**Reconstructing collapsed complex network to find most influential nodes**

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Solution of Datacastle Master Competition

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**Abstract**

This solution paper is to demonstrate the solution of algorithm in identifying vital nodes in complex networks for Datacastle Master Competition . Compared with traditional algorithms including Betweenness[bet], Closeness[clo], Degree[ciheap], PageRank[page] and Collective Influence[ci] [ciheap], the new proposed algorithm of reconstructing collapsed complex network to find most influential nodes is able to achieve the better performance on the 8 competition datasets in terms of robustness[rb] and speed. The new implementation by c++ of the popular algorithm Collective Influence (CI) is introduced as well. All code in the paper can be found at the link <https://github.com/zhfkt/ComplexCi> [doicomp]

**Competition background[match]**

Disparate networks, including social networks, communication networks and biological networks, are playing an increasingly important role on natural and social-economic systems. A core problem, therein, is to measure the significance of individual nodes. For instance, a super spreader in HongKong triggered transmission of SARS to a significantly greater number of other people than 100 normal infected persons; a rumor re-tweeted by a celebrity may spread much broader than that by an obscure person.

Therefore it is necessary to develop a method to identify the virulence genes in large-scale gene regulatory networks, to find the super-spreaders in large-scale social networks, and to detect the key enterprises with serious systematic financial risk in large-scale financial networks.

Those tasks could be formalized as a generic challenge that is identifying vital nodes in networks that are important for sustaining connectivity. This challenge, aka optimal percolation, is a well-documented issue in network science. With great anticipation of making big progress on this problem, we successfully invited some experts and hope the great participants will create novel and effective solutions.

The competition provides 4 real networks from different fields, including autonomous system network, Internet network, road network and social network, and 4 classical artificial networks as well (total 8 datasets). The numbers of nodes of these networks range from 0.7 million to 2 million. All of them are considered as undirected networks. <TABLE 0> shows the network name and corresponding numbers of nodes

<TABLE 0>

**Introduction**

Overall, the target of finding most influential nodes algorithm is to give a ranking list of nodes according to their importance. The top-ranked nodes will have more importance. We can remove the nodes from the top-ranked ones in the ranking list generated by algorithm and calculate the size of giant component after each removal, which will break down the network into many disconnected pieces. The ratio of giant component will reach zero with the one-by-one removal operation finally. Therefore, the better algorithm, the sooner the network will collapse to the zero giant component with smaller count of provided nodes. Robustness[rb] is introduced in the Competition to quantify the performance of ranking nodes methods.

There are several traditional algorithms such as Betweenness[bet], Closeness[clo], Degree[ciheap], PageRank[page] and Collective Influence[ciheap] for the target. In this paper, the new algorithm is proposed for reconstructing collapsed complex network in order to find most influential nodes. Compared with the traditional algorithms, the new method is able to achieve the better performance in terms of robustness and speed.

This solution paper will be organized as follows. First, several traditional algorithms will be used to investigate the performance of 8 competition datasets as comparative algorithms. Next, the new reconstructing algorithm will be introduced and verified on datesets in performance. The verification will also include the process of searching parameters for the best result. Lastly, the conclusion will be given. All code in this paper can be found at the link <https://github.com/zhfkt/ComplexCi> [doicomp]

**Experiments on the current algorithms**

In this section, tradition algorithms of Betweenness[bet], Closeness[clo], Degree[ciheap], PageRank[page] and Collective Influence[ciheap] will be verified on 8 Datacastle datasets .

**Betweenness**

Betweenness is a centrality measure of a vertex within a graph . Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes[wikibet][bet] . Here Betweenness is used to find the most influential nodes in the complex networks. Robustness value after applying Betweenness on 8 competition datasets is shown in the <TABLE 1>

<TABLE 1>

8 datasets are all verified in parallel supported by GraphTools [gt] on the 4-core CPU machine (Intel Xeon E5-2667v4 Broadwell 3.2 GHz).

Although Betweenness algorithm is supported to be executed in utilizing all CPU cores in parallel by GraphTools [gt] to boost , it is still obvious that Betweenness spends nearly 24 days/ 1 month in completing the verification of 8 datasets. Considered the time and effort , robustness value of Betweenness is not very well. Betweenness fails to process the networks of million scale to find most influential nodes.

**Closeness**

In a connected graph, the Closeness centrality of a node is the average length of the shortest path between the node and all other nodes in the graph. Thus the more central a node is, the closer it is to all other nodes [wikiclo][clo] . Here Closeness is also used to find the most influential nodes in the complex networks. Robustness value after applying Closeness on 8 competition datasets is shown in the <TABLE 2>

<TABLE 2>

8 datasets are all verified in parallel supported by GraphTools [gt] on the <Tencent>. Pls notice that CPU cores in verifying Closeness are 8 cores, double than above CPU cores of machine verifying Betweenness

Similar with Betweenness , although Closeness algorithm is supported to be executed in utilizing all CPU cores in parallel by GraphTools [gt] to boost , it is still obvious that Closeness spends nearly 7 days/ 1 week in completing the verification of 8 datasets. Considered the time and effort , robustness value of Closeness is also not very well. Closeness fails to process the networks of million scale to find most influential nodes as Betweenness .

**PageRank**

PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites [wikipage][page]. Here PageRank is also used to find the most influential nodes in the complex networks. Robustness value after applying PageRank on 8 competition datasets is shown in the <TABLE 3>

<TABLE 3>

8 datasets are all verified in single thread supported by GraphTools [gt] on the CPU (Intel Xeon E5-2667v4 Broadwell 3.2 GHz).

Compared with Betweenness and Closeness , algorithm PageRank gets much better result in robustness and speed. Especially , PageRank just run in single thread and uses less resources than Betweenness and Closeness. Robustness value of PageRank is 1.436 and also better than Betweenness and Closeness

**Degree**

Historically first and conceptually simplest is degree centrality, which is defined as the number of links incident upon a node . i.e. the number of ties that a node has.[degreewiki]. The nodes are ranked by degree, and sequentially removed starting from the node of highest degree. The concept of High Degree Adaptive (HDA) is purposed in the [ci] as a better strategy which is a slightly different from the original Degree algorithm. Degree of the remaining nodes in the adaptive version will be recomputed after each node removal. HDA is used here to find the most influential nodes in the complex networks. Robustness value after applying HDA on 8 competition datasets is shown in the <TABLE 4>

<TABLE 4>

8 datasets are all verified in concurrent on the 4-core CPU machine (Intel Xeon E5-2667v4 Broadwell 3.2 GHz). The time doesn't cover IO read/write from/to disk. Betweenness and Closeness are using multiple CPU cores for one dataset in parallel . However , experiments of HDA including below Collective Influence are using one CPU per each dataset and just start at the same time in concurrent.

We can see that the simple greedy algorithm of HDA performs well and effectively in getting million-scale networks using less than 30 seconds.

**Collective Influence**

The problem of finding the minimal set of influencers can be mapped to optimal percolation. Collective Influence (CI) algorithm using optimal percolation for localizing the minimal number of influential nodes is introduced in [ci][ciheap]. As mentioned in [lv], Collective Influence takes effectively for detecting most influential nodes guaranteeing the global connection of the network in terms of Robustness. Collective Influence is also the method of optimal percolation mainly suggested by the official challenge tips.

Collective Influence accepts “ball radius” as its input parameters. The higher radius, the better result but more time and effort will be spent. Especially, if radius is set to zero, the Collective Influence will degenerate to HDA algorithm described above.

In [ci][ciheap], they also develop the reinsertion step, which is the post-process and refinement of CI algorithm. After the networks break down into many pieces through removing nodes using Collective Influence , reinsertion process will be called in the following steps from the original paper[ciheap]

“Reinsertion adds back one of the removed nodes, which is chosen such that, if once reinserted, it joins the smallest number of clusters. Reinsertion algorithm does not require that the reinserted node joins the clusters of smallest sizes, but only the minimum number of clusters, independently from their sizes. When the node is reinserted reinsertion also restores the edges with its neighbors which are in the network (but not the ones with neighbors not yet reinserted, if any). The procedure is repeated until all the nodes are back in the network. When implementing the reinsertion, Reinsertion add back a finite fraction of nodes at each step. In their simulations they reinserted 0.2% of nodes at each step and a fraction smaller than 0.2% does not change the results.”

In order to get the Collective Influence on competition dataset results, I use 2 implements of the algorithm. One is provided by the original paper written in c language [ccode\_ci]. The other is written in c++ implementation myself [doicomp]. Radius of 0,1,2 as input parameters is used to verify the performance on 8 competition datasets both for my c++ implementation and original c code. I am also curious about what roles reinsertion plays in the overall performance, so I get the result in 2 cases when disabling and enabling reinsertion . Here are the results without reinsertion

<TABLE 5>

<TABLE 6>

<TABLE 7>

<TABLE 8>

<TABLE 9>

<TABLE 10>

Here are the results with reinsertion

<TABLE 11>

<TABLE 12>

<TABLE 13>

<TABLE 14>

<TABLE 15>

<TABLE 16>

8 datasets are all verified in concurrent on the 4-core CPU machine (Intel Xeon E5-2667v4 Broadwell 3.2 GHz). The time doesn't cover IO read/write from/to disk. Pointsmin and pointsmin2 are also involved into the result to evaluate the performance as brief reference. Pointsmin means/ Pointsmin2 means