

Assignment 5

CS834-F16: Introduction to Information Retrieval

Fall 2016

Erika Siregar

CS Department - Old Dominion University

December 17, 2016

Question 10.3

Compute five iterations of HITS (see Algorithm 3) and PageRank (see Figure 4.11) on the graph in Figure 10.3. Discuss how the PageRank scores compare to the hub and authority scores produced by HITS.

Answer

Figure 1 shows the directed graph from the textbook [1] on which we will calculate the scores of HITS and PageRank. Computing HITS (authorities and hubs) and PageRank scores are pretty easy since we can just utilize the Link Analysis procedure that is provided by python library 'networkx' [2].

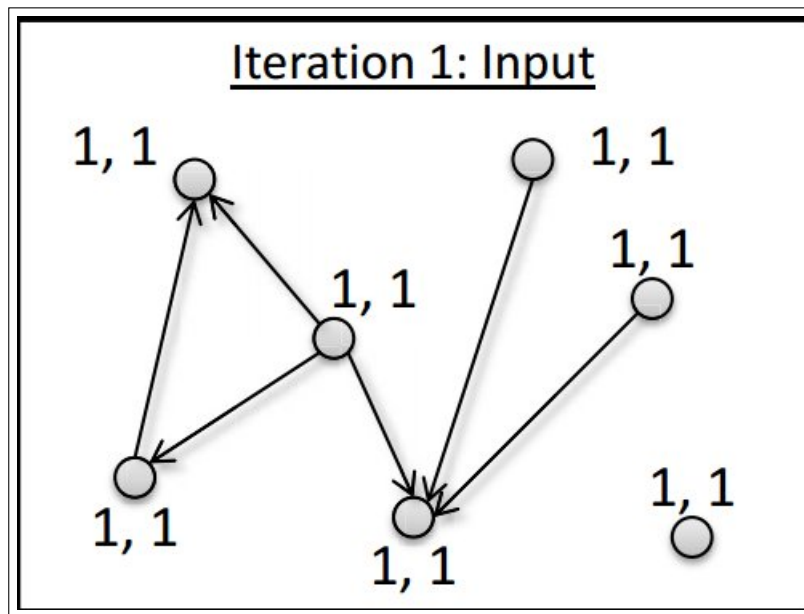


Figure 1: Figure 10.3 from the textbook [1]

Figure 2 shows the scores of HITS (authorities and hubs) and PageRank, which are obtained by running the code in listing 1. We only need to set the number of iterations.

```

erikaris@erikaris-Inspiron: /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assign
erikaris@erikaris-Inspiron: /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a5/code_report$ PS1='\u:\W\$ '
erikaris:code_report$ PS1='\u@\h: '
erikaris@erikaris-Inspiron: python 10_3.py
HITS Algorithm (5 iterations)
=====
Hubs values = {1: 0.19870751068593528, 2: 0.19870751068593528, 3: 0.258854060655404,
4: 0.1789639731325056, 5: 0.0823834724201099, 6: 0.0823834724201099, 7: 0.0}
Authorities values = {1: 0.20153417015341699, 2: 0.20153417015341699, 3: 0.25232450023245, 4: 0.18816829381682937, 5: 0.07821943282194328, 6: 0.07821943282194328, 7: 0.0}

Pagerank Algorithm (5 iterations)
=====
Pagerank values = {1: 0.15415210590313183, 2: 0.15415210590313183, 3: 0.2151836555953412, 4: 0.2730700543561289, 5: 0.08952435340504106, 6: 0.08952435340504106, 7: 0.024393371432183873}
erikaris@erikaris-Inspiron: █

```

Figure 2: HITS and Pagerank for Figure 10.3 with 5 Iterations

To make the analysis and comparison easier, I transformed the output into a neat table format as can be seen on table 1. From table 1, we can see that, generally, the authorities values are linearly proportional to those of PageRank. After 5 iterations, node 3 gets the highest score for ‘authorities’ and the second highest score for ‘PageRank’. Nodes 1 and 2 get lower ‘authorities’ score than that of node 3, but higher ‘authorities’ score compare to nodes 5 and 6. The same thing can also be concluded by comparing the PageRank scores for those five nodes (1, 2, 3, 5, and 6). The strange thing happens on node 4, where its ‘authorities’ score is lower than node 3, but its ‘PageRank’ score is higher than node 3. This anomaly takes place probably because we only do 5 iterations. Maybe, if we continue iterating until the values converge into certain number, this anomaly will not happen.

Node	Score		
	Hubs	Authorities	PageRank
1	0.198707510685935	0.201534170153416	0.154152105903131
2	0.198707510685935	0.201534170153416	0.154152105903131
3	0.258854060655404	0.252324500232450	0.215183655595341
4	0.178963973132505	0.188168293816829	0.273070054356128
5	0.082383472420110	0.078219432821943	0.089524353405041
6	0.082383472420110	0.078219432821943	0.089524353405041
7	0.000000000000000	0.000000000000000	0.024393371432184

Table 1: HITS and Pagerank for Figure 10.3 with 5 Iterations

```

1 #!/usr/bin/python
2
3 import networkx as nx
4

```

```

5 def hits(G, iter=100, nstart=None, normalized=True):
6 if type(G) == nx.MultiGraph or type(G) == nx.MultiDiGraph:
7 raise Exception("hits() not defined for graphs with multiedges.")
8 if len(G) == 0:
9 return {},{}
10 # choose fixed starting vector if not given
11 if nstart is None:
12 h=dict.fromkeys(G,1.0/G.number_of_nodes())
13 else:
14 h=nstart
15 # normalize starting vector
16 s=1.0/sum(h.values())
17 for k in h:
18 h[k]*=s
19 i=0
20 while True: # power iteration: make up to max_iter iterations
21 if i >= iter: break
22
23 hlast=h
24 h=dict.fromkeys(hlast.keys(),0)
25 a=dict.fromkeys(hlast.keys(),0)
26 # this "matrix multiply" looks odd because it is
27 # doing a left multiply  $a^T = hlast^T * G$ 
28 for n in h:
29 for nbr in G[n]:
30 a[nbr]+=hlast[n]*G[n][nbr].get('weight',1)
31 # now multiply  $h = Ga$ 
32 for n in h:
33 for nbr in G[n]:
34 h[n]+=a[nbr]*G[n][nbr].get('weight',1)
35 # normalize vector
36 s=1.0/max(h.values())
37 for n in h: h[n]*=s
38 # normalize vector
39 s=1.0/max(a.values())
40 for n in a: a[n]*=s
41
42 i+=1
43 if normalized:
44 s = 1.0/sum(a.values())
45 for n in a:
46 a[n] *= s
47 s = 1.0/sum(h.values())
48 for n in h:
49 h[n] *= s
50 return h,a
51
52 def pagerank(G, alpha=0.85, personalization=None,
53 iter=100, nstart=None, weight='weight',
54 dangling=None):
55 if len(G) == 0:
56 return {}
57
58 if not G.is_directed():
59 D = G.to_directed()
60 else:
61 D = G
62
63 # Create a copy in (right) stochastic form

```

```

64 W = nx.stochastic_graph(D, weight=weight)
65 N = W.number_of_nodes()
66
67 # Choose fixed starting vector if not given
68 if nstart is None:
69     x = dict.fromkeys(W, 1.0 / N)
70 else:
71     # Normalized nstart vector
72     s = float(sum(nstart.values()))
73     x = dict((k, v / s) for k, v in nstart.items())
74
75 if personalization is None:
76     # Assign uniform personalization vector if not given
77     p = dict.fromkeys(W, 1.0 / N)
78 else:
79     missing = set(G) - set(personalization)
80     if missing:
81         raise nx.NetworkXError('Personalization dictionary '
82                                 'must have a value for every node. '
83                                 'Missing nodes %s' % missing)
84     s = float(sum(personalization.values()))
85     p = dict((k, v / s) for k, v in personalization.items())
86
87 if dangling is None:
88     # Use personalization vector if dangling vector not specified
89     dangling_weights = p
90 else:
91     missing = set(G) - set(dangling)
92     if missing:
93         raise nx.NetworkXError('Dangling node dictionary '
94                                 'must have a value for every node. '
95                                 'Missing nodes %s' % missing)
96     s = float(sum(dangling.values()))
97     dangling_weights = dict((k, v/s) for k, v in dangling.items())
98     dangling_nodes = [n for n in W if W.out_degree(n, weight=weight) == 0.0]
99
100 # power iteration: make up to max_iter iterations
101 for _ in range(iter):
102     xlast = x
103     x = dict.fromkeys(xlast.keys(), 0)
104     danglesum = alpha * sum(xlast[n] for n in dangling_nodes)
105     for n in x:
106         # this matrix multiply looks odd because it is
107         # doing a left multiply  $x^T = xlast^T W$ 
108         for nbr in W[n]:
109             x[nbr] += alpha * xlast[n] * W[n][nbr][weight]
110     x[n] += danglesum * dangling_weights[n] + (1.0 - alpha) * p[n]
111
112 return x
113
114 if __name__ == '__main__':
115     iter = 5
116     G = nx.Graph()
117
118     # Add 7 nodes
119     G.add_nodes_from(range(1,8))
120
121     # Add 6 edges
122     G.add_edges_from([(1,2), (3,1), (3,2), (3,4), (5,4), (6,4)])

```

```

123
124 # Compute hubs and authorities normalized values using hits
125 h, a = hits(G, iter=iter)
126
127 print 'HITS Algorithm ({0} iterations)'.format(iter)
128 print '=====',
129 print 'Hubs values = {}'.format(h)
130 print 'Authorities values = {}'.format(a)
131 print ''
132
133 # Compute pagerank of each nodes
134 pr = pagerank(G, iter=iter)
135
136 print 'Pagerank Algorithm ({0} iterations)'.format(iter)
137 print '=====',
138 print 'Pagerank values = {}'.format(pr)

```

Listing 1: Computing HITS and PageRank

Question 0.3

Answer:

answer 2

Question 8.5

question 3

Answer

answer 3

Question 8.7

question 4

Answer

answer 4

References

- [1] Bruce Croft, Donald Metzler, and Trevor Strohman. *Search Engines: Information Retrieval in Practice*. Addison-Wesley Publishing Company, USA, 1st edition, 2009.

- [2] NetworkX Developers. Networkx - Link Analysis. https://networkx.github.io/documentation/networkx-1.9/reference/algorithms.link_analysis.html, 2016. [Online; accessed 14-December-2016].