)
# the following two lines - now commented out - were used to identify duplicates in the origin
# import collections
# print [l for l, count in collections.Counter(every_link).items() if count > 1]
# define a function to clean & store speeches from 'every_link' repository
def processURL(1):
       open_url = urllib2.urlopen(1).read()
       x=urllib2.urlopen(obama_4427_url).read()
       item_soup = BeautifulSoup(x)
       item_div = item_soup.find('div', {'id':'transcript'}, {'class':'displaytext'})
       item_str = item_div.text.lower()
```

```
item_str_processed = punctuation.sub('',item_str)
                 item_str_processed_final = item_str_processed.replace('|','')
                 splitlink = 1.split("/")
                 president = splitlink[4]
                 speech_num = splitlink[-1].split("-")[1]
                 filename = "{0}_{1}".format(president, speech_num)
                 return filename, item_str_processed_final # returning a tuple
         # right now, this loop only works for 423 speeches - where are the remaining ones?
         for l in every_link[1:423]:
             filename, content = processURL(1) # tuple unpacking
             with open(filename, 'w') as f:
                 f.write(content)
In [3]: import os
        from os import path
        root = "F:/topicmodel_speeches"
        files = os.listdir(root)
In [4]: #load speeches into a list
        docs = list()
        for file in files:
            with open(path.join(root, file), 'r') as fd:
               txt = fd.read()
               docs.append(txt)
In [5]: import re
        def clean(doc):
            doc = re.sub(r'[^\w\s]*', '', doc)
            doc = re.sub(r'[\s]+', '', doc)
            doc = doc.lower().strip()
            return doc
In [6]: clean_docs = list()
        for doc in docs:
            doc = clean(doc)
            clean_docs.append(doc)
In [5]: #tokenize speeches
        token_docs = list()
        for doc in clean_docs:
            token_docs.append(doc.split())
In [6]: #remove stopwords
        stopwords = list()
        with open('F:/2060724/topicmodel_stopwords.txt', 'r') as fd:
            for line in fd.readlines():
                stopwords.append(line.strip())
In [7]: sw_token_docs = list()
        for doc in token_docs:
            sw_doc = list()
            for token in doc:
                if not token in stopwords:
```

```
sw_doc.append(token)
                                                                                    sw_token_docs.append(sw_doc)
In [8]: # perform topic modelling
                                                       from gensim import corpora, models, similarities
                                                        dictionary = corpora.Dictionary(sw_token_docs)
                                                        corpus = [dictionary.doc2bow(doc) for doc in sw_token_docs]
In [7]: from __future__ import division
                                                        import graphlab as gl
                                                        import pandas as pd
                                                        import pyLDAvis
                                                        import pyLDAvis.graphlab
                                                      pyLDAvis.enable_notebook()
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:98: DeprecationWarning: DisplayFo
              def _formatters_default(self):
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:677: DeprecationWarning: PlainTexters.py:677: De
              def _deferred_printers_default(self):
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:669: DeprecationWarning: PlainTexters.py:669: De
              def _singleton_printers_default(self):
 \verb|C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:672: Deprecation \verb|Warning:PlainTexages|| The latest the packages of the latest theorem of the lates
              def _type_printers_default(self):
In [8]: doc=gl.SFrame(clean_docs)
                                                        sf_paragraphs = doc.rename({'X1': 'paragraph'})
                                                        doc.head()
 [INFO] graphlab.cython.cy_server: GraphLab Create v2.1 started. Logging: C:\Users\pankaj\AppData\Local\T
This non-commercial license of GraphLab Create for academic use is assigned to pankajvshrma@gmail.com a
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:92: DeprecationWarning: DisplayFo
              def _ipython_display_formatter_default(self):
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:669: DeprecationWarning: PlainTexters.py:669: De
              def _singleton_printers_default(self):
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:672: DeprecationWarning: PlainTexters.py:672: De
              def _type_printers_default(self):
C:\Users\pankaj\Anaconda2\lib\site-packages\IPython\core\formatters.py:677: DeprecationWarning: PlainTexters.py:677: De
              def _deferred_printers_default(self):
Out[8]: Columns:
                                                                                                               paragraph
                                                                                                                                                                                                                                      str
                                                       Rows: 10
                                                       Data:
                                                                                                                                         paragraph
                                                         | fellow citizens of the sen... |
                                                         | whereas it is the duty of ... |
                                                         | fellow citizens of the sen... |
```

| fellow citizens of the sen... |

```
| i the president of the uni... |
      | i meet you upon the presen... |
      | gentlemen of the house of ... |
      | fellowcitizens of the sena... |
      | whereas i have received au... |
      | fellowcitizens i am again ... |
      +----+
      [10 rows x 1 columns]
In [9]: re_words_split = re.compile("(\w+)")
      sf_paragraphs['paragraph_words_number'] = sf_paragraphs['paragraph'].apply(lambda p: len(re_wor
      sf_paragraphs = sf_paragraphs[sf_paragraphs['paragraph_words_number'] >=25]
In [10]: docs = gl.text_analytics.count_ngrams(sf_paragraphs['paragraph'], n=1)
In [11]: stopwords = gl.text_analytics.stopwords()
       # adding some additional stopwords to make the topic model more clear
       stopwords |= set(['man', 'mr', 'sir', 'make', 'made', 'll', 'door', 'long', 'day', 'small'])
       docs = docs.dict_trim_by_keys(stopwords, exclude=True)
       docs = docs.dropna()
In [12]: topic_model = gl.topic_model.create(docs, num_topics=10)
Learning a topic model
     Number of documents
                         622
        Vocabulary size
                       36392
  Running collapsed Gibbs sampling
+----+
| Iteration | Elapsed Time | Tokens/Second | Est. Perplexity |
+----+
l 10
        | 952.857ms | 5.83093e+006 | 0
                                                  - 1
+----+
In [13]: topic_model.get_topics().print_rows(100)
+----+
        word | score
| topic |
+----+
| 0 | people | 0.0518808217563 |
| 0 | peace | 0.0280909494448 |
```

```
0
           nations
                      0.0240855117597
    0
           america
                     | 0.0215886155404
                      | 0.0190136913143
    0
             time
1
    1
             law
                      | 0.0212298873226
    1
            state
                      0.0205198576463
    1
             part
                      0.0158104771399
    1
           question
                     | 0.0157235347306
    1
            power
                      0.0139557057405
    2
          government
                     0.0582714339429
    2
           congress
                     | 0.0272801740345
    2
           country
                      0.0252658860182
    2
            great
                         0.022455474643
    2
           national
                     | 0.0166140393956
    3
            states
                      0.0565825654513
    3
                      | 0.0503400597837
            united
    3
            world
                     | 0.0381020882464
    3
                      | 0.0305768759347
             war
    3
                      0.0113647808662
            great
    4
                        0.020797494843
             time
    4
             meet
                      0.0151005711818
    4
           citizens
                     | 0.0131829792304
    4
                      0.0129223356642
             plan
    4
            party
                      0.0120659353753
    5
                      1 0.0253373614164
        1
             year
    5
         president
                     0.0210878095595
    5
           vietnam
                      0.00948435615977
    5
           federal
                      | 0.00917202829502
    5
           security
                     | 0.00914363485277
    6
                      | 0.0408231758269
            years
    6
                      | 0.0224122673637
             work
    6
            future
                      0.0163026950611
    6
          president
                        0.016165709135
    6
           progress
                        0.014494480837
    7
                     | 0.0311206720485
           american
    7
                      0.0252488471337
             good
   7
            rights
                      0.0114762600909
   7
            health
                      0.00935326618581
    7
                      | 0.00909796945039
             past
   8
            today
                      | 0.0241819637855
   8
          americans
                     | 0.0204738860966
    8
                     | 0.0186510075688
             men
   8
                        0.015644037006
             hope
    8
             life
                      1 0.0118113180502
    9
            order
                      | 0.00801987346995
    9
            effect
                      0.00778655912923
    9
                     | 0.00773744032065
          attention
    9
           treasury
                     | 0.00722169283062 |
                      | 0.00689014087275 |
```

[50 rows x 3 columns]

In [17]: import pyLDAvis
 import pyLDAvis.graphlab
 pyLDAvis.enable\_notebook()

pyLDAvis.graphlab.prepare(topic\_model, docs)

Out[17]:	PreparedData(topic_coordinates=			es=	Freq cluster topics			x	У
	topic					_			
	5	13.00334			520 -0.236946				
	0	12.87356			203 -0.214329				
	3	12.63340			032 -0.088049				
	2	11.86821			315 -0.055087				
	6	10.83490			124 0.071484				
	7	8.59841		6 0.016					
	4	8.09062	0 1	7 0.057					
	9	7.96565	3 1	8 0.109					
	1	7.54492	7 1	9 0.027					
	8	6.58694	1 1	10 0.118	869 0.024682	2, topic_i	nfo=	Category	Freq
	term								
	20294	Default	5914.000000	government	5914.000000	30.0000	30.0000		
	25665	Default	5613.000000	states	5613.000000	29.0000	29.0000		
	9471	Default	6089.000000	people	6089.000000	28.0000	28.0000		
	17743	Default	5031.000000	united	5031.000000	27.0000	27.0000		
	10151	Default	3461.000000	congress	3461.000000	26.0000	26.0000		
	22802	Default	3239.000000	president	3239.000000	25.0000	25.0000		
	996	Default	3912.000000	world	3912.000000	24.0000	24.0000		
	27835	Default	3275.000000	time	3275.000000	23.0000	23.0000		
	3583	Default	3461.000000	american	3461.000000	22.0000	22.0000		
	8394	Default	3159.000000	peace	3159.000000	21.0000	21.0000		
	27527	Default	2647.000000	nations	2647.000000	20.0000	20.0000		
	20907	Default	3040.000000	war	3040.000000	19.0000	19.0000		
	3065	Default	2399.000000	america	2399.000000	18.0000	18.0000		
	18513	Default	3535.000000	country	3535.000000	17.0000	17.0000		
	710	Default	2895.000000	years	2895.000000	16.0000	16.0000		
	15690	Default	1885.000000	national	1885.000000	15.0000	15.0000		
	4564	Default	1851.000000	men	1851.000000	14.0000	14.0000		
	18886	Default	2440.000000	nation	2440.000000	13.0000	13.0000		
	34361	Default	2132.000000	public	2132.000000	12.0000	12.0000		
	29025	Default	3378.000000	great	3378.000000	11.0000	11.0000		
	29621	Default	1888.000000	work	1888.000000	10.0000	10.0000		
	31546	Default	1815.000000	state	1815.000000	9.0000	9.0000		
	28328	Default	1845.000000	power	1845.000000	8.0000	8.0000		
	20350	Default	2547.000000	year	2547.000000	7.0000	7.0000		
	34242	Default	1566.000000	free	1566.000000	6.0000	6.0000		
	22598	Default	1563.000000	freedom	1563.000000	5.0000	5.0000		
	9496	Default	1546.000000	citizens	1546.000000	4.0000	4.0000		
	32565	Default	1525.000000	americans	1525.000000	3.0000	3.0000		
	13727	Default	1252.000000	rights	1252.000000	2.0000	2.0000		
	6249	Default	1576.000000	today	1576.000000	1.0000	1.0000		
	 11889	 Topic10	 247.166930	 revolution	 262.430748	2.6602	-5.3745		
	6465	Topic10	133.060869	concerns	139.710721	2.6713	-5.9938		
	33157	Topic10	241.508778	benefits	257.720889	2.6551	-5.3977		
	4046	Topic10	715.850503	meet	790.762126	2.6206	-4.3111		
	15690	Topic10	1655.103698	national	1885.743368	2.5896	-3.4729		
	4564	Topic10	1612.667560	men	1851.105520	2.5822	-3.4989		
	6237	Topic10	325.438030	entire	355.139931	2.6327	-5.0994		
	4394	Topic10	158.522552	payments	169.135260	2.6553	-5.8187		
	1004	1011010	100.022002	Paymonos	100.100200	2.0000	0.0107		

```
24129 Topic10
                 613.060745
                                 common
                                          752.771266
                                                        2.5148 -4.4661
16706 Topic10
                 414.082408
                               millions
                                                        2.5233 -4.8585
                                          504.123079
                                          277.841500
33457
       Topic10
                 239.622728
                                  hopes
                                                        2.5721
                                                                -5.4055
      Topic10
                                                        2.4179
                                                               -4.3569
21636
                 683.787643
                                history
                                          925.041694
17876
      Topic10
                 369.760219
                             individual
                                          470.064683
                                                        2.4801
                                                               -4.9717
12168
      Topic10
                             proportion
                                          112.284762
                                                        2.6508 -6.2328
                 104.770110
       Topic10
                 619.661922
                                service
                                          878.346339
                                                        2.3712 -4.4554
217
      Topic10
                                                        2.3117 -4.7692
10866
                 452.746445
                                   high
                                          681.120506
35389
       Topic10
                 267.913487
                                 return
                                          364.687393
                                                        2.4117
                                                               -5.2939
                                                        2.2232 -4.7589
1177
       Topic10
                 457.461571
                                   full
                                          751.871988
4663
       Topic10
                 217.933146
                                 school
                                          286.267257
                                                        2.4473 -5.5004
29659
      Topic10
                 687.559744
                                         1533.877279
                                                        1.9177
                                                                -4.3514
                                    law
6053
       Topic10
                 237.736677
                                   task
                                          333.871545
                                                        2.3805 -5.4134
3843
                                                        2.2833
       Topic10
                 255.654158
                                success
                                          395.679561
                                                               -5.3407
2652
       Topic10
                 256.597183
                                   hand
                                          415.540601
                                                        2.2380
                                                               -5.3371
1188
       Topic10
                 263.198360
                             experience
                                          449.411921
                                                        2.1850
                                                                -5.3116
22656
      Topic10
                 262.255335
                                                        2.1549
                                                                -5.3152
                                friends
                                          461.523022
10279
       Topic10
                 261.312310
                              resources
                                          518.732364
                                                        2.0344
                                                                -5.3188
11052
      Topic10
                 345.241561
                                                        1.3244
                                                               -5.0403
                                   hope
                                         1393.939569
10529
      Topic10
                 231.135500
                              community
                                          495.942121
                                                        1.9566
                                                               -5.4416
8394
       Topic10
                 255.654158
                                  peace
                                         3159.748604
                                                        0.2057
                                                               -5.3407
9385
       Topic10
                 238.679703
                                   life
                                         1226.344820
                                                        1.0834
                                                               -5.4094
[634 rows x 6 columns], token_table=
                                           Topic
                                                                       Term
                                                      Freq
term
23942
           2 0.997020
27531
           6 0.987603
                           acquisition
10099
             0.324132
           1
                                   act
           2 0.209732
10099
                                   act
10099
           4 0.458331
                                   act
          10 0.007333
10099
                                   act
25384
           3
              0.017692
                                action
25384
             0.423684
                                action
             0.557773
25384
           5
                                action
31839
           2
             0.995190
                                active
5765
           1
             0.050815
                                  acts
5765
           6
             0.780159
                                  acts
5765
           8 0.158423
                                  acts
5765
          10
              0.008967
                                  acts
           2
              0.014217
24883
                                actual
              0.980940
24883
                                actual
33900
              0.833128
                        administration
           1
                        administration
33900
           6
             0.163566
33900
                        administration
          10 0.002353
255
              0.096015
           2
                               affairs
255
           3
              0.184829
                               affairs
255
           6
              0.715311
                               affairs
32386
             0.991450
                           afghanistan
13186
             0.993444
                                agenda
32456
           6
             0.983734
                                 agent
           1
             0.766633
28943
                                   ago
           2 0.232985
28943
                                   ago
27894
           1 0.985668
                             agreement
           3 0.014081
27894
                             agreement
```

```
. . .
                  . . .
                            . . .
                                            . . .
                  6 0.019768
         34984
                                           ways
                   7 0.006589
         34984
                                           ways
         27537
                   6 0.924991
                                         wealth
        27537
                  10 0.069251
                                         wealth
         28130
                   1 0.997665
                                        weapons
                   2 0.993561
        911
                                           west
         911
                   3 0.002799
                                           west
                   9 0.998958
         17739
                                           weve
         22278
                   6 0.988308
                                        whilst
         34877
                   9 0.998695
                                         white
         32884
                  10 0.971625
                                         whites
                   2 0.984671
         33092
                                         wishes
         12027
                   9 0.995889
                                           wont
         29621
                   3 0.066710
                                           work
                   5 0.932879
         29621
                                          work
         26605
                   7 0.998387
                                       workers
         649
                   3 0.001764
                                       working
                   5 0.014112
         649
                                       working
         649
                   7 0.001764
                                       working
         649
                   9 0.980809
                                       working
                   3 0.129824
         996
                                         world
         996
                   5 0.212114
                                         world
                   7 0.657808
        996
                                         world
         20350
                   1 0.651352
                                          year
         20350
                   2 0.348252
                                           year
         710
                   4 0.146088
                                          years
                   5 0.248660
        710
                                          years
                   9 0.605072
         710
                                          years
                   9 0.991178
         17353
                                          youre
         23715
                   9 0.995523
                                          youve
         [1171 rows x 3 columns], R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1', 'ylab': 'PC2'}, topi
In [49]: import graphlab as gl
         import urllib2
         import gensim
         import nltk
         import re
         txt = urllib2.urlopen("https://drive.google.com/open?id=0B5g0WZIzJLuEU3hqczNEb21MaGM").read()
         re_words_split = re.compile("(\w+)")
         tokenizer = nltk.data.load('tokenizers/punkt/english.pickle')
         def txt2words(s):
            s = re.sub("[^a-zA-Z]", "", s).lower()
            return re_words_split.findall(s)
         class MySentences(object):
                def __init__(self, txt):
                     self._txt = txt.decode("utf8")
                def __iter__(self):
```

aid

20778

2 0.223032

```
11 11 11
                   Split the English text into sentences and then to words using NLTK
                   :param txt: input text.
                   :param remove_none_english_chars: if True then remove none English chars from text
                   :return: list of words in which each list consists of single sentence's words from
                   :rtype: str
                   # split text into sentences using NLTK package
                   for s in tokenizer.tokenize(self._txt):
                       yield txt2words(s)
        sentences = MySentences(txt)
        model = gensim.models.Word2Vec(sentences, size=100, window=5, min_count=3, workers=4)
In [55]: print model.most_similar("obama")
[(u'com', 0.7005459666252136), (u'google', 0.685105562210083), (u'a', 0.6578261256217957), (u'true', 0.
In [60]: import numpy as np
        def txt2avg_vector(txt, w2v_model):
            words = [w for w in txt2words(txt.lower()) if w in w2v_model]
            v = np.mean([w2v_model[w] for w in words],axis=0)
            return v
        sf_paragraphs['mean_vector'] = sf_paragraphs['paragraph'].apply(lambda p: txt2avg_vector(p, mo
In [61]: #constructing nearest neighbors model
        nn_model = gl.nearest_neighbors.create(sf_paragraphs, features=['mean_vector'])
        #calaculating the two nearest neighbors of each paragraph from all the paragraphs
        r = nn_model.query(sf_paragraphs, k=2)
        r.head(10)
Starting ball tree nearest neighbors model training.
+----+
| Tree level | Elapsed Time |
+----+
1 0
          | 17.634ms
+----+
+----+
| Query points | % Complete. | Elapsed Time |
```

```
| 1
         | 0 | 5.003ms
| Done
         | 638.43ms
+----+
Out[61]: Columns:
           query_label int reference_label int
           distance float
           rank
                  int
      Rows: 10
      Data:
      +----+
      | query_label | reference_label | distance | rank |
                         | 0.0 | 1 |
          0
                   0
                247 | 0.000894301737532 | 2 |
1 | 0.0 | 1 |
          0
              - 1
              - 1
         1
                    75 | 0.00177082049266 | 2 |
              1
         1
                    2
                          0.0 | 1
         2
               16 | 0.000928484636116 | 2
         2
              3
              - 1
                    3
                          0.0 | 1
                         | 0.00074604515377 | 2
                   110
         3
              1
                             0.0 | 1
          4
                    4
                 139
                       | 0.00162629810938 | 2
      [10 rows x 4 columns]
In [62]: #filter out paragraphs that are exactly exactly the same
     r = r[r['distance'] != 0]
      #filter out paragraphs that are with distance >= 0.1
      r = r[r['distance'] < 0.08]
     r
Out[62]: Columns:
           query_label
                      int
           reference_label int
           distance float
           rank
                  int
      Rows: Unknown
      Data:
      +----+
```

| query\_label | reference\_label | distance | rank |

```
0
            247
                     | 0.000894301737532 | 2
            75
                    | 0.00177082049266 | 2
                    | 0.000928484636116 | 2
2
      16
                    | 0.00074604515377 |
3
      110
           139
                    0.00162629810938 | 2
                    | 0.000744305314392 |
            11
            93
                     0.00553016265452 |
6
      -
                    | 0.000770922708859 | 2
7
      103
                     | 0.00120041979798 | 2
8
            214
             371
                     | 0.00371562996025 | 2
```

[? rows x 4 columns]

Note: Only the head of the SFrame is printed. This SFrame is lazily evaluated. You can use sf.materialize() to force materialization.

```
In [63]: sf_paragraphs = sf_paragraphs.add_row_number('query_label')
    sf_paragraphs = sf_paragraphs.add_row_number('reference_label')
    sf_similar = r.join(sf_paragraphs, on="query_label").join(sf_paragraphs, on="reference_label")
```

In [65]: sf\_similar[['paragraph', 'paragraph.1', 'distance']]

Out[65]: Columns:

paragraph str paragraph.1 str distance float

Rows: 622

Data:

+	paragraph.1
fellow citizens of the sen     whereas it is the duty of     fellow citizens of the sen     fellow citizens of the sen     i the president of the uni     i meet you upon the presen     gentlemen of the house of     fellowcitizens of the sena     whereas i have received au     fellowcitizens i am again	senator wagner governor le   to the house of representa   i trust i do not deceive m   fellowcitizens of the sena   by the president of the un   fellow citizens of the sen   whereas by an act of the c   fellow citizens of the sen   gentlemen of the congress

+----+

```
0.00120041979798
        0.00371562996025 |
        +----+
        [622 rows x 3 columns]
        Note: Only the head of the SFrame is printed.
        You can use print_rows(num_rows=m, num_columns=n) to print more rows and columns.
In [66]: print sf_similar[1]['paragraph']
        print "-"*100
        print sf_similar[1]['paragraph.1']
whereas it is the duty of all nations to acknowledge the providence of almighty god to obey his will to
_____
to the house of representatives of the united states having considered the bill this day presented to m
In []:
In [12]: import logging, gensim
        logging.basicConfig(format='%(asctime)s: %(levelname)s: %(message)s', level=logging.INFO)
        lda = gensim.models.ldamodel.LdaModel(corpus, id2word=dictionary, num_topics=25, update_every=
In [13]: #print 25 topics out to 20 words
        t=0
        for i in lda.show_topics(num_topics=25, num_words=20, log=False, formatted=True):
            print "Topic # ", t , i
            t = t + 1
Topic # 0 (0, u'0.007*people + 0.006*kosovo + 0.006*war + 0.006*bosnia + 0.005*army + 0.005*peace + 0.
Topic # 1 (1, u'0.007*increase + 0.007*people + 0.007*states + 0.006*government + 0.006*year + 0.006*w
Topic # 2 (2, u'0.018*business + 0.011*law + 0.010*labor + 0.009*government + 0.009*great + 0.008*publ
Topic # 3 (3, u'0.010*america + 0.009*people + 0.007*iraq + 0.006*american + 0.006*world + 0.005*nation
Topic # 4 (4, u'0.012*people + 0.008*years + 0.008*america + 0.007*american + 0.006*government + 0.006
Topic # 5 (5, u'0.016*government + 0.011*states + 0.009*united + 0.007*congress + 0.006*country + 0.00
Topic # 6 (6, u'0.009*black + 0.003*blacks + 0.003*soldiers + 0.002*negro + 0.002*cities + 0.002*santi
Topic # 7 (7, u'0.013*tariff + 0.010*schedule + 0.010*country + 0.009*articles + 0.007*rates + 0.007*c
Topic # 8 (8, u'0.009*watergate + 0.008*statute + 0.005*house + 0.005*made + 0.004*case + 0.004*court
Topic # 9 (9, u'0.016*states + 0.012*united + 0.008*government + 0.006*great + 0.006*congress + 0.005*
Topic # 10 (10, u'0.009*world + 0.008*people + 0.007*war + 0.007*president + 0.006*nations + 0.006*pea
Topic # 11 (11, u'0.011*war + 0.009*people + 0.008*government + 0.008*peace + 0.006*world + 0.005*germ
Topic # 12 (12, u'0.011*nuclear + 0.009*treaty + 0.008*cooperation + 0.007*gorbachev + 0.007*united +
Topic # 13 (13, u'0.012*vietnam + 0.008*energy + 0.007*congress + 0.007*president + 0.006*south + 0.00
Topic # 14 (14, u'0.021*president + 0.012*people + 0.009*senator + 0.008*united + 0.007*states + 0.006
Topic # 15 (15, u'0.024*president + 0.010*lebanon + 0.007*israel + 0.007*government + 0.006*middle + 0
Topic # 16 (16, u'0.014*berlin + 0.010*rights + 0.010*victims + 0.006*city + 0.005*law + 0.005*wall +
Topic # 17 (17, u'0.007*law + 0.006*judge + 0.006*crime + 0.005*justice + 0.005*negro + 0.005*race + 0
Topic # 18 (18, u'0.012*people + 0.009*nation + 0.009*men + 0.009*great + 0.008*freedom + 0.008*world
Topic # 19 (19, u'0.023*united + 0.017*states + 0.014*nations + 0.011*world + 0.008*peace + 0.007*amer
Topic # 20 (20, u'0.013*government + 0.012*people + 0.006*constitution + 0.006*power + 0.006*states +
Topic # 21 (21, u'0.010*people + 0.007*action + 0.007*affirmative + 0.006*women + 0.005*opportunity +
Topic # 22 (22, u'0.007*ireland + 0.007*northern + 0.004*people + 0.003*belfast + 0.003*peace + 0.003*
Topic # 23 (23, u'0.014*united + 0.014*peace + 0.011*world + 0.011*soviet + 0.010*states + 0.009*vietn
Topic # 24 (24, u'0.014*care + 0.014*health + 0.009*insurance + 0.008*people + 0.008*system + 0.006*go
In [14]: #print topic weight in each speech
        count=1
        for doc in sw_token_docs:
```

```
#print first 100 words of speech to verify correct speech
             print doc[0:100]
             count = count + 1
Speech # 1 [(9, 0.50640713197693921), (18, 0.1351239923731434), (20, 0.35489200038374513)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'vicissitudes', 'incident', 'life', 'event
Speech # 2 [(9, 0.48031336104297279), (18, 0.038903812756833481), (20, 0.47563662736909162)]
['duty', 'nations', 'acknowledge', 'providence', 'almighty', 'god', 'obey', 'grateful', 'benefits', 'hu
Speech # 3 [(9, 0.85788618980384024), (18, 0.016940799056699755), (20, 0.12264427550532239)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'embrace', 'great', 'satisfaction', 'oppor
Speech # 4 [(9, 0.96433459673170208), (20, 0.033974226797508569)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'meeting', 'feel', 'satisfaction', 'repeat
Speech # 5 [(2, 0.01920174642871823), (9, 0.88722024552655465), (18, 0.091920757573697401)]
['president', 'united', 'states', 'mouth', 'written', 'speech', 'signed', 'hand', 'sealed', 'seal', 'sp
Speech # 6 [(9, 0.78537066381864251), (20, 0.21360483729484889)]
['meet', 'present', 'occasion', 'feelings', 'naturally', 'inspired', 'strong', 'impression', 'prosperou
Speech # 7 [(6, 0.27893439469922354), (9, 0.70598363808641584)]
['gentlemen', 'house', 'representatives', 'maturely', 'considered', 'act', 'passed', 'houses', 'intitle
Speech # 8 [(5, 0.1033456691486738), (9, 0.73556906389931564), (20, 0.16015108436167524)]
['fellowcitizens', 'senate', 'house', 'representatives', 'abatement', 'satisfaction', 'meet', 'present'
Speech # 9 [(9, 0.98829268292546646)]
['received', 'authentic', 'information', 'lawless', 'wicked', 'persons', 'western', 'frontier', 'state'
Speech # 10 [(9, 0.25859419927253813), (20, 0.60129730499773759), (21, 0.12381219943145229)]
['fellowcitizens', 'called', 'voice', 'country', 'execute', 'functions', 'chief', 'magistrate', 'occasi
Speech # 11 [(9, 0.99030303030214084)]
['appears', 'state', 'war', 'exists', 'austria', 'prussia', 'sardinia', 'great', 'britain', 'united', '
Speech # 12 [(9, 0.88265064894725132), (20, 0.11615764120806112)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'commencement', 'term', 'called', 'office'
Speech # 13 [(9, 0.72357720365982547), (11, 0.011938779270439888), (19, 0.010541064522359263), (20, 0.72357720365982547)
['combinations', 'defeat', 'execution', 'laws', 'laying', 'duties', 'spirits', 'distilled', 'united', '
Speech # 14 [(7, 0.018133486774113052), (9, 0.44330317229990956), (20, 0.53530408166642396)]
['hope', 'combinations', 'constitution', 'laws', 'united', 'states', 'western', 'counties', 'pennsylvan
Speech # 15 [(9, 0.59240198311730441), (20, 0.40681370315712201)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'call', 'mind', 'gracious', 'indulgence',
Speech # 16 [(9, 0.6702256451312204), (19, 0.32429816439210213)]
['commissioners', 'appointed', 'president', 'united', 'states', 'confer', 'citizens', 'western', 'count
Speech # 17 [(5, 0.041331081800033434), (9, 0.93454316645196434), (20, 0.023064231844384046)]
['trust', 'deceive', 'indulge', 'persuasion', 'met', 'period', 'present', 'situation', 'public', 'affai
Speech # 18 [(5, 0.12960732717010376), (9, 0.84264425898816653), (15, 0.025602072378076039)]
['gentlemen', 'house', 'representatives', 'utmost', 'attention', 'considered', 'resolution', '24th', 'i.
Speech # 19 [(9, 0.436783365099843), (18, 0.11973421854646764), (23, 0.44194931530817533)]
['beloved', 'cherokees', 'years', 'passed', 'white', 'people', 'america', 'long', 'space', 'time', 'goo
Speech # 20 [(5, 0.0446205804212585), (9, 0.46322136792961477), (20, 0.49176147661528574)]
['period', 'election', 'citizen', 'administer', 'executive', 'government', 'united', 'states', 'distant
Speech # 21 [(9, 0.99919597989940534)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'recurring', 'internal', 'situation', 'cou
Speech # 22 [(9, 0.35106488356826915), (18, 0.12482873671106175), (20, 0.52316419556639571)]
['perceived', 'early', 'times', 'middle', 'america', 'remained', 'unlimited', 'submission', 'foreign',
Speech # 23 [(9, 0.79778067186820123), (20, 0.20148332813171665)]
['personal', 'inconveniences', 'members', 'senate', 'house', 'representatives', 'leaving', 'families',
Speech # 24 [(9, 0.99443260414873924)]
['time', 'apprehensive', 'account', 'contagious', 'sickness', 'afflicted', 'city', 'philadelphia', 'con
```

vec = dictionary.doc2bow(doc)
print "Speech # ", count, lda[vec]

```
Speech # 25 [(9, 0.40104233439592768), (19, 0.11996710957901698), (20, 0.47589196447541182)]
['safety', 'prosperity', 'nations', 'ultimately', 'essentially', 'depend', 'protection', 'blessing', 'a
Speech # 26 [(9, 0.99894505494495411)]
['gentlemen', 'senate', 'gentlemen', 'house', 'representatives', 'reverence', 'resignation', 'contempla
Speech # 27 [(5, 0.027370856210638651), (9, 0.96811538629562466)]
['peculiar', 'satisfaction', 'meet', '6th', 'congress', 'united', 'states', 'america', 'coming', 'parts
Speech # 28 [(9, 0.23453777754934166), (18, 0.11579102538112021), (20, 0.1733092603627969), (23, 0.474
['gentlemen', 'senate', 'gentlemen', 'house', 'representatives', 'letter', 'herewith', 'transmitted', '
Speech # 29 [(19, 0.99244094488118917)]
['late', 'wicked', 'treasonable', 'insurrection', 'authority', 'united', 'states', 'sundry', 'persons',
Speech # 30 [(5, 0.12387825239535569), (9, 0.83718340782554423), (20, 0.037389044004312436)]
['gentlemen', 'senate', 'gentlemen', 'house', 'representatives', 'immediately', 'adjournment', 'congres Speech # 31 [(5, 0.059212222414988573), (9, 0.16329735374043625), (18, 0.14270853820030646), (20, 0.63
['friends', 'fellowcitizens', 'called', 'undertake', 'duties', 'executive', 'office', 'country', 'avail
Speech # 32 [(3, 0.23087777237722912), (5, 0.13633792959815047), (9, 0.30263448899650519), (20, 0.3282
['gentleman', 'received', 'remonstrance', 'pleased', 'address', 'appointment', 'samuel', 'bishop', 'off
Speech # 33 [(9, 0.80179540059271404), (20, 0.19653934487244712)]
['fellow', 'citizens', 'senate', 'house', 'representatives', 'circumstance', 'sincere', 'gratification'
Speech # 34 [(1, 0.012259525161309346), (9, 0.34292872090760096), (18, 0.17105285946269452), (20, 0.46
['gentleman', 'affectionate', 'sentiments', 'esteem', 'approbation', 'good', 'express', 'behalf', 'danb
Speech # 35
                                                    Traceback (most recent call last)
        ValueError
        <ipython-input-14-d5357dc7b030> in <module>()
          3 for doc in sw_token_docs:
                vec = dictionary.doc2bow(doc)
    ---> 5
                print "Speech # ", count, lda[vec]
                #print first 100 words of speech to verify correct speech
                print doc[0:100]
          7
        C:\Users\pankaj\Anaconda2\lib\site-packages\ipykernel\iostream.pyc in write(self, string)
        315
        316
                         is_child = (not self._is_master_process())
    --> 317
                         self._buffer.write(string)
        318
                         if is_child:
        319
                             # newlines imply flush in subprocesses
        ValueError: I/O operation on closed file
In [15]: lda.print_topics(20)
Out[15]: [(3,
           u'0.010*america + 0.009*people + 0.007*iraq + 0.006*american + 0.006*world + 0.005*nation +
           u'0.014*care + 0.014*health + 0.009*insurance + 0.008*people + 0.008*system + 0.006*governme
```

(11,

u'0.012\*vietnam + 0.008\*energy + 0.007\*congress + 0.007\*president + 0.006\*south + 0.005\*amer

```
(1,
u'0.007*increase + 0.007*people + 0.007*states + 0.006*government + 0.006*year + 0.006*work
u'0.023*united + 0.017*states + 0.014*nations + 0.011*world + 0.008*peace + 0.007*american +
u'0.024*president + 0.010*lebanon + 0.007*israel + 0.007*government + 0.006*middle + 0.005*p
u'0.010*people + 0.007*action + 0.007*affirmative + 0.006*women + 0.005*opportunity + 0.005*
u'0.009*watergate + 0.008*statute + 0.005*house + 0.005*made + 0.004*case + 0.004*court + 0.
u'0.012*people + 0.008*years + 0.008*america + 0.007*american + 0.006*government + 0.006*con
u'0.007*law + 0.006*judge + 0.006*crime + 0.005*justice + 0.005*negro + 0.005*race + 0.004*m
u'0.007*ireland + 0.007*northern + 0.004*people + 0.003*belfast + 0.003*peace + 0.003*lands
u'0.014*united + 0.014*peace + 0.011*world + 0.011*soviet + 0.010*states + 0.009*vietnam + 0
u'0.007*people + 0.006*kosovo + 0.006*war + 0.006*bosnia + 0.005*army + 0.005*peace + 0.005*
u'0.021*president + 0.012*people + 0.009*senator + 0.008*united + 0.007*states + 0.006*kenne
u'0.013*tariff + 0.010*schedule + 0.010*country + 0.009*articles + 0.007*rates + 0.007*consu
u'0.012*people + 0.009*nation + 0.009*men + 0.009*great + 0.008*freedom + 0.008*world + 0.00
u'0.016*government + 0.011*states + 0.009*united + 0.007*congress + 0.006*country + 0.005*ye
u'0.011*nuclear + 0.009*treaty + 0.008*cooperation + 0.007*gorbachev + 0.007*united + 0.007*
(20,
u'0.013*government + 0.012*people + 0.006*constitution + 0.006*power + 0.006*states + 0.005*
```

u'0.011\*war + 0.009\*people + 0.008\*government + 0.008\*peace + 0.006\*world + 0.005\*germany +

## In []: !