Bridging Network Science and Vision Science: Mapping Perceptual Mechanisms to Network Visualization Tasks

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***Abstract*—Network visualizations are understudied in graphical perception. As a result, most network visualization designs still largely rely on designer intuition and algorithm optimizations rather than being guided by knowledge of human perception. The lack of perceptual understanding of network visualizations also limits the generalizability of past empirical evaluations, given their focus on performance over causal interpretation. To bridge this gap between perception and network visualization, we introduce a framework highlighting five key perceptual mechanisms used in node-link diagrams and adjacency matrices: attention, visual search, perceptual organization, ensemble coding, and object recognition. Our framework describes the role these perceptual mechanisms play in common network analytical tasks. We use the framework to revisit four past empirical investigations and outline future design experiments that can help produce more perceptually effective network visualizations. We anticipate this connection will afford translational understanding to guide more effective network visualization design and offer hypotheses for perception-aware network visualizations.**

***Index Terms*—Network visualizations, perceptual mechanisms, design framework.**

I. Introduction

VISUAL representations of networks often default to node-link diagrams, adjacency matrices, and their respective derivatives [1]. The visual characteristics behind many network layouts [2], [3] or re-ordering algorithms [4] are based on aesthetic metrics grounded in designer experience and convention rather than empirical data about how people perceive networks. These metrics often focus on individual microscale characteristics (e.g., do two edges cross) rather than on the macroscale relationships between characteristics that define the visual structure of a network visualization. We currently have limited insight into *how* people perceive patterns even in common network visualizations as they are understudied in graphical perception [5].

This limited insight is challenging, in part, because compared to other visualization types, conventional network visualizations use physical space differently. Most common visualizations represent values using absolute space (e.g., mark position or length). For example, scatterplots and bar charts directly map values to spatial positions. In contrast, the spatial placement of nodes in a node-link diagram does not directly encode values. Rather, network layout algorithms often leverage *relative* spatial relationships among nodes to reveal higher-level features, such as clusters. Density in adjacency matrices is loosely correlated with connectedness but is highly dependent on the matrix row and column order. For example, a continuous path in the network may be encoded by non-adjacent cells in the matrix. We turn to vision science—the study of how humans perceive and reason about the visual world—to systematically understand how we can design network visualizations that leverage human perception.

Elements of vision science have long been applied to network visualization perception, with prior work bridging vision science and visualization yielding actionable guidelines to inform the design and development of more effective visualizations [5], [6]. The present paper acknowledges the critical interplay between foundational principles rooted in vision science and algorithmic intuition, re-emphasizing the importance of applying a cohesive interdisciplinary framework to network visualizations. By leveraging vision science principles, we can renew our understanding and inspire new frontiers to advance techniques that augment network visualizations through their unique use of physical space.

We introduce a framework (Table I) that maps five relevant perceptual mechanisms when using node-link diagrams and adjacency matrices for common network analysis tasks [7]: attention, visual search, perceptual organization, ensemble coding, and object recognition.

Our framework concentrates on relatively simple networks to establish a *foundational mapping* of perceptual mechanisms

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TABLE I
SUMMARY OF HIGHLIGHTING THE PERCEPTUAL MECHANISMS THAT PLAY A ROLE FOR COMMON NETWORK TASKS (SEE SECTION II-B) FOR NODE-LINK DIAGRAMS AND ADJACENCY MATRICES

Network Task	Task Description	Node-link Diagram					Adjacency Matrix				
Topology											
Direct connection	Find a set of nodes directly adjacent to a given node	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
	Find the number of nodes adjacent to a node	Attention	Visual Search	–	Ensemble Coding	–	Attention	Visual Search	–	Ensemble Coding	–
	Find the maximally/minimally connected nodes	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
Accessibility	Find sets of nodes accessible from a node	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
	Find number of nodes accessible from node A to node B	Attention	Visual Search	–	Ensemble Coding	–	Attention	Visual Search	–	Ensemble Coding	–
	Find sets of nodes accessible within a distance $\leq n$	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
Common Connection	Find the shortest path between two nodes	Attention	Visual Search	Perceptual Organization	Ensemble Coding	Object Recognition	Attention	Visual Search	Perceptual Organization	–	–
	Identify clusters	Attention	Visual Search	Perceptual Organization	–	Object Recognition	Attention	Visual Search	Perceptual Organization	–	–
	Identify connected components	Attention	Visual Search	–	–	Object Recognition	Attention	Visual Search	–	–	–
	Find bridges	Attention	Visual Search	Perceptual Organization	–	Object Recognition	Attention	Visual Search	–	–	–
End Points	Find articulation points	Attention	Visual Search	–	–	Object Recognition	Attention	Visual Search	–	–	–
Attributes											
Nodes	Find nodes having a specific attribute value	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
	Filter sets of nodes	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
	Find a range of values for a set of nodes	Attention	–	–	Ensemble Coding	–	Attention	Visual Search	–	Ensemble Coding	–
	Look at the distribution of a set of nodes	Attention	–	–	Ensemble Coding	–	–	–	–	Ensemble Coding	–
Edges	Find the nodes connected by certain kinds of links	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
Browsing											
Edges	Follow a given path	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
	Return to a previous node	Attention	Visual Search	–	–	–	Attention	Visual Search	–	–	–
Overview											
Estimation	Estimate size of the graph	–	–	Perceptual Organization	Ensemble Coding	Object Recognition	–	–	Perceptual Organization	Ensemble Coding	–
	Find larger-scale structural features	–	Visual Search	–	–	–	–	Visual Search	–	–	–
Hypothesis Testing	Compare network features to a mental representation (e.g., discover a network's topology)	–	Visual Search	Perceptual Organization	–	Object Recognition	–	Visual Search	Perceptual Organization	–	Object Recognition
Comparison	Isomorphism	Attention	Visual Search	Perceptual Organization	–	–	Attention	Visual Search	Perceptual Organization	–	–
Disambiguate Structure	Determining the level of detail needed to disentangle a network's structure at multiple resolutions	–	–	Perceptual Organization	Ensemble Coding	Object Recognition	–	–	Perceptual Organization	Ensemble Coding	Object Recognition

Legend: Attention; Visual Search; Perceptual Organization; Ensemble Coding; Object Recognition.

to network visualizations. For instance, the scale of networks discussed in this work is in line with most experiment studies of network visualizations [8]. This paper assumes networks with the following characteristics:

- Scale: Medium, sparse networks where the number of nodes is [21,50] and the linear density is [1.01, 2.0] (note: we adhere to the definitions provided by Yoghourdjian et al.'s survey [8])
- Network Structure: Unweighted
- Network Visualizations: Static adjacency matrices and node-link diagrams

We start with these basic characteristics for our framework to serve as a *roadmap* for the network visualization and vision science communities. The goal is to i) revisit results from past investigations to connect past findings and generalize results across a broader set of use cases (Section V-A) and ii) pose novel investigations into network visualization efficacy and design (Section V-B). These two goals lay the foundation for *bootstraping* new research directions at the intersection of network visualizations and human perception. Consequently, novices and experts in network visualization can benefit from our framework by having a succinct understanding of the current landscape and challenges.

By achieving both goals, our framework offers a new lens for evaluating network visualizations beyond task performance such as time and accuracy. The five perceptual mechanisms discussed in the context of network visualizations can equip researchers with the tools to identify *why* certain features or aspects of a visualization design can change people's interpretation and task performance. For example, existing work has produced a widely-known guideline that reducing link crossings in node-link diagrams can enhance perceivability [9], [10]. However, empirical work by Dwyer et al. [11] revealed that participants performed with worse time and accuracy when searching for cliques with the orthogonal layout than the force-directed layout, even though the former has fewer link crossings. This finding contradicts best-practice guidelines.

Our framework can help reconcile contradictions like these by identifying the perceptual mechanisms underlying the empirical observations, helping improve best practice guidelines by understanding when to generalize. In this case, the "object recognition" mechanism can explain the contradiction. Participants performed better with force-directed layouts because the layout creates more clusters that resemble familiar perceptual structures users have learned to recognize in network analysis. We discuss this case more deeply and offer additional examples in Section V-A. From these case studies, we note two actionable insights in Section VI-B on how others can build upon this work, specifically experimental design suggestions for future interdisciplinary work. Together, these case studies and future experimental designs demonstrate the value of our interdisciplinary framework in guiding researchers to study network visualization.

This framework can also lay the foundation for developing *perception-aware network visualizations:* visualizations that are more than simply informed by perceptual principles, but rather designed to actively coordinate with an analyst's perceptual processes as they accomplish a given set of tasks. Future research can systematically examine the effect of network design features on these perceptual operations to generate guidelines for perception-aware network visualizations.

Contributions: We contribute (i) an interdisciplinary framework that considers how perceptual mechanisms affect network tasks in canonical network visualizations, including (ii) preliminary application of the cognitive and perceptual mechanisms behind common network tasks and (iii) theoretical investigations of how we can design experiments to ground hypotheses and generate generalizable design guidance emerging from these applications.

II. Background & Related Work

To generate an interdisciplinary framework for reasoning about how people perceive network visualizations, we draw on existing literature on network visualizations, network tasks, perceptual studies for visualizations, and graph aesthetics.

A. Network Visualizations

A network is a data structure that contains a set of data points (i.e., entities of interest) and their relational data. In this paper, we exclusively use network terminology and denote these data points as *nodes* and the pairwise connections between them as *edges*. People visualize networks in a wide range of domains (e.g., biology, engineering, social sciences) [12], [13], and as such, network visualizations hold strong precedence within visualization research and practice [1], [14]. While networks can also be geospatial [15], multi-variate [16], [17], dynamic [18], or even hypergraphs [19], our focus on undirected and unweighted networks aligns with the network complexity used in most evaluations [8]. Though many network representations exist [20], [21], [22], the two most common representations of undirected networks are node-link diagrams and adjacency matrices.

Adjacency matrices visualize a network as a table with $n \times n$ cells, where n is the number of nodes. The matrix as a whole (i.e., the n^2 cells) provides an overview of all possible connections (i.e., edges) between nodes. A cell is filled only if an edge exists between the nodes of the corresponding row and column within the dataset. The order of rows and columns dictates the patterns displayed. Reordering the elements of the matrix can assist with high-level tasks (e.g., network comparison [23], identifying groups or highly connected vertices [24]). The ordering of the rows and columns can be arbitrarily decided (e.g., alphabetically) or algorithmically computed [4]. Node-link diagrams provide a structural layout of a network. Each node within the dataset is traditionally visualized as a circle, and edges connecting the nodes are represented with lines (straight or curved). A node-link's spatial structure, or *layout*, is determined algorithmically. The most popular layout is the force-directed layout, which treats the network as a physical system [3]. Nodes repel each other with a pre-determined force while edges act as springs pulling connected nodes together. There are other layouts, including, but not limited to, hierarchical layouts [25], centrality-based layouts [26], grid-like layouts [2], topology-based layouts [27]. Despite the popularity of node-link diagrams, they become easily cluttered. We refer readers to Tamassia's handbook [28] for an overview of the various graph drawing algorithms to address this challenge. Similarly, graph aesthetics quantify the visual characteristics of a node-link layout and can be used to tune algorithms to reduce measurable clutter, such as edge crossings, while maximizing desirable properties, such as clusters [9], [10].

B. Network Tasks

Bertin [29] proposed three levels at which tasks operate: i) an elementary level, comprised of individual graphic elements and the task to understand their specificities; ii) an intermediate level, for comparisons among subsets of graphic elements; and iii) an overall level, comprised of global trends and relations. This hierarchy echoes observations in more modern task taxonomies for networks [7], [30], [31]. Our work is built upon the task taxonomy proposed by Lee et al. [7], which describes four groups of network-related tasks—topology-based, attribute-based, browsing, and overview—while considering well-established theories of visualization tasks broadly, including canonical low-level visual analytic tasks [32] and Bertin's task hierarchy [29].

The work by Lee et al. [7] serves as a common foundation for extended discussions of network tasks [18], [30], [33], [34], which we briefly summarize below. *Topology-based tasks* concern a network's topology— the structure of how nodes and edges are arranged within a network. Topological properties can apply to the network as a whole or to individual nodes and edges. Lee et al.'s topology-based tasks address i) individual elements, such as nodes (e.g., "Find the set of nodes adjacent to a node") and links (e.g., "Find the shortest path between two nodes"), ii) sub-networks, such as groups or cliques (e.g., "Identify clusters," "Are the given two groups neighbors?") and iii) the entire network (e.g., "Estimate the size of the network"). *Attribute-based tasks* focus on deriving specific values from selected data through either filtering, computing, or finding the range or distribution on a network's edges or links (e.g., "Filter sets of nodes", "Find the nodes having a specific attribute value"). Similarly, *browsing* tasks focus on tracing the network's connections to follow a given network path (e.g., "Follow a given path," "Return to a previously visited node"). Lastly, *overview* focuses on summative properties of a network (e.g., "Find larger-scale structural features").

C. *Perception in Visualization*

Once uncommon [35], visualization researchers are increasingly incorporating perceptual and cognitive methods to evaluate visual perception for data-driven displays [5], [6]. Now, a growing number of interdisciplinary studies illustrate how vision science methods can lead to improved design recommendations [36], [37] and reduce bias [38]. However, these efforts are not tailored for nor do they typically include network visualizations as part of their investigations.

Networks are understudied in graphical perception [5]. Most network user studies focus on comprehension, particularly on network layouts and aesthetics [39], or determining the upper limit of a network's size and complexity [8], [40]. Some studies investigated physiological measurements like eye-tracking [41], [42], [43] but are limited. We argue the lack of perceptual studies for networks stems largely from one reason: network representations use physical space differently. In contrast, past perceptual studies for other visualization idioms are predominantly spatially oriented (e.g., scatterplots, bar charts, line graphs). The spatial positioning of a node for a node-link diagram does not necessarily convey visual significance with many layout algorithms. For example, variants of force-directed layouts [44], [45], [46] focus on better distributing the nodes' positions while retaining the relative positions of their neighbors. The algorithms behind several network layouts, including force-directed, are generally developed based on some heuristic or aesthetic criteria [9], [10]. A similar reasoning applies to adjacency matrices. Thus, past visualization investigations do not translate well to network visualizations. Network visualizations require a different set of approaches to understand how people perceive and reason with them.

Previous evaluations of network visualizations (see these surveys [8], [40] for a comprehensive overview) often focus on visual features of nodes or edges (e.g., color) as opposed to how the visual system processes the visualization. Visual features certainly impact the efficiency of perceptual operations (discussed further in Section IV) [47], [48] but note that visual features act as *building blocks* for perceptual mechanisms.

Past evaluations mainly focused on performance measures (e.g., response time and accuracy) to evaluate different network layouts [11] and compare different visualization approaches [24], [49]. Recent studies offer insight into the processes people use to perceive and reason about networks. For example, Huang et al. [50] use cognitive load to measure a network visualization's effectiveness at different scales and levels of complexity. Research has also focused more on the human aspects of network layouts (e.g., memorability [51]) by asking participants to produce network visualizations [52], [53], verifying that node-link diagrams should reduce link crossings and support visual features that highlight clusters. Though these studies also share our goal of connecting perceptual and cognitive processes to network visualizations, their small number also highlights our relatively limited empirical understanding of how people make sense of network data. We aim to connect relevant concepts from perception to a range of network task types to highlight opportunities for more effective network visualization guidelines and practices.

D. *Graph Aesthetics*

The graph drawing community recognizes the challenges of producing readable network visualizations, notably node-link diagrams. As mentioned in Section II-A, as networks get larger and more densely connected, node-link diagrams become easily cluttered. To amend this challenge, the graph drawing community proposed *graph aesthetics*. Graph aesthetics are heuristics intended to help designers create more readable network visualizations. Examples of these aesthetic metrics include symmetry [54], [55], minimizing edge crossing [56], and minimizing bends [57]. Though most graph aesthetics target node-link diagrams, Beck et al. [58] introduced an aesthetic dimensions framework to help translate existing graph aesthetics to dynamic adjacency matrices.

Prior work [59], [60], [61] aimed to perceptually validate various graph aesthetics with empirical studies. We refer our readers to these two surveys [10], [40] for a more comprehensive list of related studies. As an overview, participants are evaluated based on how well they solve certain tasks using different network visualizations. These network visualizations may differ based on layout or aesthetic criteria. For instance, Purchase [61] investigated which graph aesthetics heuristics had the greatest effect on the shortest-path task. The study revealed that minimizing edge crossings was the most important criterion. While such studies provide empirical evidence, they still largely reflect the limitation of solely relying on performance measures (e.g., response time and accuracy; see Section II-C). As a result, we still lack fundamental understanding of *why* certain graph aesthetic criteria outperform others.

Huang [62] also mirrors our motivation, emphasizing the need to evaluate fundamental perceptual mechanisms behind these network tasks and even graph aesthetics. A limited number of studies [63], [64], [65], [66] use vision science methods, namely eye-tracking, to target perceptual operations. While eye tracking reveals perceptual complexities from acuity and attentional limitations, it fails to account for broader knowledge built through processes like ensemble coding or memory. There are other aspects of perceiving networks that are not as directly reflected in eye movements. We build upon these past efforts to create a stronger connection between key topics and highlight other vision science methods researchers can use for future work (Section V-B).

III. Framework Overview

We introduce a framework (Table I) describing the visual perceptual mechanisms involved in conducting analytic tasks (see Section II-B) with network visualizations, with a focus on node-link diagrams and adjacency matrices. As discussed in Section II, most network visualizations are designed based on algorithms [67], aesthetics [68], or a combination of the two [69]. We take an interdisciplinary perspective by proposing a

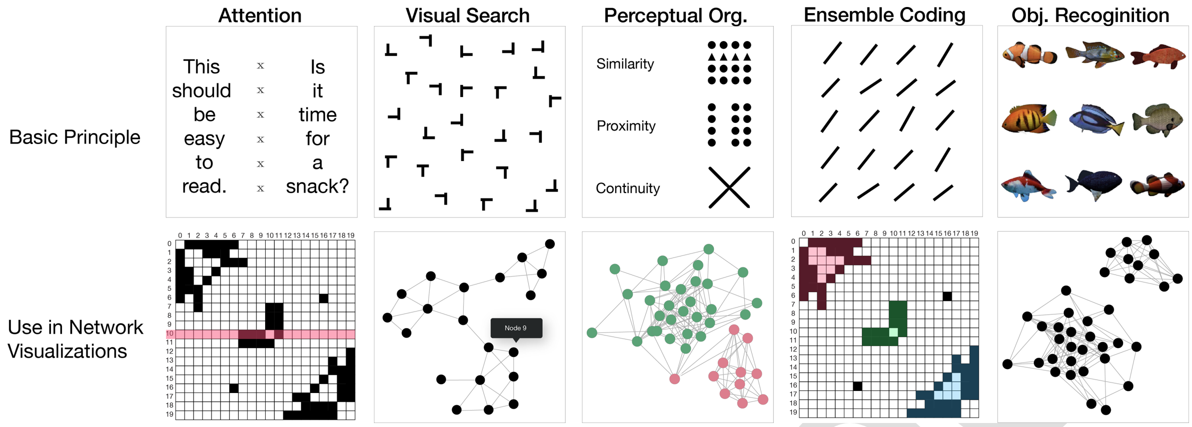

Fig. 1. Visual examples of perceptual mechanisms (Section IV). Top row illustrates each perceptual operation's basic principles. Bottom row shows how these perceptual mechanisms are applied to network visualizations. *Attentional selection* illustrates how people can attend to only a subset of information at a time (e.g., we cannot read the two sentences nor look at two cells in the adjacency matrix simultaneously). *Visual search* illustrates how our eyes will serially search for the target object amongst other objects (try finding the letter "T" or the target node in a node-link diagram). *Perceptual organization* illustrates our ability to form a visual configuration from the spatial organization of individual components (e.g., people can see different clusters within a node-link diagram based on the node's color and spatial proximity). *Ensemble coding* allows the estimation of distributional characteristics of visual features (e.g., orientation, size, or color) over a set of objects (e.g., the different colored clusters summarize high-density regions in the adjacency matrices). *Object recognition* occurs when a visual object's representation matches an individual's representation of the object in long-term memory (e.g., we recognize all the figures are fish; analysts can recognize two connected components in the network visualization).

framework structured by perceptual operations from theories of human visual cognition. This broader perspective aims to identify visualization design opportunities for networks and theoretical gaps in our understanding of network perception.

A. Key Network Tasks and Perceptual Mechanisms

We scope our framework to cover two common network visualization representations: adjacency matrices and node-link diagrams. The authors, with backgrounds spanning across human perception and cognition, information visualization, and network visualization, reflectively synthesized existing work to identify a set of common analytic tasks with networks. We consider shared, underlying perceptual mechanisms associated with each task to come up with seven task categories and five perceptual mechanisms.

The seven task categories are inspired by Lee et al.'s task taxonomies for network tasks [7], the low-level visual analytic tasks in information visualization from Amar et al. [32], the multi-level typology from Brehmer & Munzner [70], as well as extensive discussion at the Network Perception Dagstuhl workshop in 2023 [71]. These categories include: topology, attributes, browsing, overview, hypothesis testing, comparison, and disambiguating structures at multiple resolutions (e.g., identifying a network's topology).

For the perceptual mechanisms, four of the authors first collectively identified 27 specific perceptual phenomena from human vision science that may play a role in network analysis through group discussions and referring to prior work in vision science (see the supplemental material for an overview). For example, centrality comparison and density comparison are both examples of ensemble coding [72]. We then grouped these phenomena into six classes of *perceptual operations*—perceptual functions that rely on related visual processes—to provide more concrete and direct connections between networks and visual processes.

The classes include scene perception, visual search, object recognition, internal representation, perceptual organization, and ensemble coding. During the grouping process, we also identified a set of low-level visual features that could impact the efficiency of perceptual operations. These features include visual density, numerosity, connectedness, path traceability, distance, contrast, area, and centrality. While this paper focuses on higher-level perceptual operations and does not extensively discuss the effect of these low-level visual features, we recognize that design decisions manipulating these visual feature parameters can impact the efficiency of all perceptual operations. The perceptual operations we discuss offer a context for future researchers to systematically examine the effect of individual visual features on network visualization design and interpretation. Readers can reference the work by Burch et al. [40] for a comprehensive survey of the effect of these low-level features.

The authors—one of whom is a researcher in perception and cognition, three of whom work at the intersection of perception and visualization, and two of whom have extensive experience in network visualization—iterated on the six classes, refining them into five core operations for network visualization perception listed below. See Section IV for more details and Fig. 1 for visual examples.

- *Attention:* Restricting visual processing to only a subset of information at any one time to prevent distractor interference [37], [73]
- *Visual search:* Adjusting attentional allocation over time as some items are deemed irrelevant and when other new items are considered
- *Perceptual organization:* Linking items together to allow them to be processed as a visual configuration [52]
- *Ensemble coding:* Estimating distributional characteristics of visual features (e.g., orientation, size, color) over a set of objects or regions [74]

- *Object recognition:* Categorizing a visual object based on its match to object representations stored in long-term memory [75]

While not exhaustive, this list reflects common themes we observed across different network tasks per network visualization type and reflects the common areas of vision science research [72], [76]. Attentional selection, visual search, ensemble coding, and perceptual organization are categories of perceptual mechanisms that align with past theoretical works linking vision science and visualization broadly [74], [75], [77]. Perceptual organization, in particular, is especially critical to consider as it encompasses Gestalt principles (and subsequent work on perceived grouping and relatedness) that have directly influenced past network visualization approaches and experiments [10], [52], [78], [79], [80], [81]. We add object recognition because of the role that previously stored visual representations play in identifying and differentiating specific nodes and analyzing the shape properties of complex configurations of nodes and links.

IV. Perceptual Mechanisms

Table I outlines the relevant mechanisms for each network analysis task. To enable a better understanding of each perceptual mechanism, we describe its basic principles and discuss how the perceptual mechanism operates when an analyst engages with network tasks.

A. *Attention*

Attention [73] restricts high-level processing to only a subset of information at a time, such that a target stimulus, like a mark, can be processed without interference from distractors.

Basic Principles. Attention can be internal or external. *External attention* refers to attention allocated to stimuli originating in the world, but *internal attention* refers to our ability to attend to a given line of thought. Visual attention can be overt or covert [82] by shifting attentional focus (e.g., sets of co-located nodes). *Covert attention* allows us to select a specific region within a single glance. *Overt attention*, in contrast, refers to eye movements such as saccades, which determine what part of the visualization is projecting visual information to the high-resolution retinal region of the fovea.

Selection is one aspect of attentional control, and can flexibly allocate cognitive resources to a range of information that is selected. For instance, attention can be selective or divided. In *selective attention*, we focus our processing resources on one object or group of objects (e.g., a set of nodes) and prevent other objects (e.g., irrelevant nodes) from interfering with processing [83]. In *divided attention*, we attempt to attend to multiple objects (e.g., attending to three fully-linked visualizations), which can degrade our abilities to efficiently process each object [84]. Attentional zoom refers to the size of the region selected by attention, which can be broad or narrow. With *broad attentional zoom*, we distribute our attention broadly to select a large portion of a visual scene. With *narrow attentional zoom*, we are narrowly focused on a single mark or small region.

How is attention used in network visualizations? An effective visualization directs attention to key parts of a network to accomplish the intended tasks. An analyst might process the entire node-link diagram or adjacency matrix as a single large object, setting the attentional zoom broadly to include the entire diagram. They could use selective attention to narrowly focus on just a single object, such as a node and its neighboring nodes. In Fig. 1, the red bar over the adjacency matrix illustrates specifically attending to that row. They could use divided attention to focus more broadly on multiple objects, such as two clusters connected by a bridge. During network exploration tasks, such as overview or browsing tasks, an analyst might position their eyes to take in a large portion of the network. For more localized tasks such as direct connection (e.g., finding a set of nodes connected to a given node) or common connection tasks (e.g., finding bridges), an analyst might move their eyes to the most relevant region to obtain higher acuity (i.e., spatial resolution) to make out fine details, such as tracing paths between nodes which may require moving our attention carefully down the edge to understand specific relationships robust to artifacts like edge crossings. Given the limited meaning of physical space in network visualizations, analysts must fluidly employ different forms of attention to complete most network tasks.

B. *Visual Search*

Visual search is one aspect of attentional control that is key for interpreting network visualizations. While visual attention generally focuses on what we look at, the goal of visual search specifically is to find and attend to one or more *target* objects that are surrounded by *distractor* objects. In difficult searches, attention may be directed serially from one distractor to another before the target is found.

Basic Principles. Depending on the relationship between the target and distractors, it can be much harder to find a target as the set size (i.e., the number of marks in a visual display) increases. However, search efficiency can often be improved with two types of search guidance: bottom-up and top-down. If the target is sufficiently different from distractors, bottom-up guidance (i.e., guidance originating from the features of a visual object) can move attention to it quickly (i.e., pop out), regardless of how many distractors there are [85]. If a target does not pop out, top-down guidance (i.e., guidance originating from a target goal) can help direct attention if one or more features (e.g., color, size, orientation) of the target are known [86]. In guided search, the known target features are stored in a target representation in visual working memory, and attention is restricted to the items sharing those features [87]. Unguided search can be inefficient (e.g., slow reaction times to find the correct target because attention may first be allocated to a number of distractors). Unguided searches typically involve a serial self-terminating search, in which items are serially examined one after another until the target is found or all items have been checked. To experience this phenomenon, look for the letter "T" in Fig. 1.

How is visual search used in network visualizations? Search is at the heart of most network tasks (e.g., finding a set of nodes or clusters). Search is also often necessary before other network tasks can take place. For example, to find the shortest path between two nodes, analysts must first search to locate the two target nodes within the network. People may often employ search to look for more compound topological structures within a network, such as cycles or cliques.

Visual search within node-link diagrams and adjacency matrices is mainly unguided and time-consuming. Though there are exceptions, such as Sugiyama style layouts [42], visual search remains difficult for most network visualizations. While interactive queries can change the visual features of target nodes to support bottom-up search, this unguided search can be extremely difficult for two reasons. First, the set size of networks is often non-trivial. A "small" network dataset can contain 200 nodes [8], while "large" datasets can contain thousands or more [88]. It is challenging to visually search for a particular node amongst thousands without a directed cue (e.g., highlight from an interactive query, Fig. 1). Relatedly, the features of target and distracting elements for network visualizations are largely the same for most common network visualizations (e.g., all nodes in node-link diagrams are circles, and all edges in adjacency matrices are square cells). Node-link diagrams and adjacency matrices can use labels to provide cues or may even use color to indicate group attributes. However, search can still be slow if the user does not have a priori knowledge of *where* to look.

C. *Perceptual Organization*

Understanding a visual configuration requires recognizing both individual components and the relationships among those components. Perceptual organization refers to our ability to see how different elements within a scene *relate* to one another. Perceptual organization is determined only in part by the pixels in a visualization; in many cases, the viewer can use attention and other aspects of top-down control to shape the organization imposed on the visualization (e.g., finding clusters via colors or shapes may elicit different perception of clusters). Through perceptual organization, visual elements are grouped and structure is imposed to build high-level visual objects (e.g., perceiving a house as a combination of windows, doors, roof, etc.).

Basic Principles. Perceptual organization creates hierarchical visual representations from lower-level components. Theories of perceptual organization have been influenced by Gestalt Principles of grouping [89]. Although a detailed account of how these principles shape visual perception has been elusive, these principles continue to guide current research in visual perception and also help to understand how data visualizations are interpreted. For instance, the Principle of *Similarity* states that objects with similar shapes or colors are perceived as groups. The Principle of *Proximity* suggests that elements that are close to each other are perceived as a group. The Principle of *Continuity* highlights how elements will group together if they lie on the same contour. Fig. 1 illustrates these principles. Modern research has extensively refined these principles, and their core ideas continue to serve as a foundation for modern theories of perceptual organization [90].

How is perceptual organization used in networks? In node-link diagrams, each line representing a link connects one node to another, leveraging the Principle of Uniform Connectedness [91]. Other Gestalt principles come into play in organizing nodes into groups and larger units. For example, the Principle of *Symmetry* plays a key role in network perception. People perceive symmetry in network visualizations as salient and design guidelines have suggested networks take care to display symmetry in network structures [40].

The layout chosen for a particular node-link diagram or adjacency matrix determines whether the organization created by similarity, proximity, symmetry, and continuity emphasizes the most informative aspects of the network structure. In many cases, different aspects of a network structure will be best perceived by grouping the nodes and links together in different ways. Thus, proximity might be used to emphasize one set of groupings, while similarity from shared colors [48] (e.g., Fig. 1) or shapes might emphasize another, and in a node-link diagram, a set of nodes might be aligned to allow grouping supported by continuity. Such a layout gives viewers the option of using top-down control of the perceptual organization to explore different aspects of the network structure.

D. *Ensemble Coding*

Ensemble coding allows the estimation of distributional characteristics of visual features (e.g., orientation [92], size [93], or color [94]) over a set of marks in a visualization. These characteristics are quickly and efficiently estimated prior to active attention. Like perceptual organization, ensemble coding captures group- or set-level properties rather than individual details about a given object; however, ensemble coding focuses on the distribution of visual features across a set of marks (e.g., the mean color or density) rather than grouping. For example, ensemble coding allows people to quickly estimate the mean size or position of a group of scatterplot points without attending to each point individually (see Szafir et al. [74] for a survey).

Basic Principles. Ensemble coding studies how individuals can extract information on sets of marks based on their shared properties. This perceptual mechanism uses broad attentional zoom (c.f., Section IV-A) to extract information at large. Four categories of ensemble coding are prevalent for visualizations: identify sets of values (e.g., in- and out-groups), summarize across values based on their distribution (e.g., means and variance), segment collections (e.g., estimate clusters), and estimate high-level structure or patterns (e.g., identify trends) [74]. Though these principles largely pertain to spatial relationships, ensemble coding can also summarize features over an entire set of marks. For example, people can rapidly estimate the mean size or color of a set of glyphs [93], [95]. In Fig. 1, we can notice that all lines are slanting upwards to the right at a glance. These mechanisms allow us to quickly estimate the gist of a scene (e.g., data distribution) to help orient us to group properties. However, ensemble processes only operate over a set of elements. These processes extract information about the features of the distribution, such as the mean size or position, but not attributes of individual items, such as the size of a specific mark [93].

How is ensemble coding used in network visualizations? When someone initially sees a network visualization, ensemble coding allows them to rapidly gain a high-level sense of the data. Spatial ensembles allow people to orient themselves to the position of elements in the visualization [96]. Featural ensembles allow people to gain a nearly immediate sense of the distribution of node shapes, sizes, colors, and edge lengths and orientations [97].

In a node-link diagram, ensembles cue connectedness between clusters (e.g., by summarizing edge orientation [98]) or regions of high and low density to indicate connectivity (e.g., by summarizing color variations introduced by drawing nodes and edges). Ensembles can also summarize metadata mapped to nodes and edges, such as mean and variance in color or size mappings. If attention is restricted to one part of a network, ensemble coding can provide estimates of properties within that selected region. In an extreme case, attention might be focused on a single node in order to determine the number of connections emanating from that node. If the number is less than four, the number can quickly be determined through subitizing [99]. For larger numbers of connections, the number can be estimated through ensemble coding, but with lower precision.

In adjacency matrices, these spatial and featural ensembles summarize regions of high- and low-edge density (e.g., the different colored clusters in Fig. 1). For node-link diagrams, ensembles can also summarize additional mark information, such as colors or shapes, in more complex representations.

E. Object Recognition

Object recognition occurs when a visual object representation is categorized (e.g., recognized as a house or a connected component) after it is matched to object representations stored in long-term memory.

Basic Principles. Object recognition is complicated by changes in viewpoint and the reconstruction of depth information. Many of these challenges are avoided in network visualizations, but interpreting node-link diagrams and adjacency matrices requires matching stimuli against long-term memory representations. Thus, some aspects of object recognition are critical to interpreting network visualizations.

How is object recognition used in network visualizations? At a local level, different types of nodes are sometimes distinguished from one another by depicting them with different shapes and/or colors. Object recognition uses this shape and color information, along with any attached labels, to categorize each node. On a more global level, the interpretation of a group of nodes and their connections can vary considerably depending on the shape created by their depiction in a node-link diagram [100]. A pattern of nodes will be more easily remembered if it is perceived as a real object [101]. One configuration may resemble a particular object that we are familiar with, while another configuration of the same nodes and links may evoke an entirely different object. For example, a network analyst may recognize there are two connected components in Fig. 1 due to the white space. Similarly, an experienced analyst may recognize higher-level network structures (i.e., motifs), such as a triangle subgraph, for clustering and community detection (e.g., [102]). These objects can serve to support recall and evoke a sense of a group of nodes forming a single object or structure.

V. Examining Framework Utility Through Case Studies

We demonstrate our framework's utility through a combination of case studies and speculative analyses. First, we review four past studies to demonstrate how our framework can offer more generalizable insight into network visualization design (Section V-A). These case studies cover the five perceptual mechanisms. We looked specifically for studies relevant to the perceptual mechanisms mentioned in this paper. We also considered factors such as the recency and relevance to visualization design. Second, we outline future design experiments as potential steps toward designing more effective network visualizations grounded in conceptual replication (Section V-B). Though some of these studies supported interactivity, the fundamental tasks can be done statically. We assume static analysis given our paper's scope.

Both aspects align with our motivation for this work serving as a roadmap to the network visualization and vision science community. The case studies in Section V-A can guide how the community can think about both perception and network visualization problems in conjunction. Furthermore, the experiment design proposals in Section V-B also serve as guides on how as a community we can move forward to design and conduct better experiments within this research space.

A. Case Studies

We apply our framework to four past studies to demonstrate how understanding the perceptual mechanisms underlying network perception can offer more generalizable insights. We encourage readers to use our framework as a guide to similarly revisit past works and their results. Our framework allows us to directly hypothesize *why* these performance differences occur to re-evaluate the generalizability of the results. We share aspects of these case studies that are most relevant to the paper. See the corresponding papers for more comprehensive insights and findings.

Example 1 (Perceptual Organization): Yoghourdjian et al. [22] evaluated people's ability to interpret structural details using the network visualizations in Fig. 2(a). One task involved counting the number of 1-connected components in the network visualizations (the answer in these examples is 2).

Relation to Framework: To make sense of the network structure, people must first leverage *perceptual organization* to form visual groups of spatially promixal nodes. Next, they can leverage *object recognition* to locate where the 1-connected component(s) occur in the network. We outlined the two 1-connected components in the node-link diagram representations in Fig. 2(a).

Results: Participants completed this task faster and more accurately with the node-link diagram than with the adjacency matrix. The lack of white space to separate components in the adjacency matrix hindered the perceptual organization operation. *Insight:* This example demonstrates that spatial cues are more saliently perceived than colors [79], [105], [106], such that people are more likely to prioritize spatially proximate units as a group compared to similar units using other channels. This

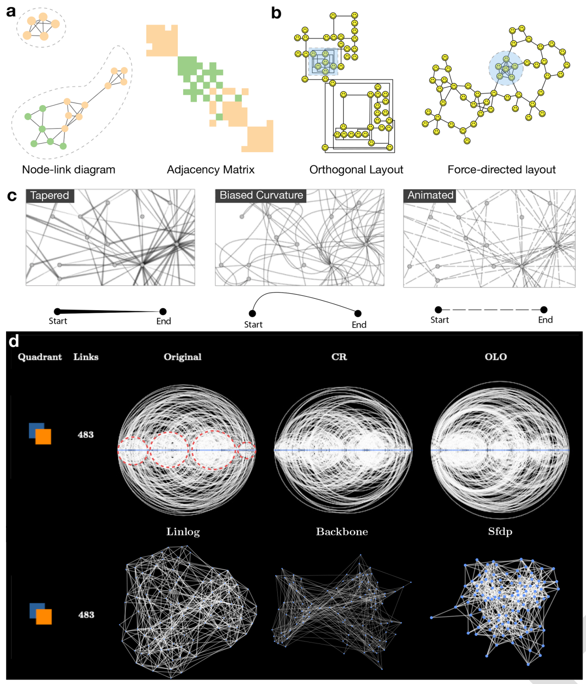

Fig. 2. Past empirical investigations that we revisit using our framework (Section V-A). (a) network visualization comparison; (b) layout comparison; (c) edge representation comparison; (d) network cluster. Image A courtesy of Yoghourdijan et al. [22], B by Dwyer et al. [11], C by Holten et al. [103], D by Al-Naami et al. [104].

serves as a prime example that considering foundational principles of vision science can inspire new perspectives to improve network visualization design. Examining encoding techniques that leverage spatial cues to facilitate the perceptual organization of network structure can improve performance in analytic tasks.

Example 2 (Object Recognition): Dwyer et al. [11] examined people's ability to identify cliques in a network using different node-link layouts. Fig. 2(b) shows two of the twelve layouts used in the study. The left is an orthogonal layout with only 7 link crossings, and the right is generated using a force-directed layout with 13 link crossings.

Relation to Framework: This task taps into a range of perceptual operations, including *attention* and *visual search*, but most saliently *object recognition*.

Results: Despite the widely-accepted guideline to reduce link crossings to enhance perceivability [9], [10], the study revealed that participants were more than three times slower in finding cliques with the orthogonal layout ($\bar{x} = 26.88$ sec) than the force-directed layout ($\bar{x} = 8.12$ sec). Participants also more accurately detected cliques with the force-directed layout (97%) than with the orthogonal layout (80%).

Insight: The mismatch between design heuristics and behavioral outcomes Dwyer et al. [11] observed calls for a deeper understanding of the perceptual mechanisms behind clique recognition. Similar to Example 1, this case study illustrates the importance of supporting quick recognition of different network "objects." The clique can be recognized by clustering and dense edge crossings in the force-directed layout (highlighted in blue).

Example 3 (Visual search, Attention): A study by Holten et al. [103] compared edge representations for node-link diagrams. Fig. 2(c) showcases the three edge representations used in their study: tapered, biased curvature, and animated. Participants were asked to determine if two highlighted nodes were connected.

Relation to Framework: Our perceptual framework enables researchers to generate testable hypotheses to uncover the underlying mechanisms behind the performance of each edge design. For example, one could hypothesize that retaining *attention* is pivotal for path-tracing (Table I), therefore edge representations that sustain viewer attention for a longer time would be associated with higher performance.

Results: Both edge representation and path length impacted behavior. Participants were faster and more accurate with the tapered and animated links than with the biased curvature. For medium-length links, the tapered edge condition was significantly faster than the animated condition. The authors noted the need for future work to understand why tapered was faster in this case.

Insight: The work by Holten et al. [103] highlights how a general recommendation (e.g., tapered edges) can be risky without understanding the driving factors behind their higher performance. An experiment can test whether tapered and animated edges require less attention shifting compared to biased curvatures (see Section V-B1) by measuring eye-gaze shifts and participants' perceived effort in completing this task. The experiment can be extended to examine a range of path lengths. Longer paths would likely be associated with a higher attention demand, and thus poorer performance.

Example 4 (Ensemble Coding): Al-Naami et al. [104] evaluated people's ability to count network clusters using three variants of orderable node-link layouts versus three variants of force-directed layouts (Fig. 2(d)). They define orderable node-link layouts where "nodes can be ordered along such a curve e.g., based on topological or attributed-based critera" [104]. Fig. 2(d) shows the three variants of orderable node-link layouts: a baseline node order (Original), a cross-reduction ordering (CR), and an optimal leaf ordering (OLO).

Relation to Framework: People will need to quickly extract the gist of the network visualization and then count its clusters. This task uses *ensemble coding* to initially perceive clusters at a high level. This perception will be influenced based on the distribution of shapes, size, number, and density.

Results: People identified graph clusters faster and more accurately with orderable layouts than force-directed layouts when networks have loose and/or inseparable clusters. The orderable layouts create locally concentrated link clusters that form more distinct density regions. A viewer can quickly extract the gist of the network visualization based on mean density patterns and then count the resulting clusters. The four clusters form dense, white circles connected by less dense regions, which makes them easy to see in the original baseline layout (GEN). The clusters become more ambiguous in the CR and OLO layouts, despite them being designed to optimize node cluster patterns as the edge density is more uniformly distributed.

Insight: We re-emphasize the same call for future work that Al-Naami et al. [104] expressed to better understand *why* the

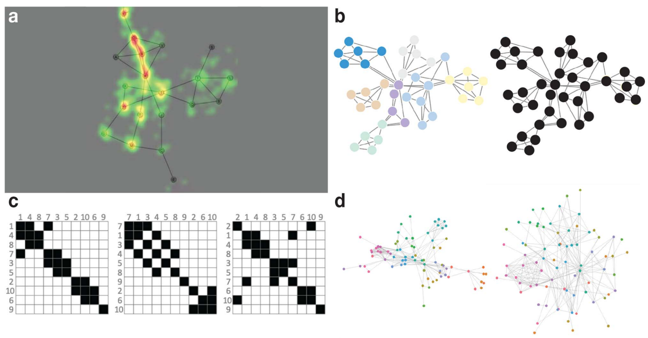

Fig. 3. Experiments to study how perceptual mechanisms operate with network visualizations. (a) eye tracking to study attention fixation; (b) visual search efficiency comparing colored versus all-black node-link diagram; (c) perceptual organization of clusters using different matrix-reordering; (d) different network layouts to extract ensemble features and object recognition of clusters. Image A courtesy of Pohl et al. [41] and C by Behrisch et al. [4].

orderable layouts facilitate cluster identification. Following our framework, we caution network designers from relying on a specific algorithm without computing its ability to support segmentation (and other ensemble coding operations) that describe the global feature distribution people perceive.

B. Design Experiments

Our framework allows us to reflect on past studies and also to guide new experiments to generate more generalizable insight into network visualization design. We illustrate several open questions our framework can help address to demonstrate how a mechanistic approach helps bridge network and vision science for more effective visualization.

1) Attention: Experiments can reveal how attention is allocated to different parts of a node-link diagram or adjacency matrix while people extract different types of information (e.g., Fig. 3(a)). We generally expect that performance will be faster and less error-prone when a task can be accomplished with fewer shifts of attention. Consider a task in which people must determine which nodes in a network have the most connections. Eye tracking will provide a fairly accurate record of which nodes are examined and how much time is spent. Fixation records can determine if nodes with many connections are missed, and if some nodes with few connections capture attention unnecessarily and delay the final response. These data can indicate which strategies people adopt to accomplish the task, which might involve starting at one part of the network and systematically working their way through, or starting with a quick scan of the whole network and then focusing on just a few selected regions (e.g., Examples 1 and 2 in Section V-A). Highlighting common strategies will help researchers identify design opportunities to facilitate those strategies during analysis. We advocate for leveraging perceptual mechanisms as a basis for metrics that measure the efficiency of a strategy. For example, a strategy might be deemed more efficient if a person can accomplish it with fewer shifts of attention.

As seen in Example 3 [103] in Section V-A, attention plays a major role in tasks that involve curve and link tracing, such as finding the shortest path between two nodes, browsing a given path, and finding the number of adjacent nodes to a node in a node-link diagram. Curve tracing determines whether nodes are connected by a link. A handful of studies have measured curve tracing [107] and their results indicate that people can quickly trace curves (average rate of 40° of visual angle per second). Though these studies do not directly test visualizations, the results are likely applicable to tracing links in node-link diagrams and perhaps in adjacency matrices. However, link tracing has an additional layer of complexity because there are more opportunities for confusion from links crossing links in node-link diagrams than by adjacent rows and columns in adjacency matrices.

2) Visual Search: Visual search is relevant for the majority of network visualization tasks. The following design experiments specifically focus on how to design nodes that pop out to accelerate the search for individual nodes. Though related, we discuss design experiments on recognizing different network objects (e.g., cliques, bridges) based on a network's topology in Section V-B5.

In conventional node-link diagrams or adjacency matrices, all items are the same color and all nodes are the same shape, offering little opportunity to guide search for a specific node. If the target node can only be identified by a string of letters indicating its name, then search is likely to be long and laborious and visual clutter amongst nodes may make it impossible. Distinguishing different categories of nodes and links by color and/or shape can make search more efficient. If a small number of nodes have a sufficiently contrasting color from the rest, they will pop out and be found easily. Even if nothing pops out, coding different categories by color, shape, or size can drastically reduce search time if the analyst knows the feature designating the category of the target (e.g., finding red versus blue nodes).

Future work can test the optimal number of colors, shapes, or sizes for a given network visualization design by using methods from perception research (see [6]). Search efficiency can be evaluated in a number of ways, including response time and accuracy. The gain in search efficiency from color-coding different categories of nodes can also be measured by comparing the number of eye fixations between color-coded and monocolored versions of a network diagram or adjacency matrix (Fig. 3(b)). This has been similarly investigated in Example 1 in Section V-A. A more detailed analysis of the eye-tracking record can reveal which fixations can be avoided in the color-coded version, and how the path of the search changes as the structure of the visualization changes.

3) Perceptual Organization: How viewers organize nodes and links into larger units will affect the conclusions they draw about global patterns within a network. The perceptual organization of a network can be manipulated by changing the spatial relationships among the nodes, and the effects can be measured experimentally. Experiments can uncover optimal layout designs that support perceptual organization processes for a given dataset or set of tasks (e.g., spatial or by color).

Consider the following: each node represents one student in a university, and each link represents a social connection between two students. In one node-link diagram or adjacency matrix, nodes can be clustered together according to the students' majors. Viewers can assess the degree to which students socialize with others in their same major versus other majors by comparing the number of connections among clusters. Using the same data, another version of the visualizations can cluster students according to where they live on campus. Experiments could test how to design the diagrams (e.g., what parameters to designate for their visual features) to facilitate perceptual organization that most effectively supports comparisons between these two groupings (Fig. 3(c)).

4) Ensemble Coding: We expect that people can quickly and easily extract summary information about groups of nodes or links [74], [93]. If the rows and columns of an adjacency matrix are organized so that items in different categories are grouped together, then we can test if subjects can easily judge whether there is more connectivity within some categories than others by quickly judging the density of connections in each category. However, we anticipate ensemble coding may play a more nuanced role in adjacency matrices depending on how the node-edge connections are spatially encoded. These judgments likely change as features of the ensemble change, as with variations in color or glyph use. Identifying the optimal categories to group rows and columns to facilitate user performance through these experiments will allow network designs to build more effective visualization tools.

Ensemble coding also likely plays a strong role in node-link interpretation, especially in helping people ascertain the coarse-grained structure of a network. For example, layout algorithms often group nodes based on their connectedness or relatedness as captured by a range of metadata. Ensemble processes can leverage these groupings to identify dense and sparse clusters, detect highly connected components (by finding areas of high edge density), assess general patterns in connectedness (by means of edge density and orientation), identify bridges (by identifying connections between dense regions), and quickly find outlier nodes (Fig. 3(d)). However, ensembles may also falsely suggest connectedness in dense spatial ensembles by treating all edges in an area as a distribution of pixels rather than as individual items.

Designers may leverage complementary attributes of a node-link diagram to support a wider range of network tasks. Imagine a diagram in which each node is a cell phone user, with links to other users with whom they regularly exchange texts. The nodes might be color-coded by age. The size of each node might indicate the number of text messages that each user generates. Experiments could test whether ensemble coding allows viewers to accurately judge how text usage varies across different age groups. We might expect that they will be able to focus their attention on nodes of one color (age group) and use ensemble processes to quickly estimate the average size of these nodes. By shifting attention from one color group to another, they can form successive estimates of text usage for each age group. Our abilities to estimate featural ensembles may also translate to edge encodings. For example, featural ensembles may explain our abilities to assess homophily—the degree to which similar nodes are connected—in a network when edge color indicates in- and out-group relations [108].

5) Object Recognition: Experiments can investigate how to optimally arrange the network so people can quickly recognize different topological "objects" (e.g., cliques). See "Common Connection" in Table I for a full list.

Experiments could investigate how to globally arrange nodes when participants are looking for emergent topological features. If subsets of nodes have many connections and fewer connections across each subset, the nodes can be arranged so that the different subsets are perceived as different parts of the larger object, with the boundaries between the different parts being salient. Experiments can test the effect of these arrangements on task performance. These experiments can investigate well-known heuristics, such as reducing edge-crossings to avoid clutter. In Example 2 in Section V-A, we speculate that this heuristic may not have been appropriate for this task given how the high clutter enabled participants to identify the clique. At a local level, experiments can test if layout algorithms might manipulate the shapes of important substructures of a network (e.g., connected components) to make them easier to detect or if using consistent mark design (e.g., changing node shape or color) to match data semantics accelerates network search tasks.

VI. Discussion

A. Design Implications

Our framework provides a roadmap by identifying the underlying perceptual operations required to accomplish network analytic tasks and providing actionable designs for future experiments. Future researchers can systematically examine the effect of network design features on these perceptual operations to generate guidelines and techniques for *perception-aware* network visualizations. We use the term perception-aware to imply more than simply being informed by perceptual principles, but rather working in active coordination with an analyst's perceptual processes as they accomplish a given set of tasks.

For example, a perception-aware network visualization can dynamically account for analysts' perceptual operations to optimize task performance. For a common connection task where one has to find the shortest path between two nodes in a node-link diagram, a perception-aware network visualization tool might increase the saliency of the target and source nodes by highlighting them in a different color to aid *visual search*. The tool might also help sustain *attention* through gaze-based interactions, using techniques similar to foveated rendering [109]. As the analyst moves their gaze around, the tool can continue to highlight relevant edges that construct the desired shortest path following the analyst's gaze (which also offloads work from memory by externalizing the knowledge of which paths remain relevant) and de-emphasize paths that the analyst is no longer fixating on or do not relevantly connect to the source node towards the target node.

A perception-aware network visualization can also gather a user's perceptual data to predict the analytic tasks they are aiming to accomplish, similar to interaction-based methods for intent prediction in scatterplots [110]. Generated output values would be associated with that task to reduce the cognitive or computational effort required from the user. For example, a user might want to perform a filtering task to filter out certain sets of nodes before determining how many relevant clusters are left. The network visualization might dynamically rearrange the display to optimize for *perceptual organization* so a user can easily identify the number of clusters excluding the nodes to be filtered. Alternatively, the tool can track the user's eye gaze or interaction patterns and use them to predict their goal of counting the number of relevant clusters excluding some sets of nodes to generate an answer for the user either through a numeric output (i.e., "6 clusters") or by highlighting the remaining clusters.

Furthermore, researchers and educators can leverage findings associating perceptual operations with network tasks to train data scientists to more effectively accomplish analytic tasks. For example, in relatively small networks, certain combinations of nodes and links might represent a special pattern (e.g., a connector pattern). People could leverage *object recognition* to learn to identify such patterns. Through training, people can become extremely efficient at identifying combinations of patterns by seeing such combinations as a distinct object, similar to how chess masters learn set moves by memorizing combinations of chess piece placements [111].

B. Actionable Insights

We note two actionable insights derived from our work.

First, we offer a research pipeline that empowers scientists to generate more effective and generalizable design guidelines. Often, network visualization scientists design multiple solutions and compare their effectiveness through an A/B comparison. However, without decoding *why* two designs differ in performance, the resulting recommendations or guidelines might not generalize. Researchers can face challenges of reconciling findings conflicted with existing best practices. We therefore recommend employing the framework as follows to enhance the evaluative process: 1) generate designs and compare their effectiveness per usual practices, 2) identify potential perceptual operations that might explain the increased/decreased performance (e.g., visual search), 3) conduct a follow-up experiment where the researchers manipulate that perceptual operation (e.g., making it easier or harder to perform visual search) and see if performance changes with the manipulation. This will allow the researchers to identify the driving factor behind the improved performance. 4) once the driving factor is identified, the researchers can adjust their design and/or recommendations to be more effective and generalizable. We encourage readers to revisit the four case studies as examples of this suggestion (Section V-A).

Second, we offer several perceptual-awareness metrics based on our framework for future network visualization evaluation. Many existing layouts are optimizations of quality criteria, such as minimizing edge crossings. However, as discussed in Section II-D, graph aesthetics are not always directly related to the tasks people perform on networks. Therefore, we advocate for a new category of network optimization criteria based on perceptual performance. Points of consideration might include:

- *Attention:* How quickly does the network direct user attention to key parts of the network useful for a task?
- *Visual Search:* How many eye movements did it require to complete a given task? How close in spatial proximity was the initial point of exploration from the target?
- *Perceptual Organization:* How many visual features (e.g., color, spatial proximity) are present that compete for perceptual grouping?
- *Ensemble Coding:* How quickly can the user orient themselves to the global structure of the network, including the distribution of node shapes, sizes, colors, edge length, and orientations?
- *Object Recognition:* Given a pre-defined pattern (e.g., bridges), how quickly can users recognize it in a particular configuration of the network?

These criteria could eventually become a scalable evaluation for network visualization design. We posit that a better understanding of, and more importantly, *quantitative measurements* of layout quality for task-based perception would lead to new optimization criteria, design approaches, and interaction techniques. Furthermore, these criteria can be used when re-examining past empirical studies [112].

As illustrated in Section V-A, re-examining prior work can help reflect on experimental designs and lead to more robust insights. For example, prior works on user-generated network layouts build upon each other [11], [52], [113] to uncover what features should be prioritized when developing network layout algorithms. As highlighted by Purchase et al. [114], such algorithms are "inspired by assumptions about what a human would do in generating a drawing". Extending this logic to all aspects of network visualization can lead to a foundation for establishing perception-aware network visualizations.

C. Limitations and Future Work

Our framework is non-exhaustive. First, we discuss five key perceptual mechanisms, and we listed future experiments as a result to investigate to lead to more breadth (Section V-B). We also focus on canonical network visualizations at their most basic state, with some connection to additional network characteristics where most notable. This limited scope is by necessity when considering the vast array of possible network designs and layout algorithms. As our knowledge of network perception evolves, we anticipate the framework will grow along several core dimensions of complexity.

Network Representations and Interactions: This framework only considers two static basic network visualization representations. Future work will be necessary to consider how interactions will affect perceptual mechanisms for network tasks and how the perceptual mechanisms will change for alternative representations. For example, NodeTrix [20] combines adjacency matrices and node-link diagrams into one representation. Perceptual organization and ensemble coding, for example, for this representation likely differ compared to its traditional counterparts. With

NodeTrix, it is likely difficult to infer the network structure by applying Gestalt principles as clusters of nodes are represented as adjacency matrices. People are unlikely to use the same spatial and feature ensembles as traditional node-link diagrams given how significant information about local network properties is in tabular form.

Network Scale: Our framework does not consider large networks [8], [88], [115]. As stated earlier, we assume the basic characteristics of a medium-size, sparse network, such that people can reasonably see both the local and global network structure within a traditional display. The mapping of perceptual mechanisms and tasks for large networks (e.g., 10^3 nodes) is sufficiently ambiguous that research recommends that visualizations prioritize inspecting local details as opposed to the global structure of large networks [116], [117]. Future research should extend our framework to large networks to understand how mechanisms break down at scale and how computational and visual techniques can overcome these breakdowns.

Visualization already outlines the importance of studying scalability from a vision science perspective with large networks [8], [118]. Larger networks are likely to use edge bundling [119]. Edge bundling offers an opportunity to measure the efficiency of internal processes (e.g., speed and accuracy) to trace curves and grouped edges in network visualizations (see Section V-B). Additionally, with larger networks, visual queries will contain more distractor nodes and edges and will require more thoughtful considerations of visual search and attention. However, Yoghourdjian et al. [8] highlights the challenges of inferring cognitive scalability of large network visualizations. These visualizations generally require interactivity due to their scale, but interactivity leads people to perform the tasks on a *subset* of the network (e.g., zooming into a specific subregion) rather than the entire network.

Dynamic Networks: Our framework does not consider other types of networks, such as dynamic networks [18]. Animation commonly conveys temporality (e.g., GraphDiaries [120]) for these evolving networks. Research shows that real-time monitoring for time-series visualization often leads to change blindness and cognitive overload [121], [122] but animation can be beneficial when used for short periods [123]. Building upon a psychological insight that multiple-object tracking is influenced by coherent scene perception [124], research also highlights the importance of preserving one's mental map (i.e., drawing stability) [125]. Future work will be necessary to continue to cross-pollinate knowledge across communities to advance robust visualizations.

VII. Conclusion and Future Directions

We introduce a framework describing five key perceptual operations for analytic tasks with node-link diagrams and adjacency matrices, synthesizing knowledge from visualization and visual sciences. Intended as a roadmap, we describe how this framework enables future experimental research by leveraging theories of human perception to advance network visualization research. This framework can serve as a preliminary foundation for bridging vision and network science, providing common ground for generating new theories, guidelines, and experiments to better understand how people reason with network visualizations.

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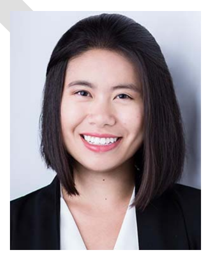

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