

James Abundis
jlabundi@calpoly.edu
Thomas Fahrner
tfahrner@calpoly.edu
Lec: CSC 466-01
Lab: CSC 466-02

Lab 5

PageRank Implementation:

We implemented the standard PageRank. At first, we built a graph data structure with heavy redundancy. While this was effective for the smaller datasets, we ran into performance issues with the large datasets. We changed our algorithm to adopt a Node data structure shown here:

```
class Node:
    def __init__(self, name):
        self.name = name
        self.num_out = 0
        self.in_node_names = set()
```

This data structure allowed us to perform very efficient iterations of PageRank. Our algorithm for building the graph representation handles the discrepancy between directed/undirected graphs.

The lack of ground truth made it difficult to determine the values of the parameters (d: probability of traveling to a connected node; epsilon/number of iterations: stopping condition). We split this parameter search into two parts for the small/large datasets respectively.

- Small datasets:
 - $d = 0.9$; we found this worked well with a quick sanity check on the results
 - $\text{num_iterations} = 1000$; this was effectively limitless because performance was not an issue on these datasets. There was no need to parameter search and instead we chose to just guarantee PageRank convergence.
- Large datasets:
 - $d = 0.9$; we figured that this parameter would suit the large datasets just as well. While it is contextually dependent, we did not find a strong argument to alter this parameter.
 - $\text{num_iterations} = n$; this was dependent on the performance evaluation (see below)

Results:

NCAA Football:

1 Read time: 0.01 Processing time: 49.53 Number of iterations: 1000
2 NorthDakota with pagerank: 0.0108389450056
3 WeberState with pagerank: 0.0106802148469
4 Montana with pagerank: 0.0105016434183
5 SouthDakota with pagerank: 0.00973324514991
6 NorthwesternState with pagerank: 0.00908179012346
7 Florida with pagerank: 0.00865189594356
8 Iona with pagerank: 0.00864197530864
9 Richmond with pagerank: 0.00849096119929
10 Utah with pagerank: 0.00840608465608
11 Oklahoma with pagerank: 0.00822651114318
12 CentralArkansas with pagerank: 0.00819334215168
13 SacredHeart with pagerank: 0.00806778098445
14 SavannahState with pagerank: 0.00806327160494
15 TexasTech with pagerank: 0.0079487333654
16 Texas with pagerank: 0.00784171075838
17 SouthCarolinaState with pagerank: 0.00775022045855
18 GramblingState with pagerank: 0.00775022045855
19 JamesMadison with pagerank: 0.00768077601411
20 BryantUniversity with pagerank: 0.00767095558762
21 Liberty with pagerank: 0.00747244268078
22 Mississippi with pagerank: 0.00747134038801
23 TCU with pagerank: 0.00739648468815
24 Drake with pagerank: 0.00734898589065
25 Samford with pagerank: 0.00732814253648
26 USC with pagerank: 0.00728405082572
27 McNeeseState with pagerank: 0.0067934303351
28 Tennessee-Martin with pagerank: 0.00669642857143
29 OregonState with pagerank: 0.00665574394741
30 PrairieViewA&M with pagerank: 0.00659281305115
31 Tulsa with pagerank: 0.00658088824755
32 NewHampshire with pagerank: 0.00648919753086
33 SanDiego with pagerank: 0.00647597001764
34 AppalachianState with pagerank: 0.00647166105499
35 NorthernIowa with pagerank: 0.00619488536155
36 Villanova with pagerank: 0.00618055555556
37 Jacksonville with pagerank: 0.00614528218695
38 Butler with pagerank: 0.00611882716049
39 SacramentoState with pagerank: 0.00610229276896
40 TexasState with pagerank: 0.0060758377425

300 DeltaState with pagerank: 0.000308641975309
301 AzusaPacific with pagerank: 0.000308641975309
302 ConcordiaCollege with pagerank: 0.000308641975309
303 Merrimack with pagerank: 0.000308641975309
304 Wisconsin-LaCrosse with pagerank: 0.000308641975309
305 ConcordiaUniversity(WI) with pagerank: 0.000308641975309
306 SouthernOregon with pagerank: 0.000308641975309
307 WestChester with pagerank: 0.000308641975309
308 WilliamPenn with pagerank: 0.000308641975309
309 Lenoir-Rhyne with pagerank: 0.000308641975309
310 Shaw with pagerank: 0.000308641975309
311 DixieState with pagerank: 0.000308641975309
312 Dartmouth with pagerank: 0.000308641975309
313 Chowan with pagerank: 0.000308641975309
314 Culver-Stockton with pagerank: 0.000308641975309
315 WesternWashington with pagerank: 0.000308641975309
316 CentralMethodist with pagerank: 0.000308641975309
317 Pace with pagerank: 0.000308641975309
318 MissouriS&T with pagerank: 0.000308641975309
319 CentralWashington with pagerank: 0.000308641975309
320 Morehouse with pagerank: 0.000308641975309
321 SoutheasternOklahoma with pagerank: 0.000308641975309
322 Carthage with pagerank: 0.000308641975309
323 ClarkAtlanta with pagerank: 0.000308641975309
324 KentuckyWesleyan with pagerank: 0.000308641975309
325 Lincoln(MO) with pagerank: 0.000308641975309

Here we show the highest and lowest ranked results. If we look at North Dakota in the dataset, it often appears first (they won a lot of games). The same follows with Weber State and the others ranked highly. If we look at some of the low ranked teams, they often had just one game represented in the dataset. With one game, often a loss, we expect their PageRank to be very low. Overall, a cursory look indicates that PageRank performed well on this dataset.

State Borders:

1 Read time: 0.0 Processing time: 1.93 Number of iterations: 1000
2 MD with pagerank: 0.0349019607843
3 GA with pagerank: 0.0341666666667
4 KY with pagerank: 0.0328921568627
5 MA with pagerank: 0.0319607843137
6 ID with pagerank: 0.02918767507
7 NH with pagerank: 0.0290196078431
8 TN with pagerank: 0.0281862745098
9 MO with pagerank: 0.0277170868347
10 SD with pagerank: 0.0275910364146
11 PA with pagerank: 0.0272549019608
12 VA with pagerank: 0.0260784313725
13 NY with pagerank: 0.0260784313725
14 CO with pagerank: 0.0247759103641
15 IA with pagerank: 0.0246778711485
16 WY with pagerank: 0.0237675070028
17 OR with pagerank: 0.023137254902
18 NV with pagerank: 0.023137254902
19 AR with pagerank: 0.0228921568627
20 TX with pagerank: 0.0210784313725

40 CA with pagerank: 0.0143137254902
41 NJ with pagerank: 0.0143137254902
42 MI with pagerank: 0.0143137254902
43 DE with pagerank: 0.0137254901961
44 ND with pagerank: 0.0133053221289
45 LA with pagerank: 0.0128431372549
46 RI with pagerank: 0.0113725490196
47 FL with pagerank: 0.0093137254902
48 SC with pagerank: 0.0093137254902
49 WA with pagerank: 0.0093137254902
50 ME with pagerank: 0.0078431372549
51 DC with pagerank: 0.0078431372549
52 MV with pagerank: 0.00710784313725



Here we show the highest and lowest ranked results. It's clear from the top results that states with a high number of borders receive a high PageRank. Conversely, the low ranked results also make sense. PageRank seems to work well on this dataset.

Karate:

```
1 Read time: 0.0 Processing time: 1.17 Number of iterations: 1000
2 34 with pagerank: 0.155588235294
3 1 with pagerank: 0.140441176471
4 33 with pagerank: 0.101557093426
5 2 with pagerank: 0.0654779411765
6 3 with pagerank: 0.0600367647059
7 4 with pagerank: 0.0353308823529
8 32 with pagerank: 0.0348291522491
9 6 with pagerank: 0.0332720588235
10 7 with pagerank: 0.0332720588235
11 24 with pagerank: 0.0287629757785
12 30 with pagerank: 0.0252335640138
13 25 with pagerank: 0.0227941176471
14 26 with pagerank: 0.0214705882353
15 28 with pagerank: 0.0212629757785
16 5 with pagerank: 0.0200367647059
17 11 with pagerank: 0.0200367647059
18 9 with pagerank: 0.0176232698962
19 17 with pagerank: 0.0161764705882
20 14 with pagerank: 0.0161526816609
21 31 with pagerank: 0.0149394463668
22 8 with pagerank: 0.0145955882353
23 29 with pagerank: 0.0115570934256
24 27 with pagerank: 0.011115916955
25 20 with pagerank: 0.00909385813149
26 13 with pagerank: 0.00900735294118
27 18 with pagerank: 0.00753676470588
28 22 with pagerank: 0.00753676470588
29 10 with pagerank: 0.00714532871972
30 15 with pagerank: 0.00670415224913
31 16 with pagerank: 0.00670415224913
32 19 with pagerank: 0.00670415224913
33 21 with pagerank: 0.00670415224913
34 23 with pagerank: 0.00670415224913
35 12 with pagerank: 0.00459558823529
```

Karate student #34 is friends with about half the class - what a popular guy! His PageRank reflects this. Student #12 has one friend - #1. While #1 is very popular, his friend #12 is not. PageRank seems to work well on this dataset.

Dolphins:

```
1 Read time: 0.0 Processing time: 2.63 Number of iterations: 1000
2 Trigger with pagerank: 0.0546606619187
3 Jet with pagerank: 0.0481221198157
4 Web with pagerank: 0.03991359447
5 Patchback with pagerank: 0.0344187264349
6 Scabs with pagerank: 0.034176790951
7 SN63 with pagerank: 0.0321543778802
8 Grin with pagerank: 0.0307896941768
9 Topless with pagerank: 0.0272182656054
10 SN4 with pagerank: 0.026555823209
11 Beescratch with pagerank: 0.0245506912442
12 Stripes with pagerank: 0.0235373900293
13 Kringel with pagerank: 0.0234389400922
14 SN100 with pagerank: 0.0231744868035
15 Gallatin with pagerank: 0.0227764976959
16 Haecksel with pagerank: 0.0218208001676
17 Feather with pagerank: 0.0204435483871
18 Ripplefluke with pagerank: 0.020017281106
19 Upbang with pagerank: 0.0187096774194
20 SN9 with pagerank: 0.0186929199832
21 DN21 with pagerank: 0.0180587557604
22 SN96 with pagerank: 0.0179608294931
23 Number1 with pagerank: 0.0176209677419
24 TR77 with pagerank: 0.0167741935484
25 Double with pagerank: 0.0165102639296
26 Shmuddel with pagerank: 0.0164809384164
27 PL with pagerank: 0.0158870967742
28 Bumper with pagerank: 0.0154032258065
29 DN63 with pagerank: 0.0149366359447
30 Jonah with pagerank: 0.0145224130708

50 TSN103 with pagerank: 0.00806451612903
51 Wave with pagerank: 0.00766129032258
52 MN60 with pagerank: 0.00645789694177
53 Zig with pagerank: 0.00645161290323
54 SN89 with pagerank: 0.00529953917051
55 Vau with pagerank: 0.00513824884793
56 Whitetip with pagerank: 0.00342741935484
57 MN23 with pagerank: 0.00322580645161
58 Quasi with pagerank: 0.00322580645161
59 SMN5 with pagerank: 0.00322580645161
60 TR82 with pagerank: 0.00322580645161
61 Fork with pagerank: 0.00306451612903
62 Cross with pagerank: 0.00306451612903
63 Five with pagerank: 0.00306451612903
```

Trigger has a lot of friends; Five has only one friend - Trigger. This is a similar social network analysis as the Karate Kids. PageRank seems to work well on this dataset.

Les Miserables:

```
1 Read time: 0.01 Processing time: 4.1 Number of iterations: 1000
2 Valjean with pagerank: 0.12636335946
3 Myriel with pagerank: 0.0912337662338
4 Gavroche with pagerank: 0.0383456953063
5 Thenardier with pagerank: 0.0333798008111
6 Javert with pagerank: 0.0323155253837
7 Fantine with pagerank: 0.0314927003859
8 Marius with pagerank: 0.0300240830598
9 MlleGillenormand with pagerank: 0.0254254289798
10 Mabeuf with pagerank: 0.0218466700763
11 Cosette with pagerank: 0.0200716965777
12 Fauchelevent with pagerank: 0.0198433919022
13 Gillenormand with pagerank: 0.0195812731356
14 MmeThenardier with pagerank: 0.0191925654559
15 Eponine with pagerank: 0.0160397010713
16 Enjolras with pagerank: 0.0156974831288
17 Courfeyrac with pagerank: 0.0144591225589
18 Tholomyes with pagerank: 0.0137742230428
19 Bossuet with pagerank: 0.0137212240937
20 MmeBurgon with pagerank: 0.0135182998819
21 Bahorel with pagerank: 0.0133216236941
22 Joly with pagerank: 0.0133216236941
23 Bamatabois with pagerank: 0.0128304048892
24 Listolier with pagerank: 0.0117254174397
25 Fameuil with pagerank: 0.0117254174397
26 Blacheville with pagerank: 0.0117254174397
27 Favourite with pagerank: 0.0117254174397
28 Dahlia with pagerank: 0.0117254174397
29 Zephine with pagerank: 0.0117254174397
30 Combeferre with pagerank: 0.0115633170657

70 Marguerite with pagerank: 0.0024025974026
71 MotherPlutarch with pagerank: 0.00236127508855
72 Woman1 with pagerank: 0.00231092436975
73 Boulatrueille with pagerank: 0.00202922077922
74 Labarre with pagerank: 0.00162337662338
75 MmeDeR with pagerank: 0.00162337662338
76 Isabeau with pagerank: 0.00162337662338
77 Gervais with pagerank: 0.00162337662338
78 Scaufflaire with pagerank: 0.00162337662338
```

Valjean has a lot of co-occurrences with other characters; Scaufflaire has only one. This is a similar social network analysis as the Karate Kids. PageRank seems to work well on this dataset.

Summary:

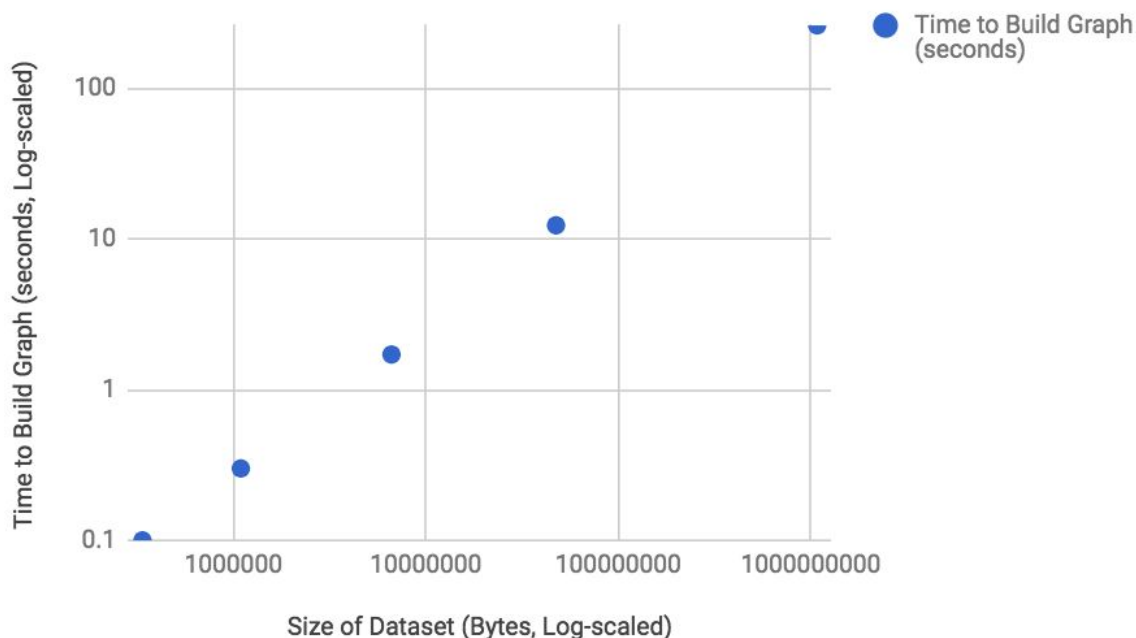
PageRank worked pretty well on every one of the small datasets. While the ranking is good, it is also important to look at the quantitative values given (the PageRank). For instance, in the Les Mes dataset, Valjean has a PageRank equal to three times the third highest ranked (Gavroche). That said, Gavroche and Valjean have a reasonably similar amount of representation in the dataset. The decay (from first to second, etc.) is less stark in the other datasets.

Performance Evaluation:

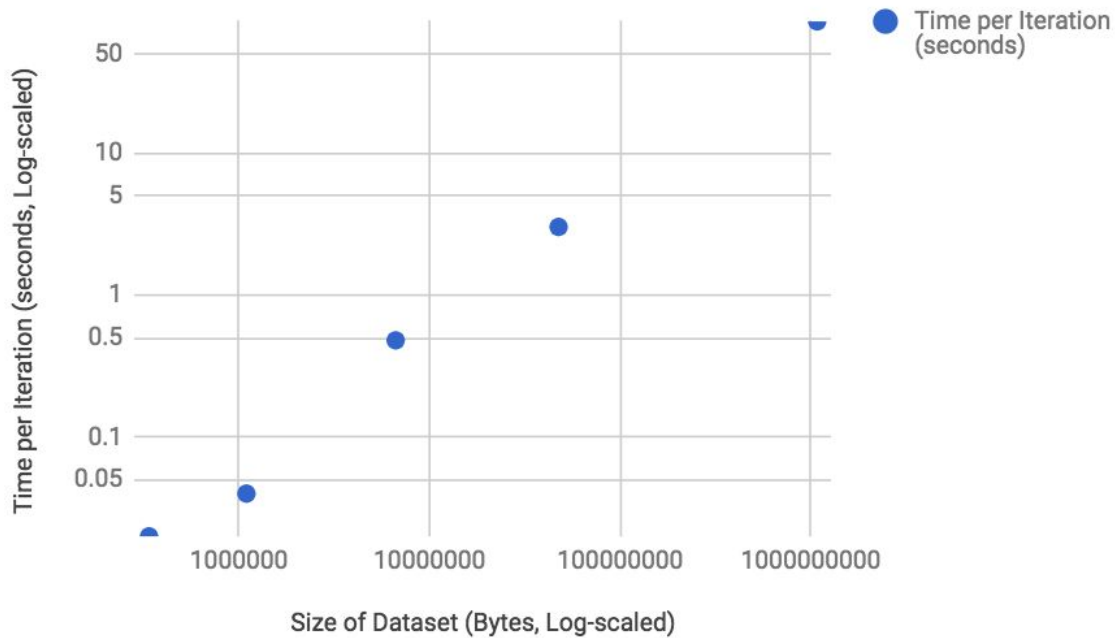
Name of Dataset	Size of Dataset (byte)	Time to Build Graph (seconds)	Time per Iteration (seconds)
Wiki	1095061	0.3	0.04
P2P	337597	0.1	0.02
Slashdot	6640838	1.71	0.48
Amazon	47532684	12.31	3.02
LiveJournal	1080598042	261.32	84.6

Log-log Plots:

Size of Dataset and Time to Build Graph



Size of Dataset and Time per Iteration



The Log-log plots suggest that the relationships `size:time_to_build_graph` and `size:time_per_iteration` scale according to a monomial. We found that the bytes of the datafiles act as a good proxy to the size of the graphs because the algorithms to both construct a graph and run PageRank iteratively scale monomially with the size of the input.

Appendix:

README:

`pageRank.py`

usage: `pageRank.py [-h] -f FILENAME -o OUTPUT`

`-f`: path to data file (`.csv` for small datasets, `.txt` for snap datasets)

`-o`: path to output file

Imports:

`argparse`

`csv`

`numpy`

`time`