Behavioral Network Science

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Overview

Structure matters in cognitive science. Whether we are asking about memory retrieval, semantic representations, categorization, language acquisition, learning from complex information, aging, or creativity, cognitive scientists often find themselves forced to reckon with structure. Network science offers a quantitative approach for doing this by allowing us to ask questions about the relationships between various entities at scales ranging from dyads, to communities, to entire systems. In this case, the entities are the nodes in the network and the relationships are the edges between them. Exploring how this plays out in actual practice is incredibly varied, aesthetically and intellectually beautiful, and deeply rewarding, allowing us to develop and test hypotheses about cognition that are not otherwise possible. As a metric ruler measures length, allowing us to compare human height with the Burj Khalifa, network science measures structure, allowing us to compare the structure of our environments with the structure of our cognitive representations, how those representations change across the lifespan, and how different processes interacting with those structures generate behavior.

Consider that in language development, children hear a complex pattern of caregiver speech and from this must develop a productive vocabulary. Given that no two children learn words in exactly the same order, how might we tell if children who learn to talk later in life are simply slower versions of typical talkers? Network science provides an answer because we can compare the vocabulary structures of different groups of children when their vocabulary sizes are similar (Beckage, Hills, & Smith., 2011). We can also compare the structure of the language they hear against the representations they encode, giving us information about the way they experience and process information in their environment (Jimenez & Hills, 2023).

In addition to helping us compare cognitive systems, network science can also be used to make predictions. For example, what concepts will be retrieved first from memory (Griffiths, Steyvers, & Firl, 2007), in what order will information be retrieved in divergent thinking tasks (Zemla, Gooding, & Austerweil, 2023), and why are some false memories more likely than others (Vitevitch, Chan, & Roodenrys, 2012). In cases like these, networks provide metaphorical landscapes on which cognitive processes navigate, helping us understand the rich structure of internal representations and the potential mechanisms we use to encode and access them.

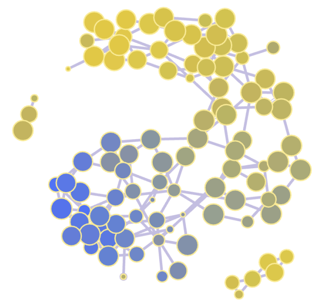

Figure 1. A social network of expressed beliefs based on a Bayesian model of authentic and socially influenced belief expression (Brown, Lewandowsky, & Huang, 2022). Nodes are individuals, with color representing more or less extreme expressed beliefs, and edges indicating social relations as a result of decisions to form or remove ties (Hills, 2025a).

Network science also provides a framework for modeling cognitive processes. This has been applied to language development (Stella et al,. 2017), cognitive aging (Hills, 2025b), collective decision making (Barkoczi & Galesic, 2016), creativity (Hills & Kenett, 2024), language evolution (Steyvers & Tenenbaum, 2005), learning (Lynn & Bassett, 2020) and many other aspects of cognition. In each case, by combining quantitative hypotheses about structure and process, we can compare alternative models and enrich our understanding of how these systems work.

Network science is a rich and growing area of research connecting disciplines ranging from physics to sociology. Its strength as a tool for understanding complex systems, such as brain development, city structure, and the scaling of human interactions (Figure 1) makes it a rewarding area of study that teaches us more broadly about systems in general. More specifically for cognitive scientists, it inspires new questions, invites new analogies, and helps us better grasp the whole cognitive enchilada, including the complex environments in which our cognitive systems are embedded.

Goals

The primary goal of the workshop is to bring cognitive scientists interested in developing their intuitions about network science, the foundational tools and understanding to do so as painlessly as possible. The workshop will introduce core network science principles, providing a solid foundation for using network science out-of-the-box, and also extend these concepts to thinking about cognitive modeling and the role of structure and process. It will also offer attendees the opportunity to apply these principles to their own data and explore how structure and process might

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work in areas of their own expertise. *Prerequisites:* I will provide and walk through the R code for all of the concepts introduced, but attendees should have a working knowledge of R and RStudio, though it need not be advanced. R code for the workshop and additional details can be found here.

Target Audience

Structure matters for many areas of the behavioral sciences and our structural intuitions often help to expand the hypothesis space about how and why systems work the way they do. This workshop should therefore be of interest to many in the cognitive science community, including psychologists, neuroscientists, computer scientists, and philosophers.

Structure of the Workshop

This half-day workshop is divided into two sessions. It will start with a brief guide to network science (getting our data into networks, network metrics, and null models). It will then move to cognitive modeling with networks, focusing on two case studies aimed at explaining empirical observations in the aging lexicon and belief polarization. The case studies are chosen to demonstrate basic principles in cognitive network modeling that can be broadly applied. The workshop will also cover basic problems specific to network science such as statistics, questions of comparison and control, and the limits of network science. The brief guide and case studies are drawn from Hills (2025), *Behavioral Network Science: Language, Mind, and Society*.

Session 1: A brief guide to network science

I will provide a brief demonstration of the core principles in network science and explore these principles using R code. The primary topics will be as follows:

- Representing networks
- Four types of networks
- Thresholding
- Turning data into networks
- Visualization
- Centrality measures
- Assortativity and homophily
- Community detection
- Small-world metrics
- Null models

Session 2: Cognitive modeling with networks

This session will tackle questions around cognitive modeling with networks. This will focus on both structure and process, with the goal of thinking beyond structural metrics to asking deeper questions about cognition as a system.

Case study 1: The aging mental lexicon

Modeling network enrichment in the aging lexicon: covering network construction, learning networks using Rescorla-Wagner, and retrieval from networks using spreading activation models (Hills, 2025b).

Case study 2: False consensus and belief polarization on adaptive social networks

Modeling Bayesian beliefs and the effect of social influence on belief polarization: Social sampling theory (Brown et al., 2022) allows agents to trade-off authenticity against social extremeness aversion. By evaluating social contacts, agents alter their beliefs and their feelings of normalcy. Various kinds of migration policies on these networks lead to greater polarization but also greater feelings of normalcy and, therefore, false consensus.

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