CentralityViz: Comprehending Node-Centrality in Large Networks

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Abstract

CentralityVis is a software tool designed for visualizing large graphs using two community-centric methods: *spiral visualization* and *linear visualization*. Both visualizations are highly scalable, capable of handling networks with hundreds of thousands of nodes and edges. The tool leverages community detection algorithms to group nodes into communities and then orders the nodes of community on centrality in descending order, arranging them in either a spiral or linear layout. CentralityVis provides clear insights into both node and community properties, facilitating the analysis of complex networks. Each visualization method has its strengths: *spiral visualization* is intuitive and resembles traditional node-link diagrams, while *linear visualization* facilitates easy comparison of communities and offers greater scalability in terms of the number of communities that can be represented. To minimize visual clutter, edges are drawn only when needed, ensuring that even large graphs remain clear and comprehensible. CentralityVis is a powerful tool for understanding complex networks, emphasizing both individual nodes and the communities to which they belong.

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Supplementary Material
Software (Source code): https://github.com/Garima17/SpiralVisualization
archived at swh:1:dir:0727514f98092fcf77f85c7326cc28d1e17882a9
Software (source code): https://github.com/Garima17/Linear-visualization/
archived at swh:1:dir:0887f83f27e634a2cac344236f467c98ebb16283

1 Introduction

CentralityVis is a powerful community-centric network visualization tool specifically designed for undirected, unweighted, and static networks. It has three primary goals: (I) drawing large networks in a compact and intuitive format, (II) visualizing node centrality within network communities, and (III) visualizing both node and community properties.

CentralityVis helps users comprehend large networks through two interactive visual solutions: (I) Spiral Visualization, published in VIS 2023 [5], can represent networks with up to 10,000 nodes, and (II) Linear Visualization, capable of visualizing up to 50,000 nodes. The tool offers flexibility in selecting the centrality measure, which determines the ordering of nodes within each community in descending order. In Spiral Visualization, these ordered nodes are arranged in a spiral layout, with higher centrality nodes positioned closer to the center, effectively highlighting node rankings within the community. Linear Visualization, on the other hand, organizes nodes in a wrap-around linear format with uniform spacing between nodes, facilitating comparisons of node centrality. Additionally, the Linear Visualization aids users in identifying important communities by ranking and arranging them sequentially based on user-selected attributes such as size (number of nodes in a community), edge density (ratio of intra-community connections to total possible connections), or inter-community connections (number of connections to other communities).

The source code for the Spiral visualization and Linear Visualization is available at `https://github.com/Garima17/SpiralVisualization` and `https://github.com/Garima17/Linear-visualization/`.

2 Key Features

Both spiral visualization and linear visualization makes it easier to identify, interpret, and comprehend different network properties, such as (1) identifying the *number of communities* within the network, (2) visualizing and comparing the *sizes* of different communities, (3) visualizing and comparing the *edge-density of communities* (i.e., the ratio of actual links within a community to the total number of possible links), (4) identifying important or *central nodes* [1, 6] within communities, (5) understanding *centrality distribution* within communities, (6) comprehending *connections between communities*, and (7) comprehending *node connections*. The following two videos briefly demonstrate Spiral Visualization `https://youtu.be/cvLdXAThIXY` and Linear Visualization `https://youtu.be/ROmKgpJF3Kw`.

Interactive Elements. CentralityViz supports zooming, panning, and tooltips for detailed exploration, as well as an interlinked view to support the comprehension of different features. Users can filter data for selective exploration. The "*Find Node*" option allows users to search for a node in the visualization based on node ID. Users can also select different centrality measures (i.e., degree [6], closeness [8], betweenness [2], or eigen centrality [10]) based on which they want to visualize the data. The CentralityViz dashboard also provide the option to rank communities based on size, edge-density and number of community connections (as demonstrated in `https://youtu.be/ROmKgpJF3Kw`).

3 Applications

Visualizing large networks [15] is challenging due to visual clutter. In large networks, communities [3] emerge as subsets of nodes that are more connected within themselves compared to the rest of the network. Community detection and analysis of central nodes [6, 2, 10, 8, 1] in communities has diverse applications across multiple fields. In *criminology* [9, 14, 12], it is used to identify criminal or terrorist groups, understand their networks, and identify key players or masterminds behind an attack. In *epidemiology* [11, 4, 13], community analysis can facilitate tracking the spread of diseases, while node centrality analysis within a community can help identify key individuals who may contribute to widespread transmission. In *smart advertising and targeted marketing* [7], identifying influential communities and key individuals can optimize the impact of marketing campaigns. Therefore, detecting and analyzing communities and central nodes is a crucial problem in data science. To the best of our knowledge, no other graph drawing technique effectively visualizes node centrality within communities in large networks [5].

Our software provides substantial value to the graph drawing community by introducing an innovative approach to visualizing and analyzing large networks. Both, spiral and linear visualization are intuitive and can be mastered by users in just 15-20 minutes of training. Our tool provides insights into both *community and node-centric* properties. It provides a global network overview while allowing users to explore specific details. It enables comprehensive interpretations of node centrality, connectivity patterns within and between communities, and supports informed decision-making based on these insights.

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