Epistemic Network Analysis Visualization

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Abstract. Visualization plays an important role in Epistemic Network Analysis (ENA), not only in graphical representation but also to facilitate interpretation and communicate research findings. However, there is no published description of the design features behind ENA network graphs. This paper provides this description from a graphic design perspective, focusing on the design principles that make ENA network graphs aesthetically pleasing and intuitive to understand. By reviewing graphic design principles and examining other extant network visualizations, we show how the current ENA network graphs highlight the most important network characteristics and facilitate sense-making.

Keywords: Epistemic Network Analysis, Network Graphs, Data Visualization, Design Principles

1 Introduction

The purpose of this paper is to explain the *network graph* visualization of Epistemic Network Analysis (ENA) from a graphic design perspective. ENA is a network analysis technique for quantifying and visualizing the connections among coded data by modeling the co-occurrence of codes [19]. Such connections are represented as weighted networks that can be interpreted both statistically and visually. Since its inception, ENA has become a dominant analytical technique used in Quantitative Ethnography (QE) studies [12]. QE is a growing field unifying rigorous computational methods and grounded ethnographic techniques to facilitate thick description at scale [18].

ENA's success is not only attributable to its analytical affordances, but also the *statistically* meaningful and *visually* interpretable network visualizations it produces. In previous work, Bowman et al. [3] discussed how the alignment between ENA network visualization and its summary statistics is achieved from a mathematical perspective. In this paper, we explore *how* ENA network graph visualizations facilitate interpretation of network models and communication of analytic findings. Thus, the intended contribution of this work is to explicate the graphic design principles manifested in ENA visualizations and to explore how ENA network graph visualizations can be used as "tools for thinking" [17].

In what it follows, we center the discussion around three guiding questions: (1) What are the graphic design principles that inform the design of ENA network graph visualizations? (2) Why do ENA networks require custom visualizations rather than existing network visualization strategies? and (3) How were the aforementioned graphic design principles applied to design ENA network graph visualizations?

2 Theory: Graphic Design

2.1 Design Elements

Design elements, also known as *elements of design*, are the most fundamental graphic design units from which all visual artifacts are created [4, 16]. In the context of graphic design, the most commonly cited seven design elements include point, line, shape, color, texture, value, and space [4, 16]. Each type of design element can be described using various attributes. For example, lines can hold attributes such as being thick, thin, dashed, dotted, horizontal, vertical, and so on.

Design elements are usually used in combination to form complex items, or *artifacts*. For example, Node-Link diagrams, as shown in Fig. 1, are a type of network graph representing the relationships between objects: the objects are represented with points (nodes), and the relationships between objects are represented with lines (links) .

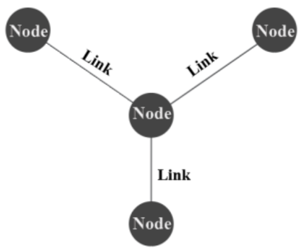

Fig. 1. A simplified representation of a Node-Link diagram.

To convey visual messages efficiently in the construction of artifacts, designers apply *design principles* to design elements in order to regulate the arrangement of and interaction among the elements [7]. Before we discuss the specifics of design principles, there are two fundamental attributes of the seven design elements that are often manipulated to apply various design principles, namely the *visual weight* and the *placement* of design elements.

Visual Weight of Design Elements. Every design element in a visualization exerts an attractive force that draws the eye of the viewer. The greater the force, the more the eye is drawn. This force is called *visual weight* [4]. For example, research shows that an object is visually heavy if it is dark or large [22, 23]. Therefore, the variance of visual weight is crucial in realizing effects of design principles that emphasize the creation of difference such as *contrast* and *visual hierarchy*, which are discussed in detail below.

Placement of Design Elements. While *visual weight* is usually applied to emphasize differences between individual elements, the *placement* of design elements is usually used to establish a visual connection among elements. For example, placement can be used to indicate relationships, such as similarity between objects. Research shows that viewers tend to interpret objects that are placed physically closer as being associated: the closer they are, the stronger the association is [4]. Placement can also be used to create flow by arranging elements with different visual weights in a certain pattern [4]. For example, when objects are placed in a way that larger or darker ones are in the foreground while smaller and lighter ones are in the background consistently, viewers tend to feel a sense of depth as larger and darker objects appear to be closer, even in a two-dimensional space. With such a sense of depth, even without explicit gestural signs such as arrows, a flow is present from near to far that guides viewers through the visualization along a particular path. These two major applications of placement manifest themselves respectively in two design principles called *proximity* and *perspective*, which are discussed in detail below.

2.2 Design Principles

Design principles are frameworks that define and regulate how design elements interact with one another, with their context, and with their viewers [7, 9]. Through the appropriate application of design principles, designers can optimize the arrangement of design elements to convey specific visual messages. While there are dozens of variations of design principles used in graphic design [4], the following four principles are most pertinent to our discussion of network visualizations specifically.

Design Principle 1: Contrast. *Contrast* refers to the use of differences in visual weight to signal differences in design elements [7]. Contrast can be formed when extra visual weight is given to one element relative to another. The greater the visual weight difference, the greater the contrast. Essentially, establishing contrast is dependent on the difference in attributes, such as shape and color.

For example, in Fig. 2 no contrast exists on the left example because visual weight is evenly distributed given the elements are identical in both shape and color. On the right, contrast is present because of the different visual weights created by differences in color and shape. For example, elements in red attracts more attention as they carry more visual weight again a white background. We can also observe that the contrast is enhanced when the two elements contrast in both shape and size.

Fig. 2. Left: no contrast in shown due to equally distributed visual weight. Right: contrast is formed between elements with different shapes or colors.

Design Principle 2: Visual Hierarchy. After we understand that *Contrast* can be achieved through the uneven distribution of visual weight, it is important to consider how we can take advantage of the distribution of visual weight to manage the distribution and path of viewers' attention. In other words, designers want to control which information in the visualization is prioritized and in what order, a design principle called *visual hierarchy*.

Visual hierarchy is the arrangement of design elements in order of importance, or in order of the intended sequence that designers expect viewers to land their eye on [4]. Because elements with similar visual weight will naturally exhibit similarity, the proper use of visual weights is foundational in signaling visual hierarchy [4]. Size and color are two primary ways to establish visual hierarchy. Research shows that the eye is naturally drawn to larger parts of a design first [23]. In design terms, that means a larger object has more priority than a smaller object. Similar to size, objects that are darker hold higher priority as well and are more likely to be seen before objects that are lighter. Therefore, it is important to make sure that the most important element that you want viewers to pay attention to holds the heaviest visual weight.

Watzman [22] proposed the Squint Test to evaluate visual hierarchy. For example, to evaluate the visual hierarchy of the two examples in Fig. 3 below, simply squint your eyes at either example. As you look at it, is there a dominant element that attracts your eye first and the most? When the visual hierarchy is set up appropriately, the element you noticed first should be the one with the heaviest visual weight, such as the thickest and darkest lines.

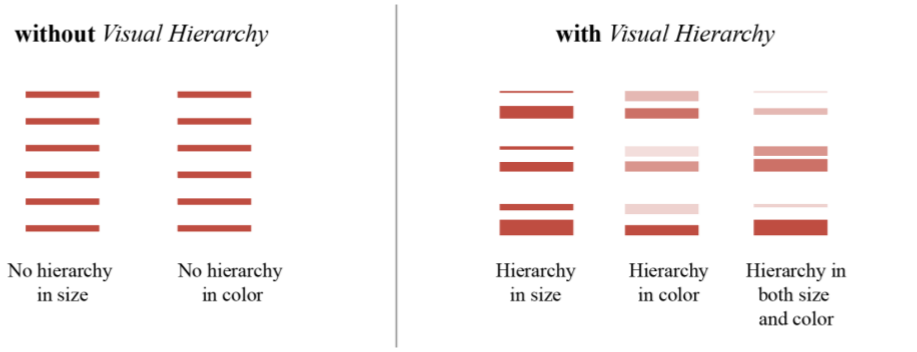

Fig. 3. Left: no visual hierarchy is present because all lines are in identical size and color. Right: visual hierarchy is formed through the variation of visual weight as represented by differences in size and/or color.

Design Principle 3: Perspective. While *visual hierarchy* triggers the intended attention sequence by manipulating visual weights, *perspective* is applied to create a flow along which viewers' eyes travel through the visualization. Specifically, *perspective* describes a sense of depth, with larger or darker objects appearing closer to the viewer [4]. Once depth is created, viewers will navigate a visualization from most proximate elements to most remote. There are many ways to create flow, such as shadows, gradient, size, and color. The two that are related to network visualization specifically are size and color given that points and lines are two major design elements used in networks.

In the three examples in Fig. 4, although nodes and lines are placed in similar arrangement, they differ in size and color. By placing larger and darker elements in the foreground in a consistent manner such as the example on the right, a sense of depth is present and viewers' eyes naturally flow from the foreground to background. Compared to the other two examples, although the middle one includes variance in size and color, a "see-through" effect is not present given that it does not have a consistent manner when it comes to the order of elements placement.

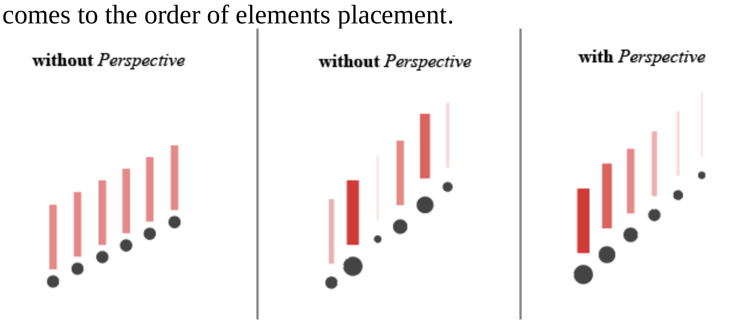

Fig. 4. Left: perspective is absent due to the absence of depth created by the unified node and line attributes. Middle: perspective is absent despite the presence of depth due to inconsistent placement of nodes and lines with different visual weight. Right: perspective is present because of the ordered variance in elements' visual weight and placement.

Design Principle 4: Proximity. *Proximity* refers to the use of relative distance between design elements to indicate relationship. When applying proximity, elements that are similar or related are placed into closer proximity to form a visual connection, while elements that are dissimilar or unrelated are place farther apart to disrupt or discourage visual connection [4].

For example, assuming that a set of 12 nodes can be divided into three categories based on their similarity, Fig. 5 below shows how proximity conveys such a message visually. On the right, more similar nodes are clustered, or placed physically closer to one another than they are to any other nodes. This makes it easy for the viewer to identify which nodes are related to one another and which are not.

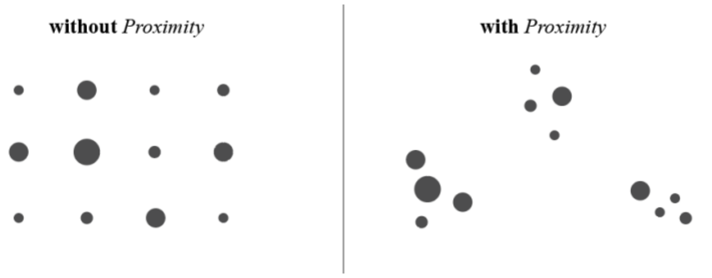

Fig. 5. Left: nodes are placed in equal distance without proximity variance, providing no information about which nodes are similar or dissimilar. Right: the distance between nodes is varied to indicate similarity and difference.

3 Background: Network Visualization

Before we explain how the aforementioned graphic design principles are applied in ENA visualizations, we briefly review other extant network graph visualizations and discuss why they are not suitable for visualizing ENA networks.

3.1 Graph Layout Algorithms

Over the past three decades, a wide range of graph layout algorithms have been developed to support visualization of network models [2, 10, 13]. Among two-dimensional layout methods that draw Node-Link diagrams, there are eight representative layouts in five families based on groupings commonly used in the literature [20, 21]. Due to space limitations, we present one popularly used and publicly available layout, the *Fruchterman Reingold* (FR) layout [10], as an example to explain why ENA models require custom visualizations.

The Fruchterman Reingold (FR) layout belongs to the *force-directed* family, a class of algorithms that produces graphs by simulating interactions as a system of forces. The resulting layout is an "equilibrium state" of the system [10]. Since its inception in 1991, new FR variants are still introduced every year [21]. While each new FR variant might have its unique affordances, the resulting FR visualizations generally share the three characteristics below [6, 10, 11, 14]:

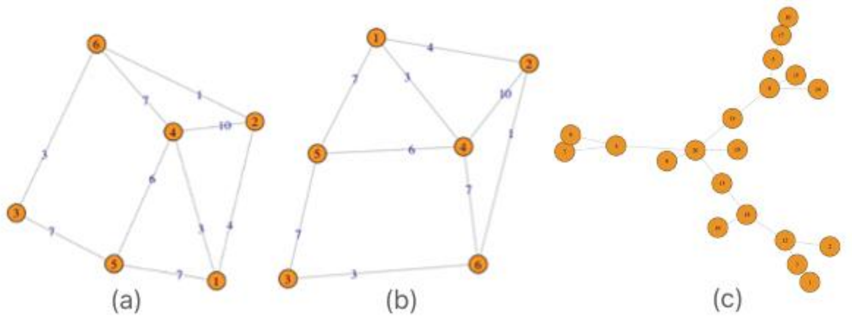

Fig. 6. Three graphs drawn in FR layout using igraph R package [5]. (a) and (b) represent the same six-node network with different node position. (c) represents a larger network of 20 nodes.

1. Node positions are not deterministic. Each time the FR algorithm is run, it will result a visualization with slightly different node layout. For example, graphs A and B in Fig. 6 represent the same network model drawn using the same FR algorithm, but they have different node positions.
2. Edge crossing and node overlapping are minimized. Since node position is not deterministic, the algorithm places nodes and edges iteratively until it approaches or fully satisfies this aesthetic criterion. For example, in relatively sparse networks such as A, B, and C in Fig. 6, edge crossing and node overlapping are fully avoided.
3. Nodes that share more connections are closer to each other. As a force-directed algorithm, nodes in FR layout repulse each other when they get close and the edges act as springs that attract connected nodes together. As a result, a force balance is achieved in the graph, and nodes that are connected more strongly are placed closer. For example, in graph C, clusters are formed visually because the more connected nodes are placed closer together.

3.2 Challenges in Visualizing ENA Networks

As Bowman et al [3] argued, a key feature that differentiates ENA from traditional network analytical approaches is that ENA produces *content-based* summary statistics that can be used to compare the *content* rather than the *structure* of networks. In other words, instead of comparing networks using structural summary statistics such as network density without reference to specific nodes, ENA compares networks in terms of which nodes are connected and how more or less strongly they are connected. Therefore, (1) enabling such content comparison visually and (2) representing the resulting differences visually become two core challenges that ENA network graph visualizations need to address.

To address the first challenge, ENA places its nodes in a network space through a process called *co-registration*, which results a single metric space with fixed node position for all networks in the same ENA model. With a set of fixed node position, multiple networks can be compared directly regarding connected nodes and connection strength. For example, in Fig. 7, since (a) and (b) share the same node position, it is visually clear that which pairs of nodes are strongly or weakly connected in one graph but not the other. However, although (b) and (c) visually look identical, they are very different networks in terms of *content*. That is, which nodes are connected and their connection strength.

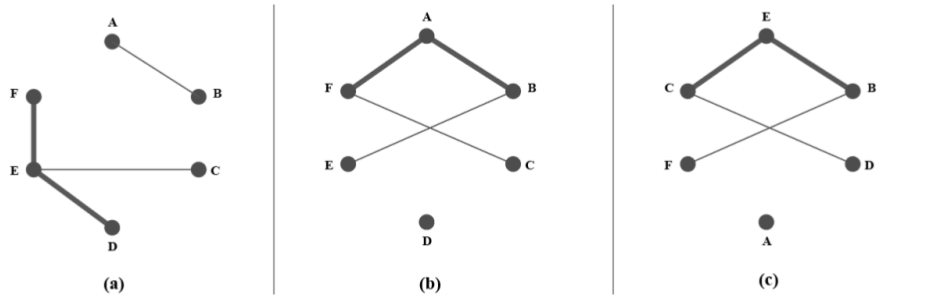

Fig. 7. Three weighted networks with same density but different patterns of connections. Specifically, (a) and (b) have identical node position but different connection pattern. (b) and (c) have different node position but appear to be but in fact not identical connection pattern.

The mathematical details of *co-registration* are beyond the scope of this paper and can be found in the work of Bowman et al. [3]. But in brief, *co-registration* is a process of producing network graph visualizations that meaningfully reflect the statistical properties of the network model. The fixed node position not only allows for meaningful comparison of the patterns of connections in multiple networks, also allows for interpretation of the metric space itself. Compared to the non-deterministic node position of FR layout (characteristics 1), ENA visualizes its network with a set of deterministic node position determined by *co-registration*. Furthermore, in ENA, the distance between nodes in the network space does not reflect connection strength as in FR layout, but represent similarity of the roles that different nodes have in network structure. The nodes that are closer to each other in an ENA space have more similar roles in the networks in which they appear. If an ENA network were visualized using *force-directed* algorithms such as FR layout, researchers would be unable to interpret the locations of networks in ENA space.

While *co-registration* addressed the first challenge in terms of enabling content comparison visually, the second challenge about how to visually represent the resulting differences between networks still remains. However, the second challenge in more of a graphic design challenge than an analytical challenge. As an analytical method, ENA is designed to model connections in weighted networks that usually have a small number of nodes but are densely connected [19]. Edge-crossings are mostly unavoidable in such networks. While edge-crossings can hinder readability and should be avoided in network visualizations [7, 15], it is hard to realize in ENA networks given its high density, fixed node position, and straight-lined edges. Although *force-directed* algorithms such as FR layout are optimized to avoid edge-crossing (characteristic 2), this affordance is not applicable to ENA visualization because of ENA's deterministic node position. Therefore, instead of removing edge-crossing, ENA visualizations need to represent connections in a readable and sensible way regardless of the potential edge-crossing challenges posed by its high network density. In the following section., we will elaborate on how the second challenge in addressed using graphic design principles.

4 Applying Design Principles in ENA Visualizations

In this section, we explain how the aforementioned four design principles—*contrast*, *visual hierarchy*, *perspective*, and *proximity*—are applied in the design of ENA visualizations. We use an undirected weighted network with density of 1.0 as a simplified example to demonstrate the transformation from a basic Node-Link diagram to an ENA visualization, step by step.

4.1 Use of Contrast to Emphasize Edges

Graph #1 in Fig. 7 represents a Node-Link diagram in a basic layout: nodes A, B, C, and D are connected using straight lines and connection weights are annotated using numbers next to each edge, varying from 0.2 to 1.0.

There are two noticeable problems in Graph #1. First, there is no clear focal point to draw viewers' attention. Since the structure of connections among codes are usually the primary research interest in ENA studies, we hope to attract viewers' eyes more to the edges in the network. To do so, we break the evenly distributed visual weight in Graph #1 by increasing the color contrast between nodes and edges to make edges stand out, as shown in Graph #2. With the increased color contrast, the connections between nodes represented by edges become more easily noticeable.

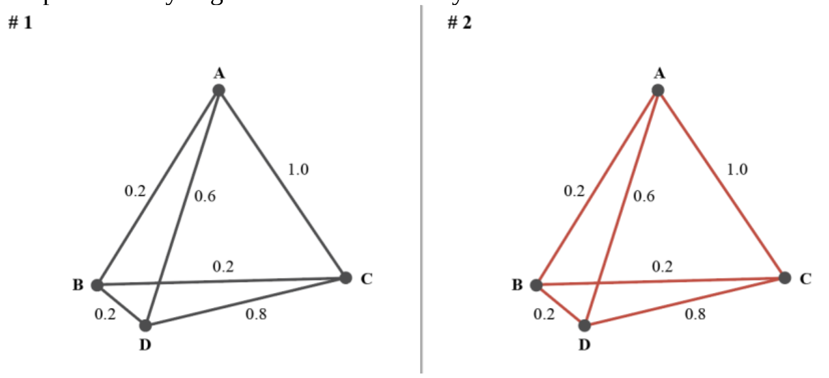

Fig. 8. Left: no color contrast between nodes and edges. Right: edges stand out because edges in red against white background creates stronger contrast

Second, in Graph #1, in order to understand differences in connection strength, viewers have to process the magnitude differences of the numbers next to each edge, which increases cognitive load. Also, in dense networks where edge-crossing is unavoidable, placing numerals next to already crossed edges adds additional ambiguity to the visualization. Therefore, the visual appearance of the edges not only needs to help viewers discriminate between edges base on their weights but also needs to keep the visualization as clean as possible. In next section, we explain how used the principle of visual hierarchy to emphasize stronger connections (edges with larger weights) and deemphasize weaker connections (edges with smaller weights).

4.2 Use of Visual Hierarchy to Differentiate Connection Weights

To help researchers identify the strongest connections between coded elements in ENA network graphs, we assign the highest prominence to the edge with heaviest weight. For example, in Graph #2, we want edge AC to be the edge that attracts the most attention.

There are two ways to do this. One approach is to vary edge saturation (Graph #3), the other is to vary edge thickness (Graph #4). To vary saturation, we first assign the fully saturated color to edge AC, which has the largest weight, so that AC is the visually heaviest element in the graph. Then, we make the level of saturation of all the other edges proportional to their weights. For example, edge CD has a weight that is 80% of the weight of edge AC, so the level of saturation in edge CD is 80% that of edge AC. The end result of creating visual hierarchy through color saturation is shown in Graph #3. To vary edge thickness, we use the same process. The edge with the largest weight is assigned some maximum thickness, and the thicknesses of the remaining edges are scaled proportionally. The end result is shown in Graph #4.

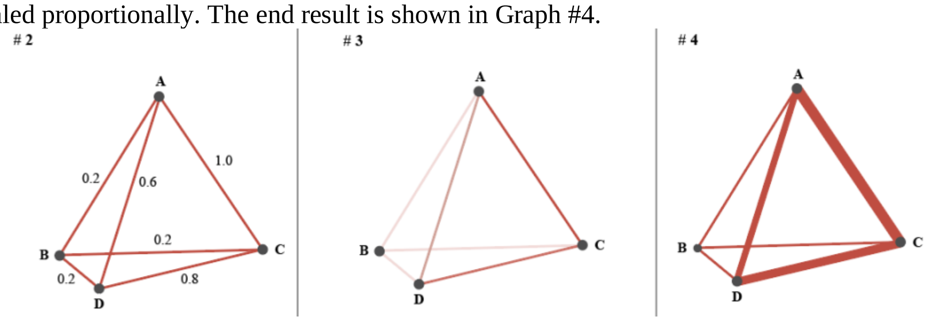

Fig. 9. The *saturation* of the edges in Graph # 3 is proportional to their weights. The *thickness* of the edges in Graph # 4 is proportional to their weights.

While either Graph #3 or # 4 is sufficient to address the problem we identified in #2 by representing edge weigh differences visually, both of them can be improved. In Graph #3, the equal edge thickness makes the visual hierarchy difference not as noticeable as in Graph #4. In Graph #4, although the edge weight differences are immediately clear, the edge-crossings appear to decrease readability due to all edges being fully saturated. Therefore, we create the clearest visual hierarchy by using size and color simultaneously as represented in Graph # 5.

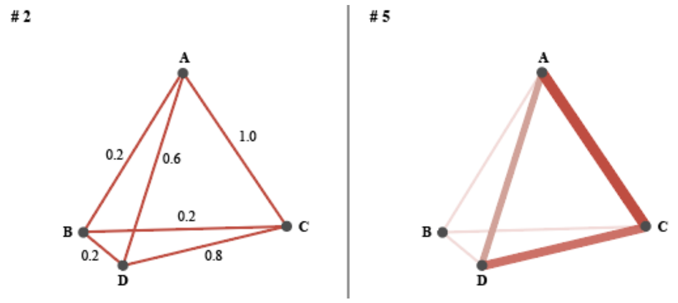

Fig. 10. Edges in Graph #5 are in different thickness and saturation to reflect actual edge weights. Heavier edges are thicker and more saturated than lighter edges.

In Graph #5, by proportionally scaling both thickness and saturation, viewers can easily estimate the differences in edge weights not only for any two edges but also across the network structure as a whole. In scientific visualizations, the degree of visual weight difference should mirror the intended analytic difference [1, 15], and the proportional scaling of saturation and thickness accomplishes this.

4.3 Use of Perspective to Guide Navigation

As of now, in terms of inspecting edge weight differences, the version presented by Graph #5 is readable. To further guide viewers navigate the visualization as a whole, we applied *perspective* to create a flow. As discussed before, by placing larger and darker elements in the foreground in a consistent manner, a sense of depth will present and viewers' eyes naturally flow from the foreground to background. To create such flow, on the basis of Graph #5, we adjust size of each node based on the connection made by that node. Since heavier edges are already placed on top of lighter edges and appear physically closer to viewers, large nodes automatically follow this pattern because node size in ENA is proportional to all the connection made by that code. By doing so, elements with heavier visual weight such as thicker and darker edges and large nodes are placed to be closer to viewers, while elements with relative lighter visual weight appear to be in the background. Such visual layering creates a flow to guide viewers' attention travel from the strongest connection to the weakest connection in the network.

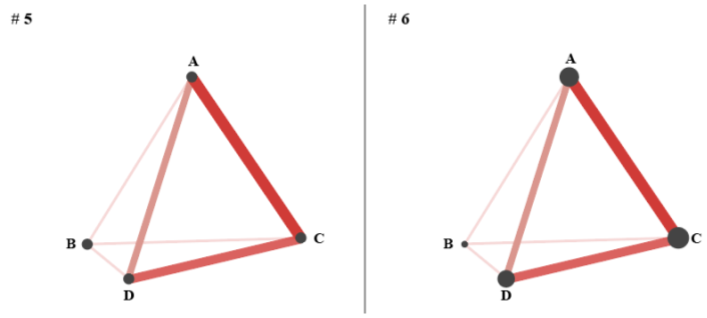

Fig. 11. Node sizes in Graph #6 are adjusted accordingly based on the connection weights

From Graph #1 to Graph #6, using a simplified four-node weighted network, we demonstrated the transformation of an individual ENA network from a basic Node-Link diagram to a version that reflects the current ENA visualization layout in use. By comparing Graph #1 and Graph #6 side by side as shown in Fig. 12, Graph #6 presents viewers with a visualization that is not only visually self-explanatory, but also takes less time to identify the connection strength differences across the network, even without the numerals next to edges.

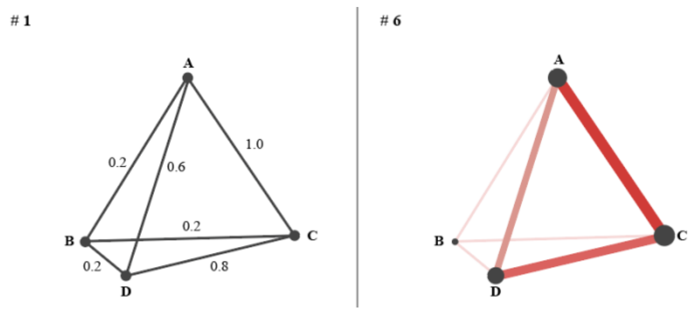

Fig. 12. Compare the initial Graph #1 with the finalized ENA visualization Graph #6

4.4 Use of Proximity to Indicate Similarity and Difference

As discussed, instead of arbitrarily placing nodes in a network space, ENA co-register its network space with its summary statistics and generates a set of fixed node position for an ENA model [3]. In an ENA network space, nodes that are placed more physically closer are more similar in terms of the role they play in the network. For example, in Graph #6 below, node B has more similarity with node D in the network as indicated by the close distance between them. This phenomenon of using physical distance to indicate relationship is an application of *proximity*. *Proximity* helps viewers quickly identify nodes that share similarity or difference based on the distance between them.

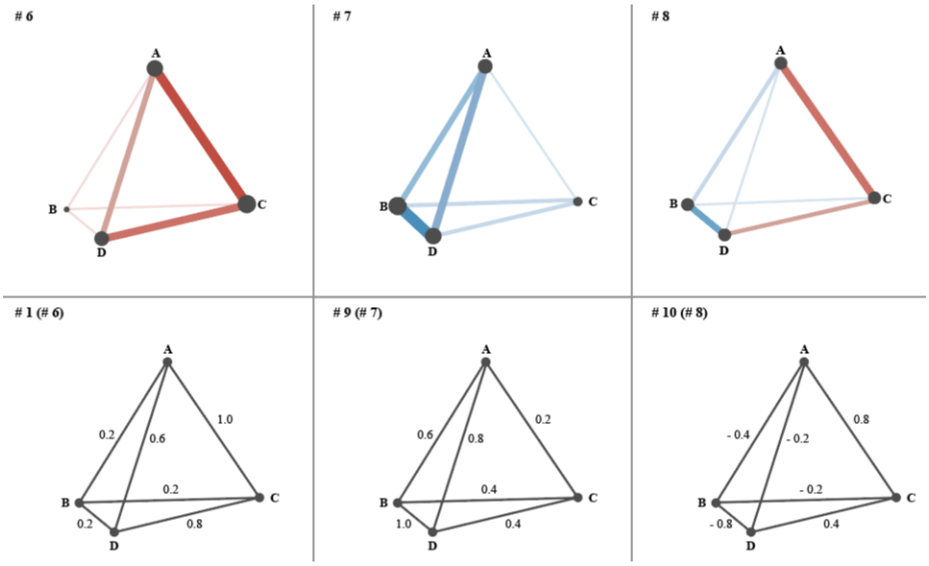

Fig. 13. In the too row, Graph #8 is the difference graph of Graph #6 and Graph #7. Edges in red in #8 represents the salient characteristics of #6, edges in blue in #8 represents the salient characteristics of # 7. Accordingly, in the bottom row, Graph #1, #9, and #10 are the basic Node-Link diagram version of Graph #6, #7, and #8.

Besides showing similarity and differences between nodes, the fixed node position is also an essential precondition to compare ENA networks visually. Because of the fixed node position, ENA can construct a subtracted network, which enables the identification of the most salient differences between two networks that belong to a same model. To do this, ENA subtracts the weight of each connection in one network from the corresponding weighted connection in another network, then visualize the connection strength difference. Similar as in individual networks, darker and thicker edges indicate larger differences in connection strength, and light and thinner edges indicate smaller differences in connection strength. Each edge is color-coded to indicate which of the two networks contains the stronger connection. For example, in Fig. 13, Graph #8 is a subtracted network of Graph #6 and #7. Based on the thickness and saturation of the color-coded edges, we can conclude that overall the subtracted network shows that relative to Graph #7, Graph #6 has the strongest connections in the upper right part of the space as presented by edge AC; although CD is also in red, the difference is not as strong as in AC because of the thinner and lighter edge of CD. Graph #7 has the strongest connections in the lower left part of the space as represented by BD relative to Graph #6.

5 Discussion

In this paper, we discussed ENA network graph visualizations from a graphic design perspective. We reviewed pertinent graphic design principles and explained how those design principles manifested themselves in the design of ENA visualizations. We also argued that ENA networks, as weighted networks that usually have a relatively small set of nodes and high density, are not suitable to be visualized using extant network layouts such as *force-directed* algorithms that apply nondeterministic node position and prioritize aesthetic criteria such as evenly node distribution and minimum edge crossings.

We have consistently emphasized that ENA visualizations are not only designed to be aesthetically pleasing, but also to convey visual messages that are mathematically consistent with its content-based summary statistics. While researchers can conduct a variety of statistical analyses to test the differences between ENA networks based on summary statistics, being able to make such comparisons directly from visualizations can not only facilitate researchers' interpretation of ENA network models, but also communicate their findings with broader audiences. For example, Fernandez-Nieto et al. [8] applied ENA to model and visualize nurses' positioning during clinical simulations and invited nurse teachers who did not have expertise in ENA to make sense of the ENA visualizations. Those teachers constructed consistent narratives about ENA network models and valued ENA visualizations as an accessible shared language for joint sense-making between researchers and practitioners.

Furthermore, we hope that this work provides a helpful perspective for visualization designers in reflecting on design choices in designing visualization for various purposes, but we recognize that designing is a versatile task and an iterative process that cannot be prescribed with fixed guidelines. Therefore, we look forward to being inspired by studies that use ENA visualizations in various contexts and disciplines.

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