Improving Graph Drawing Readability by Incorporating Readability Metrics: A Software Tool for Network Analysts

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ABSTRACT

Designing graph drawings that effectively communicate the underlying network is challenging as for every network there are many potential unintelligible or even misleading drawings. Automated graph layout algorithms have helped, but frequently generate ineffective drawings. In order to build awareness of effective graph drawing strategies, we detail *readability metrics* on a [0,1] continuous scale for *node occlusion*, *edge crossing*, *edge crossing angle*, and *edge tunneling* and summarize many more. Additionally, we define new *node & edge readability metrics* to provide more localized identification of where improvement is needed. These are implemented in SocialAction, a tool for social network analysis, in order to direct users towards poor areas of the drawing and provide real-time readability metric feedback as users manipulate it. These contributions are aimed at heightening the awareness of network analysts that the images they share or publish could be of higher quality, so that readers could extract relevant information.

Keywords: Readability metrics, aesthetic, graph drawing, social network analysis, information visualization.

1 INTRODUCTION

Graphs have long been common data structures in Computer Science, but have only recently exploded into popular culture with publishers like the New York Times now frequently including elaborate and interesting graphs with their articles. Online communities like Facebook, MySpace, Twitter, Flickr, mailing lists, and Usenet (to name only a handful) enjoyed enormous growth over the last few years and provide incredibly rich datasets of interpersonal relationships, which social scientists are now fervently exploring. Conventional visualization tools like bar and pie charts are often inadequate when faced with these varied and oftentimes immense datasets. www.visualcomplexity.com provides many beautiful alternative visualizations for these data, but one enduring visualization in particular models relationships using a node-edge diagram, where nodes in the graph represent actors in a community and the edges indicate relationships between individual actors [7]. This graph is called a *social network* and the resulting graph drawing is called a *sociogram* [34].

Sociograms have only recently been established as tools for network analysis, but have already been put to great effect. [13, 54] successfully used sociograms to detect common social roles in online discussion newsgroups such as answer person and discussion person, and [1] applied sociograms to the study of relationships between political blogs during the 2004 U.S. Presidential Election, showing the division between liberal and conservative communities as well as their internal interactions.

There is a huge array of possible sociograms for any given social network, many of which can be misleading or incomprehensible. Drawings of relational structures like social networks are only useful to the degree they "effectively convey information to the people that use them" [6]. What's more, there is no "best" layout for a social network as different layouts can highlight different features of the network being studied [7]. In fact, the spatial layout of nodes in the sociogram can have a profound impact on the detection of communities in the network and the perceived importance of individual actors [32]. Hence, significant thought must be given to properly drawing graphs so that network analysts will be able to understand and effectively communicate data like clusters in the network, the bridges between them, and the importance of individual actors.

As manual layout of nodes in the sociogram is incredibly time consuming to do well, a lot of effort has been put into developing automated graph layout algorithms. There are many that can be used for sociograms, including variants of the spring embedder [11] such as the popular Fruchterman-Reingold force-directed algorithm [15] and more scalable gravitational N-Body approaches such as [2]. The results of applying these algorithms can vary greatly depending on the size and topology of the network, and the layouts they generate are dependent on the algorithm used. Each attempts to find an optimal layout of the graph, often according to a set of *readability metrics*, which are measures of how understandable the graph drawing is, such as the number of edge crossings or occluded nodes in the drawing. While optimizing readability metrics, or RMs, does not guarantee the resulting drawing is understandable, it has been shown to promote many common analysis tasks. Traditionally these RMs have been called aesthetic criteria. We choose to call them readability metrics instead because of the ambiguity implied by the word "aesthetic". We are not concerned as much with how visually pleasing a particular graph drawing is; instead we are interested in how well it communicates the underlying data. However, many graph drawing algorithms create visually appealing visualizations, and some of the most informative visualizations are also the most beautiful.

Although each automated graph layout algorithm attempts to produce an understandable graph, the particular RMs it optimizes intentionally or indirectly may not be the correct ones for what the users are trying to demonstrate. Additionally, as the optimization of many RMs is NP-hard [6], these techniques often produce suboptimal graph drawings. The International Symposium on Graph Drawing has met annually for 16 years working to improve automated graph layout algorithms and RMs, among other things, but we believe that state of the art automated layout algorithms alone are insufficient to consistently produce understandable graph drawings.

Instead of focusing on a purely automated graph layout, we propose raising user awareness of the importance of RMs for their graph drawings and providing users with computer-assisted layout manipulation tools. Taking up where the automated layout leaves off, these tools would give users real-time feedback as to how their movement of nodes affect the RMs and potentially even provide local placement suggestions for the RMs users wish to optimize. This functionality could take a form similar to the "snap-to-grid" feature of many modern graphics applications, optionally pulling the dragged nodes to local maxima. We believe that this approach will provide users, and network analysts in particular, tools and guidelines that will allow them to create more understandable graph drawings that more accurately highlight features like communities within social networks.

We do not yet have a complete set of requirements for highly readable graph drawings, but we believe that many currently published graphs could be substantially improved with a few modest refinements. While no set of requirements can fully capture all effective graph drawings, we believe that applying RMs will improve most graph authors' output. A simple interim set of guidelines for editors and network analysts might be to aspire to these four principles that we playfully call *NetViz Nirvana*:

1. Every node is visible
2. For every node you can count its degree
3. For every edge you can follow it from source to destination
4. Clusters and outliers are identifiable

This name NetViz Nirvana is meant to be in harmony with and complement the widely cited principles in the Information-Visualization Mantra: overview first, zoom and filter, then details-on-demand [46]. These principles will need refinement to deal with large graphs where node aggregation, edge bundles, and cluster markers may be necessary to allow users to make scalable comparisons.

The remainder of this paper delves into the creation of RMs for graph drawings and a software tool for network analysts that incorporate the idea of communication-minded visualization: "visualization designed to support communication and collaborative analysis" [51]. Four RMs are outlined in detail in §2, along with an overview of additional ones. We then in §3 describe the integration of our RM framework into *SocialAction*, a tool that allows ranking by the attributes of nodes and edges and provides multiple coordinated views to help users systematically explore various statistical measures for social network analysis [36, 38, 37]. We leave the implementation of the "snap-to-grid" feature as future work (§4).

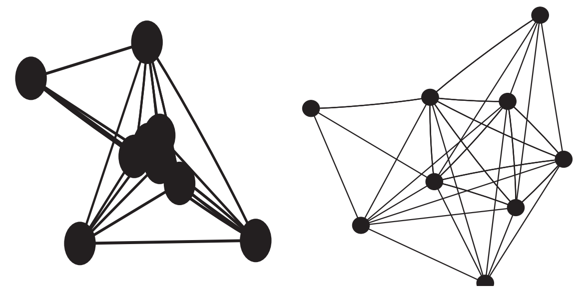
2 Readability Metrics

There is a substantial body of work aimed at developing and, more recently, empirically verifying the correctness of a wide variety of RMs. Excellent overviews of RMs for general graphs can be found in [48, 6, 52, 5, 4], and RMs specific for trees and UML diagrams are in [55] and [12], respectively. The first standard and numerical definitions of many specific RMs were given in [45] and were elaborated on by [41], which presents seven specific RM formulae. These will form the basis for many of our RMs.

Previous work in this area primarily deals with RMs for the entire graph drawing, giving, for example, a count of the total number of edge crossings. We will call such RMs *global readability metrics*, or global RMs. These serve as excellent measures for how understandable the whole graph drawing is, but do not provide the level of specificity we need to direct users to problem areas. Moreover, the computational requirements of some global RMs limit their usefulness for providing real-time feedback.

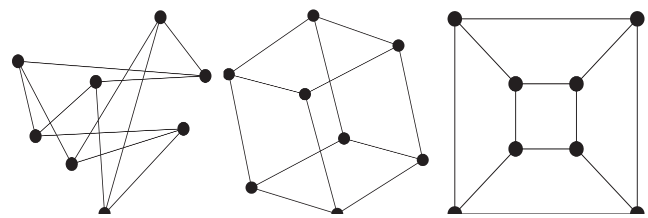
Additionally, we would like to integrate our RM framework into SocialAction's attribute ranking system, so users can intuitively move between rankings of statistical measures and those for RMs (§3). To do so, we can provide additional attributes for both nodes and edges in the network that describe how these individual components affect the global understanding. We will call these *node readability metrics* and *edge readability metrics*, or node RMs and edge RMs for short. This is an extension of the idea of individual node and edge metrics espoused in [16]. Defining RMs for individual clusters or regions would also be helpful, especially for examining large graphs, but we leave this as future work.

As per [41], each of our RMs are scaled appropriately to a continuous scale from [0,1] where 1 indicates the positive maximum of the RM. This allows us to assign graph readability requirements to particular drawings based on the content and information we want the impart. For example, a journal may recommend 0% node occlusion, <2% edge tunneling, and <5% edge crossing to publish a sociogram, while having different suggestions for UML diagrams or other kinds of graphs. However, there are many useful graph drawings that violate these limits and they shouldn't be eliminated



(a) Tight layout (b) Relaxed layout

Figure 1: We can eliminate the node occlusion that makes the center cluster in 1a so hard to understand by zooming out and reducing the the spring lengths of our layout algorithm 1b.



(a) Random layout (b) After reducing edge crossings (c) After eliminating edge crossings

Figure 2: Different drawings of the same graph with high (2a), medium (2b), and low (2c) edge crossings.

based solely on the RMs.

§2.1-§2.4 describe the RMs we will look at in depth: *node occlusion*, *edge crossing*, *edge crossing angle*, and *edge tunneling*. §2.5 provides a brief overview of additional RMs.

2.1 Node Occlusion

Euclid defined a point as that which has no part. Historically, abstract graph layout algorithms were designed around this principle, with nodes taking up little or no space [55, 33, 30]. Practical applications of graph layouts like sociograms or UML diagrams however represent nodes using text, shapes and colors, pictures, and size (§2.5). Classical algorithms can thus frequently result in nodes occluding one another. This *node occlusion* (also called overlapping or overplotting) is contrary to accepted graph readability guidelines [48], including those for trees [55] and UML diagrams [12]. Moreover, areas of the drawing with high occlusion make it very difficult for the viewer to get an accurate count of the number of individual nodes in a cluster to get a sense of its scale.

Misue et al. [33] first addressed this issue using the Force-Scan algorithm to adjust cluttered graph layouts. Additionally, many variants of the spring embedder [11] include a node-node repulsion force that often reduces node occlusion.

Node occlusion has largely been ignored in the recent literature and there is little direction given to tool designers or end users to reduce it. Even widely used graph drawing tools such as Pajek [3], a common social network analysis tool for sociologists, fail to properly reduce occlusion. In a recent user study [25] the authors had to hand tune the diagrams produced by Pajek to avoid occlusion. Fig. 1 shows how node occlusion can be eliminated by zooming out and increasing default spring lengths, at the cost of decreasing implied clustering.

Node Occlusion Readability Metrics: We are not aware of any suitable existing readability metrics for node occlusion. We suggest a global RM proportional to the number of uniquely distinguishable items in the graph drawing, where an item can be either a node or a connected mass of overlapping nodes. On a continuous scale from 0 to 1, 1 indicates that every node is uniquely distinguishable from its neighbors (possibly including a spacing requirement) and 0 indicates that all nodes in the graph drawing are overlapping, creating one large connected mass. Similarly, a node RM can be proportional to the ratio of the node's representation area (possibly including a spacing requirement) that is obscured by other nodes. Naturally there is no edge RM for node occlusion, however node occlusion is usually grouped in the literature with edge tunneling (§2.4), which provides additional RMs.

2.2 Edge Crossing

The number of *edge crossings* or intersections is the most widely accepted RM in the literature. In 1953, Moreno [34] wrote, "The fewer the number of lines crossing, the better the sociogram." Edge crossings is listed as an important general RM in many books on graph drawing, including [6, 48, 52], as well as for automated UML diagram layout [12]. Substantial work has been done in the design of graph drawing algorithms that reduce the number of edge crossings [49, 10, 15, 8, 9, 35].

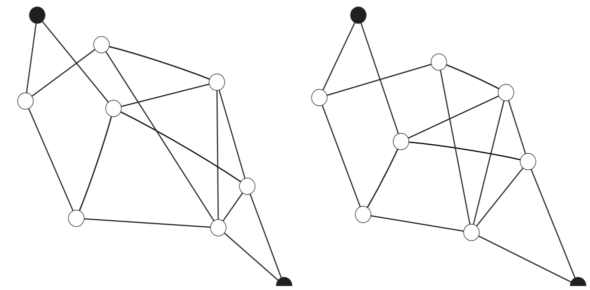
Purchase's seminal RM comparison user study identified edge crossings as having the greatest impact on human understanding of general graphs of the five RMs she studied [39]. This finding has been empirically validated in [44, 40, 43]. These studies focus on edge tracing tasks like finding the length of the shortest path between two nodes, though use a global count of the number of edge crossings. [53] suggests the number of edge crossings along the relevant edges is more important than a global measure. Additional evidence for the importance of edge crossing comes from [29], which deals with visualizing ordered sets. Moreover, user preference studies identify minimizing edge crossings as the most important RM for UML diagrams [42, 43] as well as for sociograms [23], and when given the option of improving on an initial force-directed or random layout, users created graph drawings with 60% fewer edge crossings on average [50]. [29] theorizes that crossed lines could be salient properties which distract the user's visual system from the relationships the drawing was designed to convey.

However, [35] suggests that allowing some edge crossings can sometimes result in more readable graph drawings and recent literature points to restricting edge crossing angles being almost as effective as reducing edge crossings (§2.3). Furthermore, recent research on sociograms comparing edge tracing tasks like finding groups to node importance tasks indicates that while reducing edge crossings improves edge tracing task performance and user preference, it has little effect on node importance tasks [24, 22, 26]. This was further verified in eye tracking studies [17, 19, 21]. They postulate that this indicates the effects of edge crossings can vary depending on the situation. Further discussion of the cognitive load imposed by edge crossings quantified using eye tracking is in [28, 25, 18, 21]. Fig. 2 demonstrates how reducing edge crossings can lead to a much more understandable drawing.

Edge Crossing Readability Metrics: [41] defines a global RM based on the number of edge crossings in the graph drawing scaled against an approximation of the upper bound of the number of possible crossings on a continuous scale from 0 to 1. We define a similar node RM, counting only edges directly connected to that node and scaling by a similar upper bound. Likewise, we specify an edge RM that scales the number of crossings along that edge appropriately.

2.3 Edge Crossing Angle

The impact of *edge crossing angles* was first introduced as a global RM by [53], which is based on a neurophysiological view of the user. Ware et al. claim rapid early-stage neural processing causes certain features to "pop out" to users, and that these neurons are coarsely tuned when examining angles, roughly between +/- 30 degrees. Though they did not find the impact of edge crossing angles to be significant, they did find that another angular measure, path continuity (§2.5), was. This neurophysiological view supplies an explanation for the results of [20, 17, 19, 18, 27], which use an eye tracking user study to verify that the angle of edge crossings has a significant impact on user response time for edge tracing tasks. Moreover, response time significantly decreased as the crossing angle tended towards 90%, though tended to level off or even slightly increase beyond 70%. This is attibuted to extra back-and-forth eye movements around accute crossings. However, as the size of the graph increases creating longer searching paths, the impact of even near-perpendicular crossings can build up and become significant [19]. See Fig. 3 for a demonstration of how more perpendicular edge crossing angles promote path finding tasks.



(a) Original layout

(b) After making edge crossings more perpendicular

Figure 3: In edge tracing tasks such as finding the length of the shortest path between the bottom right and top left nodes in 3a, increasing the edge crossing angles approaching 90 degrees (3b) improves user path finding performance.

Edge Crossing Angle Readability Metrics: We believe the global RM for angular resolution (§2.5)can be modified to incorporate the average deviation of edge crossing angles from the ideal angle of $\tilde{7}0$ degrees instead. [53] uses the average cosine crossing angle as their global RM metric, and our planned experiments with these metrics may suggest that modification as well. The associated edge RM follows simply by removing the sum over all nodes and the relevant scaling. The node RM is somewhat harder to define, though it can be based on the combining the edge RMs for the node's connected edges.

2.4 Edge Tunnel

There is little literature dealing with nodes occluding edges and vice versa, and it is often lumped together with node occlusion (§2.1). Because of the limited definitions available for this RM, we will call the specific case of a node occluding an edge an *edge tunnel*. The reverse can be called an *edge bridge*, but as many modern graph drawing tools (e.g. SocialAction, NodeXL [47]) draw nodes with higher priority than edges we are ignoring this case.

Both cases are accounted for by the simulated annealing graph drawing algorithm from [9], which incorporates the distance between every node and edge in a fine-tuning step. [48] calls avoiding edge tunnels a basic rule, and for UML diagrams, [12] specifies that nodes should not be too close to edges unless they are connected or a more important RM forces their proximity. However, many algorithms do not take this into account, including [30] and the commonly used Fruchterman-Reingold algorithm [15]. Even tools using algorithms that remove edge tunnels are not guaranteed to do so. The excellent user study [53] used 200 generated graph

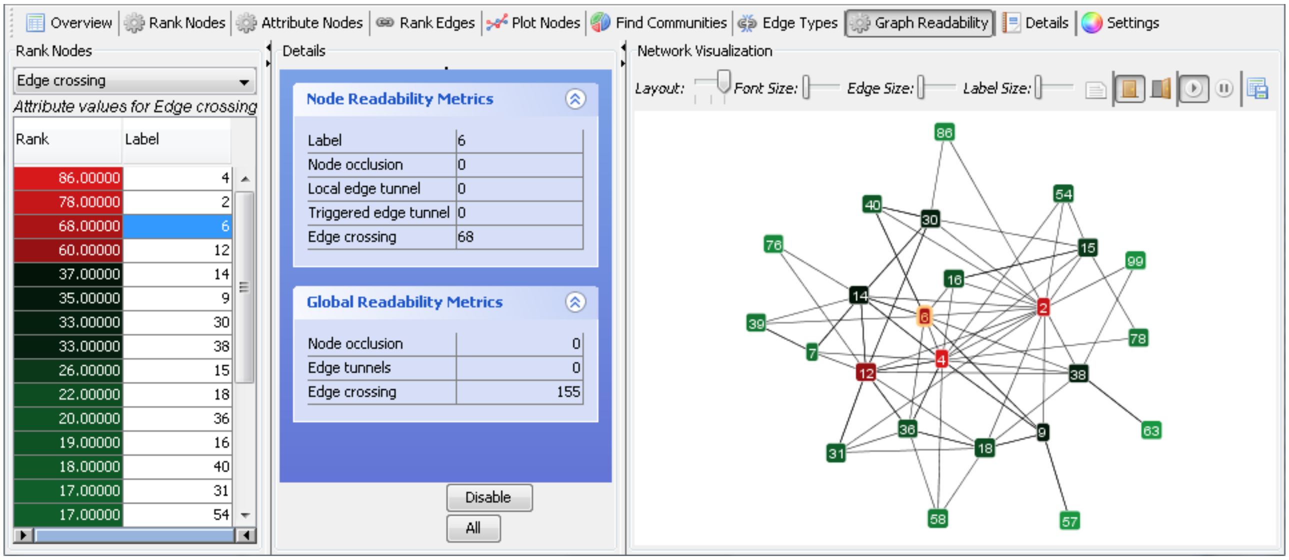
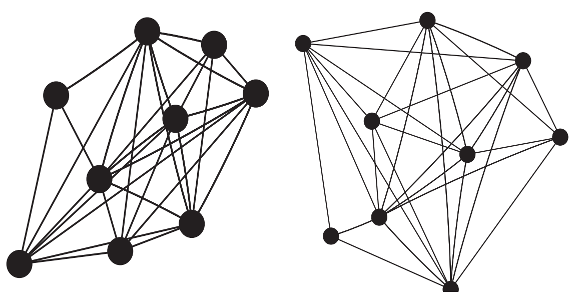


Figure 5: SocialAction with the integrated Graph Drawing Readability Metric framework rapidly shows problem areas in the graph drawing highlighted in red and listed in a ranked table. It is currently showing a subset of the reply relationships within the Alberta Politics discussion newsgroup, and the graph drawing has been optimized for the node occlusion and edge tunnel readability metrics. The steps in SocialAction's Systematic Yet Flexible framework are shown along the top. The Graph Readability panel (middle-left) shows node or edge readability metrics as well as global ones. The Rank Nodes panel at the far left ranks nodes by the edge crossing readability metric and provides the color scale for the Graph pane.



(a) Original layout (b) After removing edge tunnels

Figure 4: In 4a it is difficult to tell which edges connect to which nodes because of the number of edge tunnels. By zooming out and hand tuning the layout (4b) we can completely eliminate edge tunnels (but not crossings).

drawings with 42 nodes each, of which the results from 7 graph drawings had to be excluded from the final analysis because of unexpected edge tunnels that implied nonexistent connections. The standard users of graph drawing tools are more likely to overlook such problems than RM researchers. Fig. 4 shows how zooming out and hand tuning a layout to reduce edge tunnels allows for a much clearer picture of the network topology.

Edge Tunnel Readability Metrics: The global RM for edge tunnels can be built upon the global RM for edge crossings (§2.2), comparing the number of edge tunnels in the graph drawing to an appropriate upper bound. A simple edge RM is thus an appropriate scale of the number of edge tunnels that edge has. *Local edge tunnels* is defined as a node RM for the number of edges that tunnel under that node. An second node RM for *triggered edge tunnels*, the edge tunnels of all edges connected to that node, can be specified in terms of the combined edge RMs for those edges.

2.5 Additional Readability Metrics

There are many potential RMs that can be taken into account to produce effective graph drawings, and each impacts how understandable the final product is and how successfully it imparts the author's message. Many that we are investigating for standardization and inclusion in our framework are briefly discussed below.

Angular Resolution: The angular resolution RM refers to the minimum or average angle formed by all the edges incident to an individual node. [49] and [14] dealt with this early on, and [41] defines a minimum angle metric. [39] found it had no effect on path finding tasks, but this was found significant for recognizing actor status by [24].

Node Size: The size of nodes in the graph drawing can significantly affect node occlusion, edge tunneling, and the ability of users to see shapes and colors as well as read labels. We suggest outlining four size constraints depending on the amount of information to be displayed. Displaying the location of the node only requires representing a point, while adding properties like color and shape to indicate additional attributes requires more space to be identifiable. Nodes must be even larger yet in order to display meaningful text labels within the node, which are dealt with more in the following two RMs.

Node Label Distinctiveness: In many graph drawings node labels must be truncated to limit node occlusion and edge tunneling. As it is important to have uniquely identifiable and meaningful labels, users should attempt to remove common prefixes (e.g. "Department of" in an organization network). A RM for assessing the distinctiveness of individual labels in the drawing would draw attention to these problems, but must be flexible enough to accommodate unexpected prefixes. A potential solution might be found through the use of suffix trees.

Text Legibility: Similarly, the text must be sized and formatted appropriately so that it is readable in the final drawing. If this is not possible, the text should be removed to reduce node occlusion, edge tunneling, and the size of the graph. A common measure for this is the angle subtended by the text from the users point of view, though this may be difficult to translate into a RM.

Node Color & Shape Variance: As users have substantial difficulty interpreting a graph drawing using too many distinct shapes or colors to represent attributes, a RM should be defined that indicates the difficulty of keeping those combinations in memory. This might limit the publication of drawings with excessive shape and color coding.

Edge Bends: [10] stated that edges in a graph drawing should be as straight as possible. While the examples here deal with only straight-line drawings, edges with bends can be very useful for some types of graphs like UML diagrams. [41] defines a RM for edge bends, while [39] found that they have an impact on path finding tasks.

Path Continuity: How continuous a path is is inversely related to the number and size of its bends. [53] defines continuation at a node as "the angular deviation from a straight line of the two edges on the shortest path which emanate from the node." The sum of these deviations provides the basis for a path continuity RM. Their user study found path continuity to be significant for path finding tasks.

Geometric-path tendency: A path between two nodes in a graph drawing can "become harder to follow when many branches of the path go toward the target node" [19]. This is known as the geometric path tendency. Though a RM is not obvious, developing one may result in graph drawings better suited for edge tracing tasks.

Orthogonality: [41] defines a RM for orthogonality using measures for the extent nodes and edges in the graph drawing follow the points and lines of an imaginary Cartesian grid. Orthogonality is important for some kinds of drawings, especially those of UML class diagrams ([42]) and other hierarchical structures. However, it is unimportant and can even be misleading for sociograms, as by placing nodes along imaginary lines the sociogram implies to viewers that horizontally or vertically adjusted nodes are related [29]. Node and edge RMs for orthogonality would likely be of limited use.

Symmetry: [31] observed that a graph drawing is "good" when it displays as many symmetries as possible. This was verified by [39] and a RM for axial symmetry is provided by [41]. Like for orthogonality, node and edge RMs for symmetry are of limited value.

Spatial Layout & Grouping: The spatial layout of nodes in a graph drawing has a substantial impact on the ability of users to ascertain the importance of actors in the network as well as identifying groups or communities of them [32]. A RM for this might compare how effectively the visual grouping of nodes in the graph drawing conveys groupings found via a community algorithm that operates only on the structure of the graph.

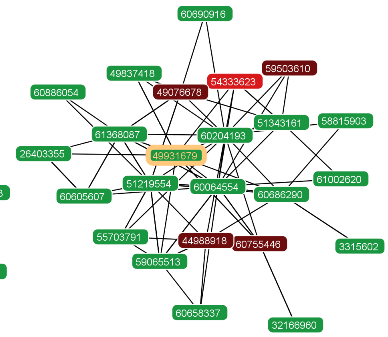
Edge Length: The most common algorithms for sociogram layout are the many variations of the spring embedder ([11]), which attempt to reduce the variance of intra-node distances in the graph drawing. However, [50] found that users prefer to space clusters of nodes proportional to number of connecting edges between them. This might lend credence to a RM that analyzes the strength of relationships between clusters and compares that to the actual visible separation, though optimizing the RM would be difficult when using spring or force based layout algorithms.

Path Branches: The number of edges branching from shortest paths within the graph drawing can also have an affect on path finding tasks [53]. A global RM might compute the number of branches along each shortest path in the graph drawing as a measure of the general difficulty of edge tracing tasks.

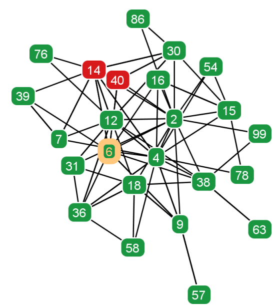
3 Implementation

We have implemented a prototype of the RM framework inside of *SocialAction*, a tool that uses attribute ranking and multiple coordinated views to help users systematically explore various statistical measures for social network analysis. In SocialAction, users can

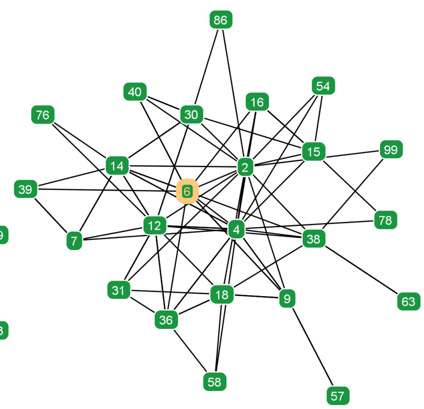
(a) Tight layout NO:14,ET:70,EC:180



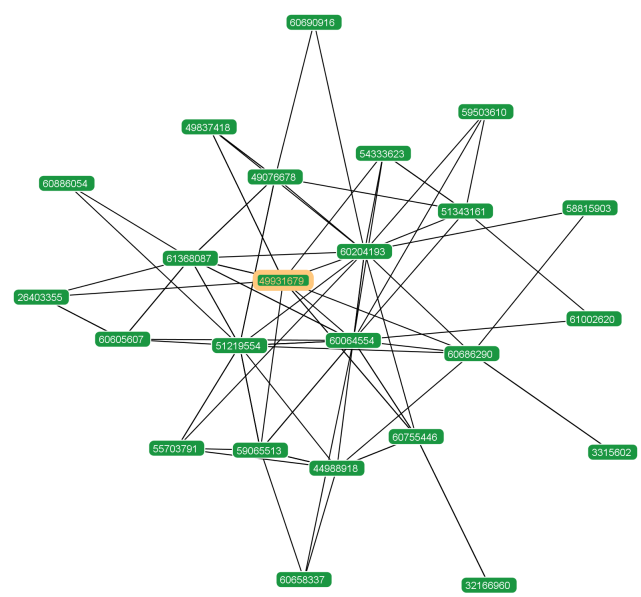
(b) Medium layout NO:4,ET:26,EC:159



(c) Concise tight layout NO:1,ET:25,EC:180

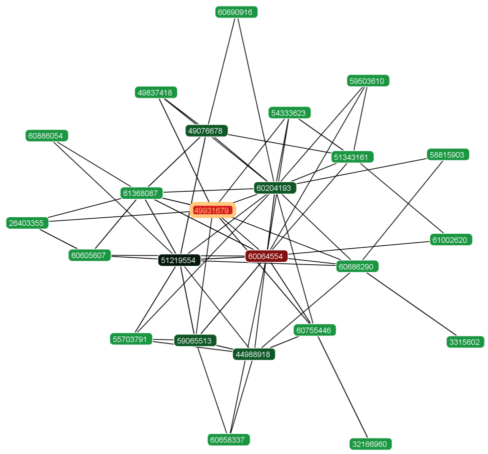


(d) Concise medium layout NO:0,ET:12,EC:159

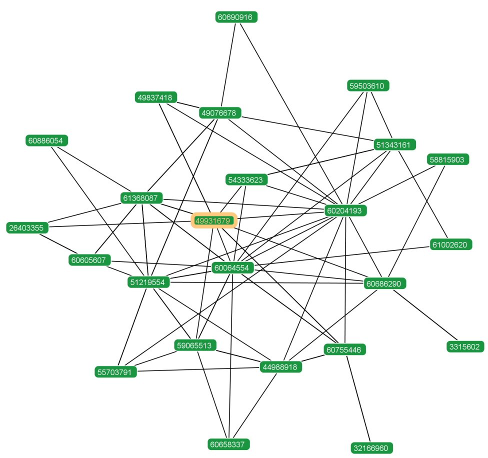


(e) Loose layout NO:0,ET:14,EC:157

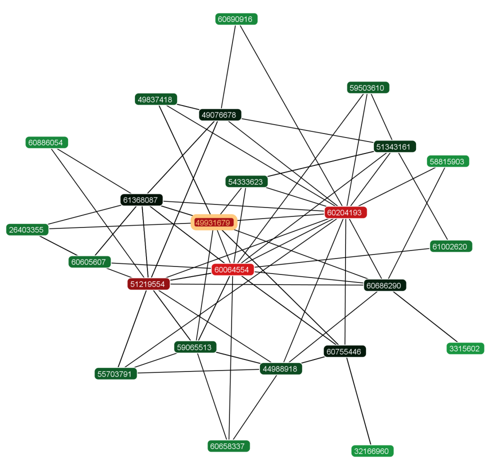
Figure 6: Ranking and coloring with the node occlusion node RM shows areas of high occlusion in red. To reduce occlusion we can relax the layout by increasing default spring lengths (Fig. 6a,6b,6e). Note that this is not the same as merely increasing the size of the drawing: the adjustment of the parameters of the layout algorithm results in a somewhat different layout as well. We can also use shorter unique, trimmed, or simplified labels (Fig. 6c & 6d), in addition to hand-tuning node position as a final step. Note that color scales may change between figures as the worst nodes become better. Metrics listed are node occlusion (NO), edge tunnels (ET), and edge crossings (EC).



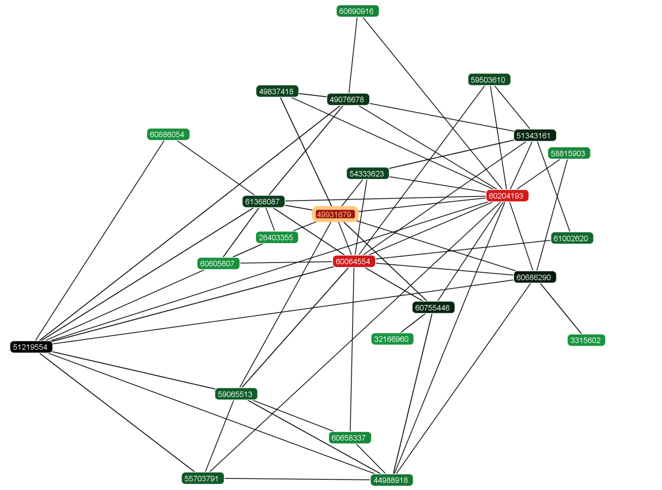
(a) Edge tunnel coloring NO:0,ET:14,EC:157



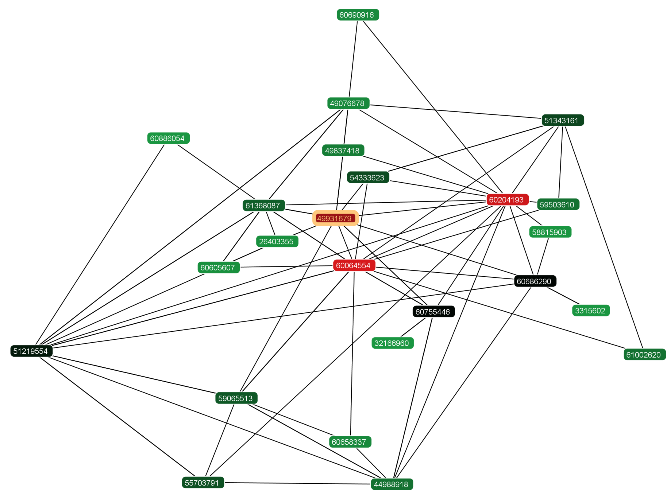
(b) Edge tunnels removed NO:0,ET:0,EC:155



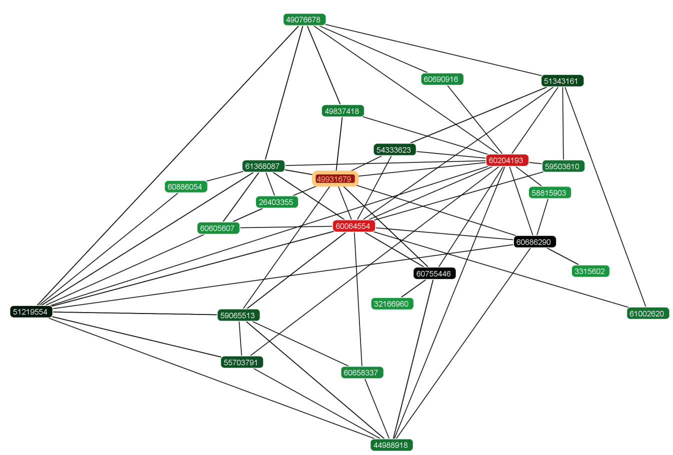
(c) Edge crossing NO:0,ET:0,EC:155



(d) Edge crossings removed (1/3) NO:0,ET:0,EC:114



(e) Edge crossings removed (2/3) NO:0,ET:0,EC:90



(f) Edge crossings removed (3/3) NO:0,ET:0,EC:85

Figure 7: Using the node RM for edge tunnels, users can see areas with edge tunnels in red and manually adjust the layout to remove them (Fig. 7a & 7b). Likewise, the node RM for edge crossings shows users areas with lots of crossings and lets them hand tune the layout to reduce them (Fig. 7d–7f). Fig. 2 gives a prime example for how minimizing edge crossings can greatly improve the readability of a drawing. Unfortunately, minimizing the number of edge crossings for less structured graphs often results in an asymmetric drawing like Fig. 7f in which the centrality and angular resolution of many nodes is reduced, decreasing their perceived importance. For larger, less structured graphs a balance must be struck between the number of edge crossings and the impact of further minimization on the spatial layout of the drawing. Note that color scales may change between figures as the worst nodes become better. Metrics listed are node occlusion (NO), edge tunnels (ET), and edge crossings (EC).

rank nodes and edges using ordered lists of the chosen attribute and simultaneously visually code the node-edge drawing using the ranking. Nodes remain in their original positions as users change the ranked attributes, which prevents the users from losing their mental map of the network. By combining multiple coordinated views with rapid transitions between statistical social network analysis measures and additional node and edge attribute rankings, SocialAction affords network analysts a quick understanding of the network properties. Extreme-valued nodes and edges are highlighted particularly effectively through the combination of ranked lists and visual coding.

We can leverage this attribute ranking system by incorporating the node and edge RMs we defined earlier into SocialAction as node and edge attributes. Like any statistical measure or additional attributes in the dataset, users can now rank nodes and edges based on their individual RMs, highlighting problem areas in the graph drawing. This allows them to rapidly flip between RM rankings and identify areas that would benefit from hand-tuning of the layout.

Users can then utilize the interactive features of SocialAction which allow them to drag nodes or groups of nodes to new positions, attempting to manually optimize the RMs. Node and edge RMs are computed in real-time for the nodes being dragged, and many global RMs can be selectively updated with these local computations to shortcut the computational complexity a complete recalculation requires. This allows users to see how their movement of nodes affects both global and node RMs simultaneously, both in a Graph Readability panel as well as real-time updating of the ranked list and color scale of the node-edge drawing. Moreover, users can switch between individual RMs and statistical measures while maintaining the same graph layout and preserving any hand tuning they've done.

Fig. 5 shows the SocialAction interface displaying a sociogram of reply relationships within a subset the Alberta Politics discussion newsgroup for which the node occlusion and edge tunnel readability metrics have been minimized. Across the top are the steps in SocialAction's Systematic Yet Flexible framework, which allows for a guided and all-encompassing while still flexible approach to social network analysis, along with the Attribute Nodes panel for categorical coloring and the Graph Readability panel (shown along the middle-left). The Graph Readability panel shows the node or edge readability metrics for the selected items, as well as global readability metrics. The Rank Nodes panel (far left) shows a ranking of nodes by the edge crossing readability metric in decreasing order, with a filtering slider at the bottom. The large Graph panel shows the node-edge drawing with color coding of nodes by their ranking in the Rank Nodes panel, with nodes having many edge crossings colored bright red. These are candidates for movement or resizing to reduce the number of edge crossings.

Underneath each figure are counts for node occlusions (NO), edge tunnels (ET), and edge crossings (EC). We use actual counts for individual RMs for clarity. Individual counts can usually be made available as tooltips or the like, but for the RMs to be useful they must be independent of the graph size, and are thus scaled to the continuous range from [0,1]. This requirement is made evident from the global count of 2954 edge crossings in the Alberta Politics dataset. Also note that figures which show a progression of graph drawings being optimized for a RM may have a changing color scale, as the worst nodes in the drawing become better.

Users can manipulate their drawings in order to minimize node occlusion using the node RM for it as a guide (Fig. 6). Coloring is scaled by the node RM, with bright red indicating areas of high occlusion. By relaxing the layout slider in SocialAction we can eliminate node occlusion entirely for this subset of the Alberta Politics dataset (Fig. 6a,6b,6e). This increases the default spring length used by the layout algorithm, allowing clusters of nodes to spread out and resulting in a larger drawing. Some graphs, especially dense ones, may require manual tweaking as well. Another way to minimize occlusion is to reduce the size of labels. One way is to move from a full label to a distinctive yet concise one (Fig. 6c & 6d). Other ways include minimizing text margins in the nodes or font size.

To reduce the number of edge tunnels in the drawing, users can rank and color by the node RM for local edge tunnels. Fig. 7a & 7b show a user removing edge tunnels by tuning node placement. This is easier for loosely connected nodes but can be difficult in dense areas. To reduce edge tunnels, we may have to increase the number of edge crossings. For manually tweaking the position of poorly connected nodes the local edge tunnel RM seems more useful. However, the triggered edge tunnel RM is better suited for moving highly connected nodes as it shows the effect a node has on its region of the drawing. As with node occlusion, one way of reducing edge tunnels is to shrink nodes. Similarly, Fig. 7d–7f show a user removing edge crossings using the node RM for it. This is often a harder RM to minimize, as it is not always obvious how moving a node will eventually affect the total count. The process often involves trial and error, as well as multiple passes through each region of the drawing. Moreover, most social networks are not planar graphs and can't be represented without edge crossings. One of the easiest approaches is to pull tightly connected nodes near the edge farther out as in Fig. 7e, so that less central nodes can be placed between its connected edges. This has the unfortunate effect of significantly worsening the angular resolution and spatial layout RMs, which can make the node seem less important or central than it is.

Improving individual RMs can be beneficial for other RMs as well, though often there are tradeoffs between them users may have to weigh. Which RMs should be improved thus depends on what users are trying to convey with their drawings. Thus, it is imperative that users of graph drawing software be made aware of which RMs their layout algorithms attempt to optimize and the effects various layout techniques have on how much of the underlying data is effectively conveyed.

4 Conclusions and Future Work

As social network analysis and graph drawing in general become more mainstream it is important to provide new entrants guidelines for effective graph drawing creation, as without them the graph drawings users produce can be unintelligible or even misleading. We advocate the creation of standardized readability metrics and the incorporation of these RMs into graph drawing tools so as to emphasize their importance in the graph drawing process to users. We discuss in depth four RMs: *node occlusion*, *edge crossing*, *edge crossing angle*, and *edge tunneling*, in addition to a brief overview of many more. We provide *global RMs* for the whole drawing, which are broken down into *node RMs* and *edge RMs* for the individual nodes and edges in the drawing. Defining RMs for individual clusters or regions would also be helpful, especially for examining large graphs, but we leave this as future work.

To aid users in their use of RMs, we have incorporated our Graph Drawing Readability Metric framework into SocialAction, a statistics and visualization tool for network analysts. SocialAction's attribute ranking system allows users to quickly and visually pinpoint problem areas in the graph drawing for each of the implemented RMs, and they now have the additional ability to drag nodes in the drawing and simultaneously see real-time feedback for each of the implemented RMs. These features will supplement real-time automated graph layout algorithms, providing a feedback loop between the algorithms and user manipulation. Future work on this tool might include providing a feature akin to the "snap-to-grid" tools of many graphics applications, which would optionally pull the dragged node to nearby local maxima of the RMs. Automated layout algorithms could also be developed that allow users to select which RMs they wish to optimize the graph drawing for and the priority for them based on their application, which could be used to redraw either the whole graph or particular subsections of it.

We have began the process of outlining and integrating RMs into tools for network analysts, but much remains to be done. We are approaching but have not yet achieved NetViz Nirvana. We hope that this work will heighten the awareness of network analysts that the images they share with others or publish in reports could be higher in readability, so that readers could extract relevant information. Moreover, we hope that network analysts might convey their desires to designers and implementers of software tools, so that they could integrate more effective algorithms and interfaces that give users better control over graph displays. Finally, we hope to trigger further research, both algorithmic and behavioral, to develop, refine, and validate graph display readability metrics.

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