# **Assignment 8**

Fall 2014 CS595 Web Science Dr. Michael Nelson

Mathew Chaney

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#### 1.1 Question

Create a blog-term matrix. Start by grabbing 100 blogs; include:

```
http://f-measure.blogspot.com/
http://ws-dl.blogspot.com/
```

and grab 98 more as per the method shown in class.

Use the blog title as the identifier for each blog (and row of the matrix). Use the terms from every item/title (RSS) or entry/title (Atom) for the columns of the matrix. The values are the frequency of occurrence. Essentially you are replicating the format of the "blogdata.txt" file included with the PCI book code. Limit the number of terms to the most "popular" (i.e., frequent) 500 terms, this is \*after\* the criteria on p. 32 (slide 7) has been satisfied.

Create a histogram of how many pages each blog has (e.g., 30 blogs with just one page, 27 with two pages, 29 with 3 pages and so on).

#### 1.2 Answer

To complete this assignment, a blog word count matrix was required. To start off, a list of blog URIs was obtained using the method described in class, implemented as the <code>get\_uris.py</code> script, which can be found in Appendix A, Listing 26. Two default blogs, F-Measure and the Old Dominion Web Science and Digital Libraries blogs, were added as defaults to the initial URI list and then, using the seed URI provided (Listing 1), the remaining 98 URIs from random blogs within the blogger.com family were added.

```
default = 'http://www.blogger.com/next-blog?navBar=true&blogID=3471633091411211117'
must_haves = ['http://f-measure.blogspot.com/', 'http://ws-dl.blogspot.com/']
```

Listing 1: referenced variables in get\_uris.py

The get\_uris main function in Listing 2 was the driver that called the get\_atom function (shown in Listing 3) to extract the atom [1] URIs from each blog and add them to the set of URIs with the add\_uri function, shown in Listing 4.

```
27
        __name__ == '__main__':
uris = set()
28
29
        with open ('blog_uris', 'a') as outfile:
            if len(sys.argv) > 1 and sys.argv[1] == 'new':
30
                 for must_have in must_haves:
31
32
                     uri = get_atom(must_have)
33
                     add_uri(uri, uris, outfile)
34
            else:
                 with open('blog_uris') as infile:
35
                     [\,uris.\,add(\,line.\,strip\,()\,)\ for\ line\ in\ infile\,]
36
            while len(uris) < 100:
37
                 uri = get_atom(default)
38
                 add_uri(uri, uris, outfile)
```

Listing 2: main for get uris.py

```
10
  def get_atom(uri):
11
       try:
12
           r = requests.get(uri)
13
       except Exception, e:
14
           return None
15
       soup = BeautifulSoup(r.text)
16
       links = soup.find_all('link', {'type':'application/atom+xml'})
17
       if links:
           return str(links[0]['href'])
       return None
```

Listing 3: get atom function

```
21 def add_uri(uri, uris, outfile):
22 if uri and uri not in uris:
23 uris.add(uri)
24 outfile.write(uri + '\n')
25 print len(uris), uri
```

Listing 4: add\_uri function

After the full list of 100 URIs was obtained, page counts for each blog were extracted and saved to a file called pagecounts using the matrix.py script. This script is a modified version of generatefeedvectors.py from the book *Programming Collective Intelligence* [2] and can be found in full in Appendix A, Listing 27.

The code responsible for downloading the blogs and counting the words in each is shown in Listing 5, which calls the get\_titles, get\_words and get\_next functions found in Listing 6. This code loops over the list of URIs that was obtained with the get\_uris.py script (Listing 26), parses each entry, and extracts all the words in each entry's title. These word counts are then saved as a python dictionary to the hard drive for later use.

```
'__main__'
 96
             with open ('blog_uris')
                                                      as infile:
 97
                    uris = [line.strip() for line in infile if line.strip()]
 98
              if len(sys.argv) = 2 and sys.argv[1] = 'get':
                    with futures. ThreadPoolExecutor(max workers=8) as executor:
 99
                           uri_futures = [executor.submit(get_titles, uri) for uri in uris]
for future in futures.as_completed(uri_futures):
    uri, title, subtitle, pages, wc = future.result()
    with open('wcs/' + md5.new(uri).hexdigest(), 'w') as out:
        out.write(title + ': ' + subtitle + '\t' + str(pages) + '\t')
100
101
102
103
104
105
                                          json.dump(wc, out)
```

Listing 5: looping over the URIs

```
def get_next(d):
10
       for item in d. feed. links:
11
            if item['rel'] == u'next':
12
                return item['href']
13
       return None
14
15
   def get_words(text):
       txt = re.compile(r'<[^>]+>').sub('', text)
16
       words = re.compile(r, [A-Z^a-z]+,).split(txt)
18
       return [word.lower() for word in words if word != '',]
19
20
       get titles (uri):
21
       print('processing {}'.format(uri))
22
       next =
              uri
23
       wc = \{\}
24
       pages = 0
25
       while next is not None:
           d = feedparser.parse(next)
26
27
            for e in d.entries:
                words = get_words(e.title.encode('utf-8'))
for word in words:
28
29
                    wc.setdefault(word, 0)
30
31
                    wc[word] += 1
32
            pages += 1
            next = get_next(d)
print('next {}'.format(next))
33
34
       title = d.feed.title.encode('utf-8')
35
36
       subtitle = d.feed.subtitle[:50].encode('utf-8')
37
       print('finished: {}: {}'.format(title, subtitle))
       return uri, title, subtitle, pages, wc
```

Listing 6: processing each blog

The parsed results were then read by the code in Listing 7. This code used the load\_data and build\_wordlist functions in Listing 8 and 9 to read each of the blog word counts and then created four collections to organize them all:

- 1. apcount: A dictionary containing the count for all words combined
- 2. wordcounts: A dictionary containing each blog's individual word count
- 3. pagecounts: A dictionary containing each blog's page count
- 4. wordlist: A list containing all of the words found in each blog

```
apcount, wordcounts, pagecounts = load_data(uris)
wordlist = build_wordlist(apcount, uris)
if len(sys.argv) == 2 and sys.argv[1] == 'pages':
with open('pagecounts', 'w') as outfile:
outfile.write('blog\tpages\n')
for blog, pagecount in pagecounts.iteritems():
outfile.write("\"" + blog.replace("\"", "") + "\"" + '\t' + str(
pagecount) + '\n')
elif len(sys.argv) == 2 and sys.argv[1] == 'wc':
write_data('blogdata1.txt', wordlist, wordcounts)
```

Listing 7: creating the blog data matrix

```
def load_data(uris):
50
51
        apcount = \{\}
52
        wordcounts =
53
        pagecounts = {}
        for uri in uris:
54
55
            with open('wcs/' + md5.new(uri).hexdigest()) as infile:
56
57
                     lines = infile.read().split('\t')
58
                     title = lines[0]
59
                     pages = int(lines[1])
60
                     wc = json.loads(lines[2])
                 except Exception, e:
61
                     print(,**** \{\}  generated an exception: \{\}, format(uri, e))
62
63
                     continue
            wordcounts[title] = wc
64
            pagecounts[title] = pages
for word, count in wc.items():
65
66
                 apcount.setdefault (word, 0)
67
                 apcount [word] += count
        return apcount, wordcounts, pagecounts
```

Listing 8: loading the data

```
71 def build_wordlist(apcount, uris):
    wordlist = []
73 for w, bc in sorted(apcount.items(), key=lambda x: x[1], reverse=True):
    frac = float(bc) / len(uris)
    if frac > 0.1 and frac < 0.5:
        wordlist.append(w)
77 return wordlist
```

Listing 9: building the master wordlist

The code in Listing 24 then created the matrix using the write\_data function using the data structures that store the blog word counts.

```
def write_data(filename, wordlist, wordcounts, form=lambda wc, word, wordcounts: wc[word]):
79
                              'w') as out:
80
        with open (filename,
            out.write('Blog')
81
            for word in wordlist [:500]:
82
            out.write('\t%s' % word)
out.write('\n')
83
84
            for blog, wc in wordcounts.items():
    print blog
85
86
87
                 out.write(blog)
                 for word in wordlist [:500]:
88
89
                     if word in wc:
                          out.write('\t{}'.format(form(wc,word,wordcounts)))
90
91
92
                          out.write('\t0')
93
                 out.write('\n')
```

Listing 10: writing the data

To build a histogram showing the blog page counts, the **pagecounts** file was parsed by the R script in Listing 11 and saved as a pdf, which is shown in Figure 1.

```
#! /usr/bin/Rscript

data <- read.table("pagecounts", sep="\t", header=TRUE, comment.char="")

counts <- table(data$pages)
pdf("hist.pdf")
barplot(counts, ylab="Number of Blogs", xlab="Page Count", main="Page Count per Blog")

dev.off()
```

Listing 11: building the histogram

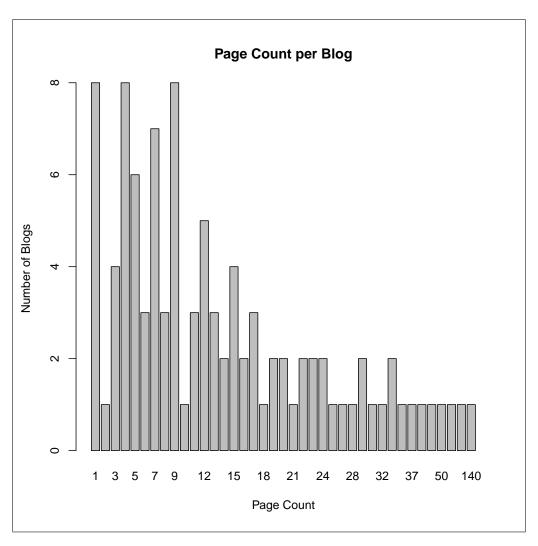


Figure 1: Page Count per Blog

#### 2.1 Question

Create an ASCII and JPEG dendrogram that clusters (i.e., HAC) the most similar blogs (see slides 12 & 13). Include the JPEG in your report and upload the ascii file to github (it will be too unwieldy for inclusion in the report).

#### 2.2 Answer

The ascii and jpeg dendrograms were created using the code shown in Listing 12, which is modeled after the example from class.

```
286
        blognames, words, data = readfile('q1/blogdata1.txt')
287
        clust = hcluster(data)
        with open ('dendrogram.txt', 'w') as outfile:
288
289
            stdout \, = \, sys.stdout
            sys.stdout = outfile
290
291
            printclust (clust, labels=blognames)
292
             sys.stdout = stdout
293
        drawdendrogram (clust, blognames, jpeg='blogclust.jpg')
```

Listing 12: creating the dendrograms

The readfile function shown in Listing 13 was used to read the data that was compiled from Question 1 into memory where it is then processed by the hcluster function found in Listing 14 to produce the clustered representation of the blogs.

```
def readfile (filename):
     lines = [line for line in file(filename)]
     # First line is the column titles
     colnames=lines [0]. strip().split('\t')[1:]
     rownames = []
9
     data = []
10
     for line in lines [1:]:
       p=line.strip().split('\t')
# First column in each row is the rowname
11
12
13
       rownames.append(p[0])
                        this row is the remainder of the row
         The data for
       data.append([float(x) for x in p[1:]])
15
     return rownames, colnames, data
```

Listing 13: creating the dendrograms

```
48
  def hcluster (rows, distance=pearson):
49
     distances={}
50
     currentclustid=-1
51
     # Clusters are initially just the rows
clust=[bicluster(rows[i],id=i) for i in range(len(rows))]
52
53
54
55
     while len(clust)>1:
56
       lowestpair = (0,1)
       closest=distance(clust[0].vec,clust[1].vec)
57
58
59
       # loop through every pair looking for the smallest distance
60
       for i in range(len(clust)):
61
          for j in range(i+1,len(clust)):
                                            distance calculations
62
63
            if (clust[i].id, clust[j].id) not in distances:
              distances [(clust[i].id, clust[j].id)] = distance(clust[i].vec, clust[j].vec)
65
            d=distances [(clust[i].id,clust[j].id)]
68
            if d < closest:
              c losest=d
```

```
70
                lowestpair=(i,j)
\frac{71}{72}
        # calculate the average of the two clusters
73
        (\ clust \ [\ lowestpair \ [\ 0\ ]\ ]\ .\ vec \ [\ i\ ]+\ clust \ [\ lowestpair \ [\ 1\ ]\ ]\ .\ vec \ [\ i\ ])\ /\ 2.0
74
75
        for i in range (len (clust [0]. vec))]
76
77
        # create the new cluster
78
        newcluster=bicluster (mergevec, left=clust [lowestpair [0]],
79
                                  right=clust[lowestpair[1]],
80
                                  distance=closest , id=currentclustid )
81
82
        # cluster ids that weren't in the original set are negative
83
        currentclustid -=1
        del clust [lowestpair [1]]
84
        del clust lowestpair 0
85
        clust.append(newcluster)
86
      return clust [0]
```

Listing 14: hcluster function

The printclust function from Listing 15 prints the ascii dendrogram of the cluster object parameter to sys.stdout, which is redirected to write to a file with the code in Listing 12.

```
90 def printclust (clust, labels=None, n=0):
91
        indent to make a hierarchy
92
      for i in range(n): print ',',
93
      if clust.id < 0:
94
        # negative id means that this is branch
95
        print '-'
96
97
         positive id means that this is an endpoint
98
        if labels—None: print clust.id
99
        else: print labels [clust.id]
100
101
      # now print the right and left branches
      if clust.left!=None: printclust(clust.left, labels=labels, n=n+1)
102
103
      if clust.right!=None: printclust(clust.right, labels=labels, n=n+1)
```

Listing 15: printclust function

The drawdendrogram function from Listing 16 creates a jpeg image of the cluster, which is shown in Figure 2.

```
122 def drawdendrogram (clust, labels, jpeg='clusters.jpg'):
123
       h=get\bar{h}eight(clust)*20
124
125
       w = 1200
       depth=getdepth(clust)
126
127
       # width is fixed, so scale distances accordingly
128
129
       scaling=float(w-150)/depth
130
       \# Create a new image with a white background img=Image.new('RGB',(w,h),(255,255,255))
131
132
133
       draw=ImageDraw . Draw (img)
134
135
       draw.line((0, h/2, 10, h/2), fill = (255, 0, 0))
136
137
       # Draw the first node
        \frac{drawnode(draw,clust\ ,10\ ,(h/2)\ ,scaling\ ,labels)}{img.save(jpeg\ ,'JPEG')} 
138
139
```

Listing 16: drawdendrogram function

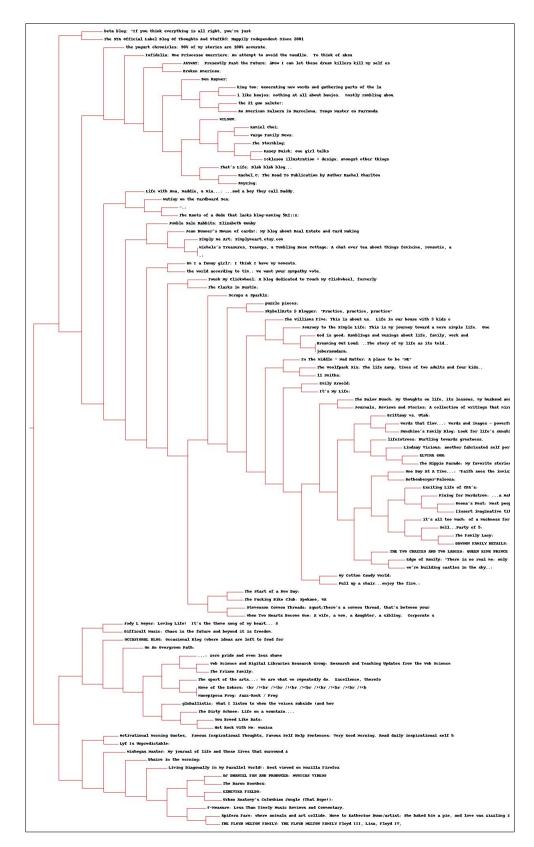


Figure 2: blog dendrogram

#### 3.1 Question

Cluster the blogs using K-Means, using k=5,10,20. (see slide 18). How many interations were required for each value of k?

#### 3.2 Answer

Using the code in Listing 17 kclustering was performed with values for n = 5, n = 10 and n = 20. The main function calls the kcluster function, which is shown in Listing 18.

Listing 17: kclustering main

```
_{\tt def\ kcluster\,(rows\,,\,distance=pearson\,,\,k=4):}
174
      # Determine the minimum and maximum values for each point ranges = [(min([row[i] for row in rows]), max([row[i] for row in rows]))
175
176
       for i in range (len (rows [0]))]
177
178
      # Create k randomly placed centroids
179
       clusters = [[random.random()*(ranges[i][1] - ranges[i][0]) + ranges[i][0]]
180
       for i in range (len (rows [0]))] for j in range (k)]
181
182
183
       lastmatches=None
      for t in range(100):
    print 'Iteration %d' % t
    bestmatches=[[] for i in range(k)]
184
185
186
187
         # Find which centroid is the closest for each row
188
         for j in range(len(rows)):
189
190
           row=rows[j]
191
            {\tt bestmatch} \!=\! \! 0
            for i in range(k):
192
              d=distance(clusters[i],row)
193
              if d<distance(clusters[bestmatch],row): bestmatch=i
194
195
            bestmatches [bestmatch].append(j)
196
         # If the results are the same as last time, this is complete
197
         if bestmatches==lastmatches: break
198
199
         lastmatches=bestmatches
200
         # Move the centroids to the average of their members
201
202
         for i in range(k):
203
            avgs = [0.0] * len(rows[0])
               len (bestmatches [i]) > 0:
204
205
              for rowid in bestmatches[i]:
206
                 for m in range(len(rows[rowid])):
207
                   avgs [m]+=rows [rowid][m]
              for j in range(len(avgs)):
   avgs[j]/=len(bestmatches[i])
208
209
210
              clusters [i] = avgs
211
212
       return bestmatches
```

Listing 18: kcluster function

The output is shown in Listing 19. As the output reads, a kcluster with n=5 required nine iterations, n=10 required four iterations and n=20 also required four iterations.

Listing 19: output of kclustering algorithm

#### 4.1 Question

Use MDS to create a JPEG of the blogs similar to slide 29. How many iterations were required?

#### 4.2 Answer

With the code in Listing 20, multidimensional scaling (MDS) was used to create a two-dimensional visualization of the blog distance graph.

```
301 coords=scaledown(data)
302 draw2d(coords, blognames, jpeg='blogs2d.jpg')
```

Listing 20: main for scaledown

This main code calls the scaledown function, which is shown in Listing 21. The algorithm continues until the error factor stops decreasing, as shown in the output in Appendix A, Listing 29.

```
{\tt def \ scaledown (data, distance=pearson, rate=0.01):}
224
225
        n=len (data)
226
        # The real distances between every pair of items
227
        realdist = [[distance(data[i], data[j]) for j in range(n)]
228
229
                         for i in range (0,n)
230
231
        \# Randomly initialize the starting points of the locations in 2D
        \texttt{loc} = \hspace{-0.2cm} \left[ \hspace{-0.2cm} \left[ \hspace{-0.2cm} \texttt{random} \hspace{.05cm} ( \hspace{.05cm} ) \hspace{.05cm} , \texttt{random} \hspace{.05cm} ( \hspace{.05cm} ) \hspace{.05cm} \right] \hspace{.2cm} \hspace{.2cm} \texttt{for} \hspace{.2cm} i \hspace{.2cm} \texttt{in} \hspace{.2cm} \texttt{range} \hspace{.05cm} ( \hspace{.05cm} n \hspace{.05cm} ) \hspace{.05cm} \right]
232
233
        fakedist = [[0.0 \text{ for } j \text{ in } range(n)] \text{ for } i \text{ in } range(n)]
234
235
        lasterror=None
236
        for m in range (0,1000):
237
           # Find projected distances
238
           for i in range(n):
              for j in range(n):
239
240
                 fakedist [i][j]=sqrt (sum ([pow(loc[i][x]-loc[j][x],2)
241
                                                       for x in range(len(loc[i]))])
242
243
244
           grad = [[0.0, 0.0] \text{ for i in } range(n)]
245
246
           totalerror=0
247
           for k in range(n):
248
              for j in range(n):
                     j≕k: continue
249
250
                 # The error
                                        percent difference between the distances
251
                 if realdist[j][k] != 0:
                       errorterm = (fakedist [j][k] - realdist [j][k]) / realdist [j][k]
252
                 # Each point needs to be moved away from or towards the other
254
                # point in proportion to how much error it has grad[k][0]+=((loc[k][0]-loc[j][0])/fakedist[j][k])*errorterm <math>grad[k][1]+=((loc[k][1]-loc[j][1])/fakedist[j][k])*errorterm
255
256
257
258
259
                 # Keep track of the total error
                 totalerror+=abs(errorterm)
260
261
           print totalerror
262
           # If the answer got worse by moving the points, we are done if lasterror and lasterror <totalerror: break
263
264
265
           lasterror=totalerror
266
267
           \# Move each of the points by the learning rate times the gradient
           for k in range(n):
268
              loc[k][0] -= rate*grad[k][0]
269
              loc[k][1] -= rate*grad[k][1]
270
271
272
        return loc
```

Listing 21: scaledown function

The scaledown function returns the coordinates for each of the blogs in 2D space. This data was then used with the draw2d function in Listing 22, which produced the two-dimensional visualation created from the MDS algorithm, as shown in Figure 3.

```
274 def draw2d(data,labels,jpeg='mds2d.jpg'):
    img=Image.new('RGB',(2000,2000),(255,255,255))
    draw=ImageDraw.Draw(img)
    for i in range(len(data)):
        x=(data[i][0]+0.5)*1000
        y=(data[i][1]+0.5)*1000
    draw.text((x,y),labels[i],(0,0,0))
    img.save(jpeg,'JPEG')
```

Listing 22: draw2d function

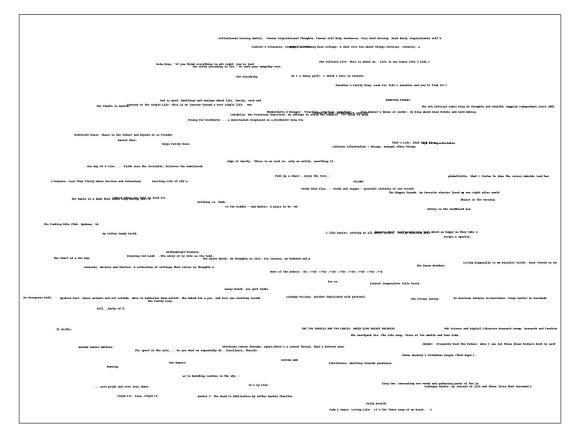


Figure 3: MDS 2d visualization

#### 5.1 Question

Re-run question 2, but this time with proper TFIDF calculations instead of the hack discussed on slide 7 (p. 32). Use the same 500 words, but this time replace their frequency count with TFIDF scores as computed in assignment #3. Document the code, techniques, methods, etc. used to generate these TFIDF values. Upload the new data file to github.

Compare and contrast the resulting dendrogram with the dendrogram from question #2.

Note: ideally you would not reuse the same 500 terms and instead come up with TFIDF scores for all the terms and then choose the top 500 from that list, but I'm trying to limit the amount of work necessary.

#### 5.2 Answer

To answer this question, matrix.py was modified to add the capability to calculate Term Frequency Inverse Document Frequency (TF/IDF). The added functions for computing TF/IDF are found in Listing 25. These functions use the master word count dictionary (wordcounts) and each blog's individual word count (wc) for each of the words in the wordlist from Question 1/2 to compute the TF/IDF value for each word in the word list.

```
elif len(sys.argv) == 2 and sys.argv[1] == 'tfidf':
write_data('blogdata2.txt', wordlist, wordcounts, form=lambda wc, word,
wordcounts: tf(wc, word) * idf(wordcounts, word))
```

Listing 23: use of thidf function

```
def write_data(filename, wordlist, wordcounts, form=lambda wc, word, wordcounts: wc[word]):
79
80
       with open (filename,
                             'w') as out:
81
           out.write('Blog')
82
           for word in wordlist [:500]:
83
                out.write('\t%s' % word)
           out.write('\n')
           for blog, we in wordcounts.items():
    print blog
85
86
87
                out.write(blog)
                for word in wordlist [:500]:
88
89
                    if word in wc:
90
                        out.write('\t{}'.format(form(wc,word,wordcounts)))
91
                        out.write('\t0')
                out.write('\n')
```

Listing 24: writing the data

```
40
       tf(wc, word):
41
       return float (wc[word]) / float (sum(wc.values()))
42
43
   def idf(wordcounts, word):
       present = 0
44
45
       for wc in wordcounts.values():
           if word in wc:
46
47
               present += 1
       return math.log(len(wordcounts) / present, 2)
48
```

Listing 25: tf idf functions

The same clustering was applied to the TF/IDF result matrix as was done in Question 2 and both images are displayed in Figures 4 and 5.

There are a many pairs that were found to be similar in both clusterings. For example, in both dendrograms, the Web Science and Digitial Libraries Research Group blog is most similar to the ...: zero pride and even less shame blog, the DJ DHANIEL FAN AND PRODUCER and The Baron Boombox, among a few others. In spite of this, the larger groupings do not appear very similar between the two clustings.

When examining the clusters on a larger scale, it seems that the TF/IDF dendrogram clustered blogs are subjectively more alike better than the raw count version did. Looking toward the bottom of the TF/IDF clustering image, one will notice a grouping of blogs that seem closely related to music: F-Measure: Less Than timely Music Reviews and Commentary., Urban Anatomy's Columbian Jungle (That Dope!) which seems to be a melding of fashion and music commentary, Ezhevika Fields a blog where info and preview samples of "lost album samples of the past" can be found, whereas these blogs are not all grouped together in the raw count version. It seems that using TF/IDF as a basis for document comparison gives much more context than a raw term count (which doesn't take into consideration the rest of the document in which each word resides).

There is another cluster in the TF/IDF driven image that seems to contain family related blogs, with blogs like  $Am\ I\ a\ funny\ girl?:\ I\ think\ I\ have\ my\ moments,\ The\ Frixen\ Family,\ When\ Two\ Hearts\ Become\ One:\ A\ wife,\ a\ mom,\ a\ daughter,\ a\ sibling.\ and\ The\ Clarks\ in\ Austin\ all\ being\ related to a particular family and their everyday lives. Some of these blogs are close to each other in the raw count version, but they are not separated into their own distinct groups.$ 

When looking at the overall structure of each dendrogram, it becomes apparent that there are more individual clusters grouped together in the TF/IDF version than are present in the raw count image, where there seems to be few small clusters and one mega-cluster in the center. This suggests that the TF/IDF algorithm is better at defining discrete subgroups within a larger context than a simple raw count driven dendrogram will produce.

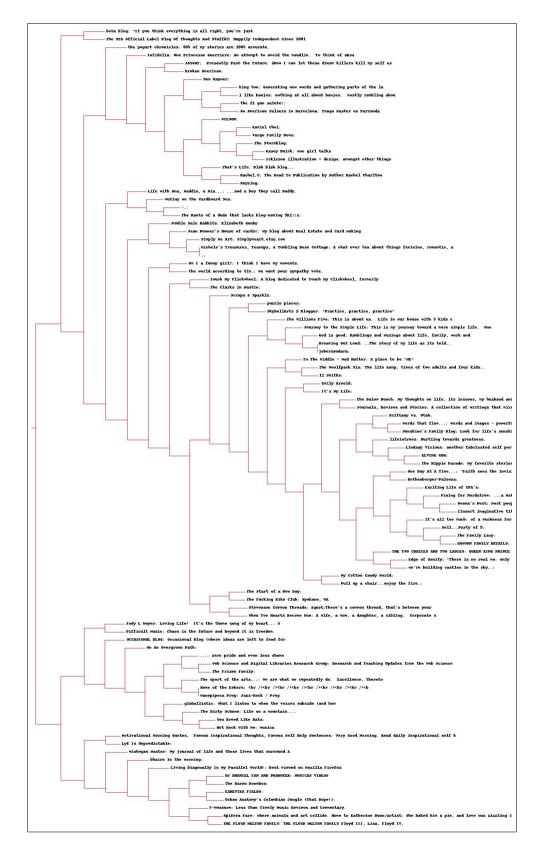


Figure 4: plain count dendrogram

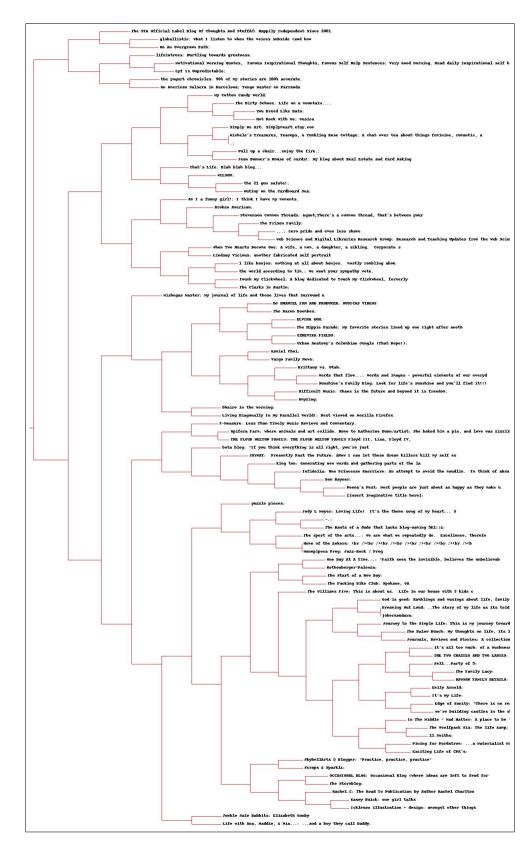


Figure 5: TF/IDF driven dendrogram

### 6 Appendix A

```
1 #! /usr/bin/env python
 2 | import requests
 4 import sys
 5 from bs4 import BeautifulSoup
   default = 'http://www.blogger.com/next-blog?navBar=true&blogID=3471633091411211117'
 8 must_haves = ['http://f-measure.blogspot.com/', 'http://ws-dl.blogspot.com/']
10 def get_atom(uri):
11
         try:
12
             r = requests.get(uri)
13
         except Exception, e:
14
             return None
         soup = BeautifulSoup(r.text)
links = soup.find_all('link', {'type':'application/atom+xml'})
15
16
17
18
              return str(links[0]['href'])
19
         return None
20
   def add_uri(uri, uris, outfile):
    if uri and uri not in uris:
21
23
              uris.add(uri)
               outfile.write(uri + '\n')
25
              print len(uris), uri
26
         __name__ == '__main__':
uris = set()
with open('blog_uris', 'a') as outfile:
   if len(sys.argv) > 1 and sys.argv[1] == 'new':
27
28
29
30
                    for must have in must haves:
    uri = get_atom(must_have)
    add_uri(uri, uris, outfile)
31
32
33
               else:
34
              with open('blog_uris') as infile:
    [uris.add(line.strip()) for line in infile]
while len(uris) < 100:
35
36
37
                    uri = get_atom(default)
38
                    add_uri(uri, uris, outfile)
39
```

Listing 26: get\_uris.py

```
import feedparser
 2 import futures
 3
  import math
 4 import md5
 5
  import re
 6 import sys
  import json
 9
   def get_next(d):
10
       for item in d. feed. links:
11
           if item['rel'] == u'next':
12
                return item['href']
       return None
13
15
   def get words(text):
       16
       words = re.compile(r, [A-Za-z]+, split(txt)
17
       return [word.lower() for word in words if word != '']
18
19
   def get_titles(uri):
20
       print('processing {}'.format(uri))
next = uri
21
22
23
       wc = \{\}
       pages = 0
24
25
       while next is not None:
26
           d = feedparser.parse(next)
27
            for e in d. entries:
                words = get_words(e.title.encode('utf-8'))
for word in words:
28
29
                    wc.setdefault (word, 0)
30
                    wc[word] += 1
31
            pages += 1
32
       next = get_next(d)
print('next {}'.format(next))
title = d.feed.title.encode('utf-8')
33
34
35
       subtitle = d.feed.subtitle[:50].encode('utf-8')
36
       print('finished: {}: {}'.format(title, subtitle))
37
       return uri, title, subtitle, pages, wc
38
39
40
   def tf(wc, word):
       return float (wc[word]) / float (sum(wc.values()))
41
42
   def idf(wordcounts, word):
43
44
       present = 0
       for wc in wordcounts.values():
45
46
            if word in wc:
47
                present += 1
48
       return math.log(len(wordcounts) / present, 2)
49
50
   def load_data(uris):
       apcount = \{\}
51
52
       wordcounts =
       pagecounts = \{\}
53
54
        for uri in uris:
55
            with open('wcs/' + md5.new(uri).hexdigest()) as infile:
56
57
                    lines = infile.read().split('\t')
58
                     title = lines[0]
59
                    pages = int(lines[1])
60
                    wc = json.loads(lines[2])
61
                except Exception, e:
62
                    print('*** {} generated an exception: {}'.format(uri, e))
                     continue
63
            wordcounts[title] = wc
64
            pagecounts title pages
65
66
            for word, count in wc.items():
67
                apcount.setdefault (word, 0)
                apcount [word] += count
68
69
       return apcount, wordcounts, pagecounts
70
71
   def build wordlist (apcount, uris):
       wordlist = []
72
73
       for w, bc in sorted (apcount.items(), key=lambda x: x[1], reverse=True):
                frac = float(bc) / len(uris)
if frac > 0.1 and frac < 0.5:
74
75
76
                     wordlist.append(w)
```

```
return wordlist
 78
     {\tt def \ write\_data(filename\ ,\ wordlist\ ,\ wordcounts\ ,\ form=\underline{lambda}\ wc\ ,\ word\ ,\ wordcounts\ :\ wc[word]):}
 79
           with open(filename, 'w') as out: out.write('Blog')
 80
81
 82
                 for word in wordlist [:500]:
                 out.write('\t%s' % word)
out.write('\n')
 83
 84
                 for blog, wc in wordcounts.items():
    print blog
 85
 86
 87
                       out.write(blog)
 88
                       for word in wordlist [:500]:
 89
                             if word in wc:
 90
                                  out.write('\t{}'.format(form(wc,word,wordcounts)))
 91
 92
                                   out.write('\t0')
 93
                       out.write('\n')
 94
           __name__ == '__main__':
with open('blog_uris') as infile:
 95
     i f
 96
           uris = [line.strip() for line in infile if line.strip()] if len(sys.argv) == 2 and sys.argv[1] == 'get':
 97
 98
 99
                 with futures. ThreadPoolExecutor (max_workers=8) as executor:
100
                       uri futures = [executor.submit(get titles, uri) for uri in uris]
                       for future in futures.as_completed(uri_futures):
    uri, title, subtitle, pages, wc = future result()
    with open('wcs/' + md5.new(uri).hexdigest(), 'w') as out:
        out.write(title + ': ' + subtitle + '\t' + str(pages) + '\t')
101
102
103
104
105
                                   json.dump(wc, out)
106
           else:
107
                 apcount, wordcounts, pagecounts = load_data(uris)
wordlist = build_wordlist(apcount, uris)
108
                 if len(sys.argv) == 2 and sys.argv[1] == 'pages': with open('pagecounts', 'w') as outfile:
109
110
                             outfile.write('blog\tpages\n')
111
                             for blog, pagecount in pagecounts.iteritems():
    outfile.write("\"" + blog.replace("\"", "") + "\"" + '\t' + str(
112
113
                                        pagecount) + '\n')
                 elif len(sys.argv) = 2 and sys.argv[1] = 'wc':
   write_data('blogdata1.txt', wordlist, wordcounts)
114
115
                 elif len(sys.argv) = 2 and sys.argv[1] = 'tfidf':
   write_data('blogdata2.txt', wordlist, wordcounts, form=lambda wc, word,
116
117
                             wordcounts: tf(wc, word) * idf(wordcounts, word))
```

Listing 27: matrix.py

```
from PIL import Image, ImageDraw
 3
   def readfile (filename):
 4
      lines = [line for line in file (filename)]
 5
       # First line is the column titles
       colnames=lines [0]. strip().split('\t')[1:]
       rownames = []
 9
       data = []
10
       for line in lines [1:]:
11
         p=line.strip().split('\t')
         # First column in each row is the rowname
12
13
         rownames.append(p[0])
         # The data for this row is the remainder of the row data.append([float(x) for x in p[1:]])
15
16
      return rownames, colnames, data
17
18
19
   from math import sqrt
20
21
   def pearson (v1, v2):
22
          Simple sums
      sum1=sum(v1)
23
24
      sum2 = sum (v2)
25
26
      # Sums of the squares
      \begin{array}{l} \text{sum1Sq=sum}\left(\left[\operatorname{pow}(v\,,2) \right] \text{ for } v \text{ in } v1\right]\right) \\ \text{sum2Sq=sum}\left(\left[\operatorname{pow}(v\,,2) \right] \text{ for } v \text{ in } v2\right]\right) \end{array}
27
28
29
30
       # Sum of the products
      pSum=sum([v1[i]*v2[i] for i in range(len(v1))])
31
32
      # Calculate r (Pearson score)
33
      num=pSum-(sum1*sum2/len(v1))
34
       \underline{\text{den=sqrt}\left(\left(\text{sum1Sq-pow}\left(\text{sum1},2\right)\right)/\text{len}\left(\text{v1}\right)\right)*\left(\text{sum2Sq-pow}\left(\text{sum2},2\right)/\text{len}\left(\text{v1}\right)\right)\right)}
35
36
       if den==0: return 0
37
       return 1.0-num/den
38
39
    class bicluster:
   def __init__(s
         ef __init__(self, vec, left=None, right=None, distance=0.0,id=None):
self.left=left
40
41
42
43
         self.right = right
44
         self.vec=vec
45
         s\,e\,l\,f . i\,d{=}i\,d
46
         self.distance=distance
47
48
   def hcluster(rows, distance=pearson):
49
       distances = \{\}
50
       currentclustid=-1
51
52
       # Clusters are initially just the rows
       clust = [bicluster(rows[i], id=i) for i in range(len(rows))]
53
54
55
       while len(clust)>1:
56
         lowestpair = (0,1)
57
         closest=distance(clust[0].vec,clust[1].vec)
58
59
         # loop through every pair looking for the smallest distance
60
         for i in range(len(clust)):
61
            for j in range (i+1, len (clust)):
62
                                                     distance calculations
               if (clust [i].id, clust [j].id) not in distances:
distances [(clust [i].id, clust [j].id)] = distance(clust [i].vec, clust [j].vec)
63
64
65
66
               d=distances [(clust[i].id,clust[j].id)]
67
68
               if d < closest:
69
                  c losest=d
70
                  lowestpair=(i,j)
71
72
         # calculate the average of the two clusters
73
         (clust [lowestpair [0]]. vec[i]+clust [lowestpair [1]]. vec[i])/2.0
74
75
         for i in range(len(clust[0].vec))]
76
```

```
# create the new cluster
        newcluster=bicluster (mergevec, left=clust[lowestpair[0]],
78
79
                                right=clust [lowestpair [1]]
80
                                distance=closest , id=currentclustid )
81
82
        # cluster ids that weren't in the original set are negative
83
        currentclustid -=1
        del clust [lowestpair [1] del clust [lowestpair [0]
84
85
86
        clust.append(newcluster)
87
88
      return clust [0]
89
90
   def printclust (clust, labels=None, n=0):
91
      # indent to make a hierarchy layout
for i in range(n): print ''',
92
93
      if clust.id < 0:
94
       # negative id means that this is branch
95
        print '-'
96
      else:
        # positive id means that this is an endpoint
97
        if labels—None: print clust.id
99
        else: print labels [clust.id]
100
101
      # now print the right and left branches
      if clust.left!=None: printclust(clust.left, labels=labels, n=n+1)
102
103
      if clust.right!=None: printclust(clust.right, labels=labels, n=n+1)
104
    def getheight(clust):
105
        Is this an endpoint? Then the height is just 1
106
107
      if clust.left=None and clust.right=None: return 1
108
109
     # Otherwise the height is the same of the heights of
110
      # each branch
      return getheight (clust.left)+getheight (clust.right)
111
112
   def getdepth(clust):
113
        The distance of an endpoint is 0.0
114
      if clust.left=None and clust.right=None: return 0
115
116
      # The distance of a branch is the greater of its two sides
117
      # plus its own distance
118
      return max(getdepth(clust.left),getdepth(clust.right))+clust.distance
119
120
121
    def drawdendrogram(clust, labels, jpeg='clusters.jpg'):
122
123
      # height and widtl
      h=getheight(clust)*20
124
      \bar{w} = 1200
125
      depth=getdepth(clust)
126
127
      \# width is fixed, so scale distances accordingly scaling=float(w-150)/depth
128
129
130
      \# Create a new image with a white background img=Image.new('RGB',(w,h),(255,255,255))
131
132
      draw=ImageDraw . Draw (img)
133
134
      draw.line((0,h/2,10,h/2),fill=(255,0,0))
135
136
137
      # Draw the first node
138
      drawnode(draw, clust, 10, (h/2), scaling, labels)
139
      img.save(jpeg,'JPEG')
140
141
    def drawnode(draw, clust, x, y, scaling, labels):
142
      if clust.id < 0:
143
        h1=getheight (clust.left) *20
144
        h2=getheight (clust.right) *20
145
        top=y-(h1+h2)/2
146
        bottom=y+(h1+h2)/2
147
          Line length
148
        ll=clust.distance*scaling
149
          Vertical line from this cluster to children
150
        draw.line((x, top+h1/2, x, bottom-h2/2), fill = (255, 0, 0))
151
152
        # Horizontal line to left item
        draw.line((x, top+h1/2, x+ll, top+h1/2), fill=(255, 0, 0))
```

```
154
         # Horizontal line to right item
155
         draw.line((x,bottom-h2/2,x+l1,bottom-h2/2),fill=(255,0,0))
156
157
         # Call the function to draw the left and right nodes
158
         drawnode(draw,clust.left,x+ll,top+h1/2,scaling,labels)
drawnode(draw,clust.right,x+ll,bottom-h2/2,scaling,labels)
159
160
161
         \# If this is an endpoint, draw the item label draw.text((x+5,y-7), labels[clust.id],(0,0,0))
162
163
164
    def rotatematrix(data):
165
166
      newdata=[]
167
      for i in range(len(data[0])):
         newrow=[data[j][i] for j in range(len(data))]
newdata.append(newrow)
168
169
170
      return newdata
171
172
    import random
173
174
    def kcluster (rows, distance=pearson, k=4):
      # Determine the minimum and maximum values for each point
175
176
      ranges = [(min([row[i] for row in rows]), max([row[i] for row in rows]))
      for i in range (len (rows [0]))]
177
178
179
      # Create k randomly placed centroids
      for i in range(len(rows[0]))] for j in range(k)]
180
181
182
183
      lastmatches=None
      for t in range(100):
    print 'Iteration %d' % t
    bestmatches=[[] for i in range(k)]
184
185
186
187
         # Find which centroid is the closest for each row
188
         for j in range(len(rows)):
189
190
           row=rows[j]
191
           bestmatch=0
192
           for i in range(k):
              d=distance(clusters[i],row)
193
           if d<distance(clusters[bestmatch],row): bestmatch=i
bestmatches[bestmatch].append(j)</pre>
194
195
196
         # If the results are the same as last time, this is complete
197
         if bestmatches==lastmatches: break
198
199
         lastmatches=bestmatches
200
         # Move the centroids to the average of their members
201
         for i in range(k):
202
203
           avgs = [0.0] * len(rows[0])
           if len (bestmatches [i]) >0:
204
              for rowid in bestmatches[i]:
205
206
                for m in range(len(rows[rowid])):
207
                  avgs [m]+=rows [rowid] [m]
              for j in range(len(avgs)):
  avgs[j]/=len(bestmatches[i])
clusters[i]=avgs
208
209
210
211
212
      return bestmatches
213
214 def tanamoto(v1,v2):
215
      c1, c2, shr = 0, 0, 0
216
217
      for i in range(len(v1)):
         if v1[i]!=0: c1+=1 # in v1
if v2[i]!=0: c2+=1 # in v2
218
219
220
         if v1[i]!=0 and v2[i]!=0: shr+=1 # in both
221
222
      return 1.0-(float(shr)/(c1+c2-shr))
223
    def scaledown ( data, distance=pearson, rate=0.01):
224
225
      n=len(data)
226
227
      # The real distances between every pair of items
      realdist = [[distance(data[i], data[j]) for j in range(n)]
                    for i in range (0,n)]
229
230
```

```
\# Randomly initialize the starting points of the locations in 2D
231
       232
233
234
235
       lasterror{=}None
236
       for m in range (0,1000):
237
           Find projected distances
238
          for i in range(n):
239
            for j in range(n):
240
               fakedist[i][j]=sqrt(sum([pow(loc[i][x]-loc[j][x],2)
241
                                                for x in range(len(loc[i]))])
242
243
          \operatorname{grad} = [[0.0, 0.0] \text{ for i in range}(n)]
244
245
246
          \mathtt{totalerror}\!=\!\!0
247
          for k in range(n):
248
            for j in range(n):
249
               i f
                  j=k: continue
                 The error is percent difference between the distances
250
251
               if realdist [j][\hat{k}] != 0:
252
                    errorterm = (fakedist [j][k] - realdist [j][k]) / realdist [j][k]
253
254
               # Each point needs to be moved away from or towards the other
255
                          in proportion to how much error
               grad [k][0]+=((loc[k][0]-loc[j][0])/fakedist[j][k])*errorterm
256
257
               \operatorname{grad}\left[k\right]\left[1\right] + = \left(\left(\operatorname{loc}\left[k\right]\left[1\right] - \operatorname{loc}\left[j\right]\left[1\right]\right) / \operatorname{fakedist}\left[j\right]\left[k\right]\right) * \operatorname{errorterm}
258
259
               # Keep track of the total error
               totalerror+=abs (errorterm)
260
261
          print totalerror
262
         # If the answer got worse by moving the points, we are done if lasterror and lasterror<br/>totalerror: break
263
264
265
          lasterror=totalerror
266
267
          # Move each of the points by the learning rate times the gradient
          for k in range(n):
268
            loc[k][0] -= rate*grad[k][0]
loc[k][1] -= rate*grad[k][1]
269
270
271
272
       return loc
273
    def draw2d(data, labels , jpeg='mds2d.jpg'):
  img=Image.new('RGB',(2000,2000),(255,255,255))
  draw=ImageDraw.Draw(img)
274
275
276
       for i in range (len (data)):
277
         x=(data[i][0]+0.5)*1000
y=(data[i][1]+0.5)*1000
278
279
          draw.\,text\,((\,x\,,y)\,\,,la\,b\,e\,l\,s\,[\,i\,]\,\,,(\,0\,\,,0\,\,,0\,)\,)
280
281
       img.save(jpeg,'JPEG')
282
283 import sys
284
285
                   _ == '__main__':
          blognames, words, data = readfile('q1/blogdata1.txt')
clust = hcluster(data)
286
287
288
          with open ('dendrogram.txt', 'w') as outfile:
289
               \mathtt{stdout} \ = \ \mathtt{sys.stdout}
290
               sys.stdout = outfile
291
               printclust(clust, labels=blognames)
292
               sys.stdout = stdout
293
          drawdendrogram(clust, blognames, jpeg='blogclust.jpg')
          print "Done with dendrograms"
print "K=5"
294
295
296
          kclust=kcluster (data, k=5)
297
          print "K=10"
298
          kclust=kcluster (data, k=10)
299
          print "K=20"
300
          kclust=kcluster (data, k=20)
          coords=scaledown(data)
          draw2d(coords, blognames, jpeg='blogs2d.jpg')
```

Listing 28: clusters.py

```
1 4827.50419137
2 3357.0495173
3 3337.77451337
4 3329.39524222
5 3325.08734145
6 3323.50421842
7 3323.33337939
8 3324.2545901
```

Listing 29: scaledown output

## 7 References

- [1] Internet Engineering Task Force (IETF). RFC-4287 The Atom Syndication Format. https://tools.ietf.org/html/rfc4287, 2005.
- [2] Toby Segaran. Programming Collective Intelligence. O'Reilly, first edition, 2007.