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Review

Local Patterns to Global Architectures: Influences of Network Topology on Human Learning

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A core question in cognitive science concerns how humans acquire and represent knowledge about their environments. To this end, quantitative theories of learning processes have been formalized in an attempt to explain and predict changes in brain and behavior. We connect here statistical learning approaches in cognitive science, which are rooted in the sensitivity of learners to local distributional regularities, and network science approaches to characterizing global patterns and their emergent properties. We focus on innovative work that describes how learning is influenced by the topological properties underlying sensory input. The confluence of these theoretical approaches and this recent empirical evidence motivate the importance of scaling-up quantitative approaches to learning at both the behavioral and neural levels.

Trends

Descriptive analytical approaches indicate that diverse facets of the environment adhere to a complex network structure.

Recent advances offer insight into how learners might acquire and access network representations. Specifically, higher-order topological properties of networks have been shown to facilitate learning.

Emerging neuroimaging techniques construe the brain itself as complex system, revealing how network dynamics support learning.

We suggest that network science approaches are compatible with statistical learning approaches to knowledge acquisition. That is, local statistical regularities extracted from sensory input form the building blocks of complex network structures. Broader architectural properties of network structures might then explain learning effects beyond sensitivity to local statistical information.

Relating Two Approaches

From the earliest stages of development, the human brain is tasked with the monumental feat of building and efficiently accessing an enormously complex constellation of knowledge. Even the most mundane interactions with our environment require a rich understanding of its component parts as well as of the scales at which they relate to form a larger system. Thus, knowledge can be represented at multiple levels, ranging from local associations between elements to complex networks built from those local associations. Until recently a dominant approach to human learning has focused on micro-level patterns, often the pairwise relationships between the constituents of sensory input. In the present review we turn our attention to exciting advances in the application of network science to the study of broader architectural patterns to which human learners are sensitive.

One source of compelling support for locally driven learning derives from demonstrations that infants can extract words from continuous speech based on the conditional probabilities between syllables [1]. Ongoing work continues to elucidate the power of statistical relationships exploited by both infants and adults, making 'statistical learning' one of the most robust and deeply explored phenomena in the field of cognitive science [2–5]. An underlying rationale has been that local associations, such as co-occurrence frequency or the conditional probabilities that facilitate word segmentation, assist in directing the learner to component parts of a cognitive system. Knowledge of these component parts not only opens up other informative cues to structure ([6] for review) but also spurs the development of sophisticated representations of dependencies between higher-order units (e.g., [7]). While evidence has thus supported a key role for local computations in complex learning environments, intriguing counter-evidence

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suggests that statistical bootstrapping mechanisms may be overwhelmed by real-world cognitive systems (e.g., natural language [8]; but see [9,10]). Because the issues of scalability in statistical learning are as yet unresolved, we stress here the value of also considering the global network structure that emerges from pairwise relationships between constituent elements in the environment.

Under a complex systems approach, the network structure of a system is studied by determining its component elements (**nodes**, see Glossary) as well as the relational links between them (**edges**). Once this scaffolding is constructed, it is possible to probe large-scale topological and dynamical properties over and above those present in the pairwise relations between elements. In fact, one defining characteristic of complex systems is that the explanatory power of their global architecture exceeds that of their local architecture [11]. Network science is increasingly applied to answer questions about the structure of immensely complex information: how might we represent or navigate spatial maps [12,13], object features [14], semantic concepts [15–17], and grammatical relationships [18]? It has also been effectively harnessed by cognitive neuroscientists to examine how structural and functional connections in the brain give rise to various cognitive capacities [19–25]. Despite these many advances, the integration of network science and cognitive science has tended to focus either on (i) the description of networks derived from the sensory world, or (ii) the mechanisms by which the human brain engages with the sensory world, with little communication between these two areas. We focus here on a related but distinct line of questioning that may begin to bridge these branches of cognitive science. Namely, how can topological properties of sensory input drive the process of human learning?

In the subsequent sections we offer examples of complex networks present in our everyday environment, focusing particularly on descriptive analyses of language networks. Next, we detail a growing body of experimental work that links topological properties of networks to knowledge acquisition. We then discuss the intersection between distributional approaches to learning, which offer insight into the acquisition of local statistical patterns, and network-based approaches to learning, which offer complementary insight into the acquisition of higher-order patterns. Finally, we describe cutting-edge neuroimaging work that construes the brain itself as a dynamical complex system, highlighting the importance of bridging internal network models of brain function with higher-order patterns in external networks.

Complex Networks Are Pervasive

Complex systems approaches rest on the premise, not tied to any particular domain, that the world can be decomposed into parts, and that those parts interact with one another in meaningful ways. Therefore, diverse facets of human knowledge can and have been studied under the lens of network science. Cognitive systems are generally thought to adhere to a complex network structure, a type of graph structure that is neither truly random nor truly regular [26]. Random graphs are collections of nodes that are linked by edges selected at random from a uniform distribution of all possible connections. Regular graphs are collections of nodes that share connections to the same number of neighbors, thus having equivalent **degree**. Falling between these two extremes (Figure 1), complex networks display their own set of unique properties including, but not limited to: **community structure** (nodes may pattern in densely connected groupings), skewed degree distribution (a few nodes may be densely connected, forming 'hubs'), and distinctive mixing patterns (nodes may be more likely to share a link with other nodes that have either similar or dissimilar properties). As we will explore in detail in the following section, human learners are adept at exploiting topological properties such as these as they extract structure from sensory input.

In principle, network analysis of cognitive systems requires only that a given dataset be parsed into discrete elements (nodes) and that some relationships between those elements be specified

Glossary

Assortative mixing: a measure of whether nodes with similar properties (e.g., high degree) are more likely to share an edge.
Clustering coefficient: the extent to which adjacent neighbors of a given node are also connected to one another. This measure may be calculated for an individual node or expressed as an average across a network.
Community structure: a graph property wherein nodes are densely connected in clusters that in turn share only weak connections with one another. Communities are commonly also referred to as modules.
Coreness: a measure of how deeply a given node is embedded in a network. A node has high coreness if it is retained in the network after recursively pruning nodes with low degree.
Degree: the number of edges incident to a given node. A node has high degree if it is densely connected to many other nodes and low degree if it is only sparsely connected. Complex networks may have skewed degree distributions such that certain nodes are far more richly connected than others, forming hubs.
Dyad: a pair of nodes sharing an edge.
Edges: links between the vertices in a network. If an edge is directed, then the order in which nodes are connected is meaningful (e.g., temporal order is important for a syntactic network, but not for a phonological network).
Nodes: vertices, or connection points, which comprise a network.
Shortest characteristic path length: a measure of network efficiency; it is, on average, the least possible distance between every pair of nodes when traversing along the edges of a network.
Small-world network: a family of networks defined by short characteristic path length and a high degree of clustering.