CHAPTER 10

Connecting the Dots

Making Sense of Sociograms

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Librarians have been slow to embrace social network analysis (SNA)[1]—a method of uncovering the hidden relationships that underlie all of society—within their research. In the 2010s, there exist only a handful of examples where librarians used SNA to explore communication flows either across library units, between librarians and faculty, or within immersive professional development programs.[2] Under the broader umbrella of data visualization, library professionals have observed that a lack of technological infrastructure and expertise has negatively impacted adoption of these tools and methods.[3] As academic libraries at large research institutions increasingly invest in offering all manner of data visualization programs and training, it is clear more students and faculty will come to expect their own libraries to provide this type of research support.[4]

Background

Statistical analysis of text-based publications like books and articles—commonly referred to as bibliometrics—has been regularly employed by librarians to illustrate citation and authorship patterns since the early 1970s.[5] These techniques provide an entry point into understanding the social connections underlying a body of research and seek to answer questions such as who has published together, which researchers have aligning interests, and which institutions may be research partners.

Just as traditional bibliometric methods make use of readily available publication data, other categories of social research similarly favor existing data sources like metadata from e-mail and social media. Presumably, it has been easier and faster for scholars to work with born-digital secondary data than it is to design and carry out primary research; however, these practices tend to overlook face-to-face interactions in their assessment of social connections. While earlier research should not be minimized, an overreliance on secondary data will result in a limited and shallow understanding of the social relationships that support today's workers. For example, an analysis of my published research will uncover associations only with my coauthors; remaining hidden are relationships with other individuals who have positively impacted my career, including colleagues, peers, classmates, friends, and family.

In any case, librarians must continue to evolve their research and add new methods to their toolbox. Rooted in sociology and social capital theory, SNA seeks to better understand and recognize the value that comes from nurturing and leveraging relationships. Collecting and analyzing primary data will result in a more nuanced and holistic understanding of personal interactions in the workplace. While quantitative metrics and statistical analysis are hallmarks of SNA research, visualization also plays a vital role, and research findings are often shared in network diagrams known as sociograms.

Drawing inspiration from the arts, the first sociograms were created ninety years ago as a means to more accurately portray social relationship data without oversimplifying its innate complexity.[6] Contemporary research confirms the importance of data visualization as the human mind more easily recognizes patterns and draws inferences when data is presented in a visual format.[7] Today's sociograms are typically created by computers from adjacency matrices—tables of 1s and 0s representing the presence or absence of relationships among groups of individuals.[8] As these underlying data sets grow, it becomes increasingly difficult to draw conclusions from a cognitive review of the raw data alone—this is why the ACRL *Framework for Visual Literacy in Higher Education*: Companion Document to the *Framework for Information Literacy for Higher Education* (VL Framework) includes "explor[ing] creative or generative engagement with visuals to conceptualize, research, and analyze complex topics, such as mind mapping, photo elicitation, visualization, and other methods" as a knowledge practice within the theme "Learners perceive visuals as communicating information."[9] The chapter begins with a review of key terms and concepts. I will then present recommendations for crafting sociograms and for deconstructing the process used to create them, followed by a brief discussion on confidentiality. Next, I will share practical examples from the fields of social psychology, human resources, and education to showcase the method's wide applicability. Finally, I will look at the potential for SNA to support diversity, equity, and inclusion (DEI) initiatives to close out the chapter, which also connects this topic to social justice as a visual literacy concept. My goal is that this chapter can act as a reference tool for academic librarians to further their own research as well as supporting the research efforts of faculty and students. Relevant visual literacy knowledge practices and dispositions from the VL Framework will be referenced throughout the chapter to help readers better contextualize sociograms within the theme of visuals communicating information.

Fundamentals

The resources in the accompanying note will be useful for those interested in creating and interpreting sociograms, as they introduce the context, methods, and tools of SNA.[10] As with any skill set, practice and experience are needed to understand complex visualizations and perform advanced testing. While data complexity, software choice, and sophistication of analysis all impact how fast fluency with these methods can be attained, the ability to graph a smaller, less complex network is reasonably achievable with software that has lower barriers to usability and cost (e.g., NodeXL, EgoWeb, Shiny Fabric). To help beginners in these techniques get started, several basic concepts are introduced below.

The study of social networks takes one of two main approaches. Visualizations that focus on a single individual and depict only their direct connections are called egocentric graphs; these will appear hub-and-spoke shaped. In contrast, graphs are referred to as sociocentric when they also showcase the interrelationships among an individual's direct connections. In the latter case, visualizations might look as if someone played connect the dots across constellations in the night sky.

Dots or points within a sociogram are referred to as nodes and most commonly represent individual people.[11] A pair of nodes may be termed a dyad. The individual providing information about their relationships is called the ego, and their connections are referred to as alters. Direct connections between individuals are expressed by drawing a line—or edge—between two nodes. Whether these edges signify professional, familial, or organizational connections will change based on research goals and the nature of the data collected.

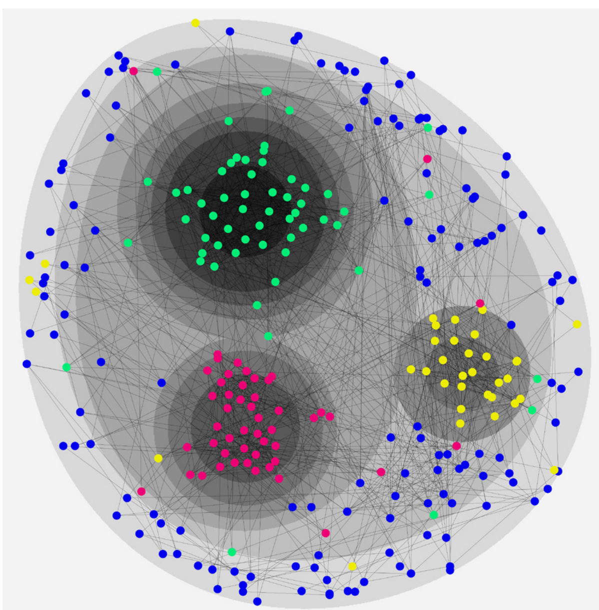

Figure 10.1

Example of a sociogram showing cohesion within organizational subgroups (Image by Klaudia Mur, cofounder, Jolint Network Analytics AB, November 2021. Used with permission.)

Attribute information may be collected about the ego, their alters, or the nature of their various relationships. Commonly studied personal characteristics of individual network members include age, gender, nationality or ethnicity, and expertise.[12] Relational characteristics routinely captured for each dyad include how the pair know each other, how frequently they interact, who typically initiates contact, and the type of knowledge they share.[13] To highlight personal or relational characteristics within a sociogram, a researcher can adjust the size or shape of the nodes, the weight of the edges, color schemes, and boundary markings (figure 10.1).[14]

It is important for a creator to include a key with their visualization to aid others in interpreting their formatting choices. For the consumer, it is important to neither make assumptions about formatting, nor be content with incomplete information from creators. Those who teach visual literacy skills should ensure that the importance of keys or legends for graphical data is incorporated into the instructional process. Because the knowledge practice "define[s] and articulate[s] the need for visuals within a project, assessing the audience for the project and the manner in which it will be shared, as well as how the use of visuals supports the purpose of the project," and places a focus on the audience's perspective, the importance of including a key when sharing sociograms should not be overlooked.[15]

For example, when examining the sociocentric diagram shown in figure 10.1, what do the different colors mean? Do the colors represent various departments within an organization, different geographical locations, or something else altogether? In speaking with the creator, I confirmed that color was used to identify workers in different geographical locations, where blue denotes those who work at the organization's headquarters. The creator's use of color allows the audience to gauge whether subgroups within the organization are tightly bonded by location; clusters of like-colored nodes indicate high cohesion, whereas multicolored clusters or loosely connected nodes of the same color connote low cohesion. Just as the VL Framework cautions that learners "recognize that a visual's communicative intent and purpose can be changed through modification, repurposing, remix, or formatting,"[16] we can see that the creator could have communicated different insights by making different formatting choices.

SNA practitioners typically calculate various network metrics including measures of connectedness, power or influence, and cliques.[17] These calculations are then often combined with other, nonnetwork data and statistically analyzed using a tool like SPSS or R. While quantitative analysis is a major component of most SNA research, given the focus of this book, subsequent discussions have been intentionally limited to focus on the visual aspect of SNA.

Data Collection and Representation

Most individuals have personal networks that include hundreds of active associations and thousands of more peripheral connections.[18] Research has shown that people will tend to name a half dozen social connections when prompted via free recall, yet practice has also shown it is reasonable to believe that the same individual could recall two to three times as many.[19] The more connections or alters a practitioner solicits and the more attributes they collect, the more burdensome the data collection process becomes. Research design should balance the desire for a comprehensive and detailed picture of an individual's social network with the time demands placed on study participants.

Although some might expect the size of an individual's network to increase with age, research offers an alternative perspective. When graphed over the course of a career, the size of an individual's active network may look more rainbow-shaped.[20] While early career workers are still building their networks to increase their personal knowledge bases, individuals late in their career have acquired and internalized the knowledge necessary to independently carry out their work.[21] As a result, the career stage of participants in SNA research may have a direct impact on the amount of data that is ultimately collected.

Practitioners must also consider the wording they will use to ask research participants about their social networks. The questions used to cue subjects' recall are referred to as name generators. Research design can incorporate multiple generators and follow-up probes, and focus on either roles or behaviors.[22] When asking respondents for alters, general practice has been to provide a time frame for their social interactions (e.g., past two weeks, last month) and to focus on interactions where substantive or important contact has occurred.[23] As an example, my research directed respondents to "Please think about the various individuals you have talked to about *work-related topics over the past year*. For example, you may have talked about best practices, how to fulfill a customer request, or about upcoming changes to the profession."[24] Choices made in name generator design directly impact recall ability, information shared, and the visual depictions you are ultimately able to produce. While SNA frequently employs surveys to collect data, research suggests that diaries may be a viable option that results in more accurate recall.[25]

Information consumers should examine accompanying disclosures to determine whether visualized data was collected from primary or secondary sources, being mindful that sociograms favoring secondary data may not represent all important relationships. Where possible, name generators should be reviewed to better understand the composition and boundaries of the social structures being depicted. Finally, we should look for a key to assist with accurately interpreting the personal and relationship characteristics highlighted in the network diagram.

Confidentiality and Security

Confidentiality and security are significant considerations because SNA methods collect and share highly personal information, some of which may be sensitive in nature. Informed decisions must be made about the types of information to be collected, how information will be securely stored, whether information should be aggregated or anonymized before being shared, and if limits will be placed on who can access the data or results—all before the data is visualized. For this purpose, institutional review boards can be a valuable partner in designing human subjects research in a responsible manner.

As confidentiality in focus groups cannot be guaranteed, consider using individual interviews or surveys to collect particularly sensitive information. Individuals may be more candid in phone interviews than when face-to-face due to an increased feeling of anonymity.[26] This increased candor may extend to similar data collection methods such as online surveys. In egocentric research, you may attempt to anonymize data during collection by asking individuals to refer to social contacts by nicknames, initials, or other unique and defining characteristics instead of by their full or proper names.[27] In contrast, collecting full contact information is necessary for sociocentric analysis in order to knit together data from multiple respondents into a single sociogram.

Consistent with the real-world examples identified in the following section, individual names are rarely depicted in sociograms—especially sociograms that are widely distributed. Despite this practice, the confidentiality of individuals in smaller or named organizations may be at risk of reidentification. To protect against this possibility, practitioners may opt not to share all their methods and results. From a visual literacy perspective, it may be helpful to think about this process in relation to "prioritiz[ing] ethical information practices" even when those practices are in conflict with "aesthetic preferences or creative objectives for visuals."[28]

SNA in Practice

SNA-based methods have been found useful in a variety of fields, providing an example for how visuals function as "meaningful contributions to research, learning, and communication."[29] In the following examples, I will summarize research goals and findings for each project. Then, I will note the ways in which the data collection and confidentiality practices used for a project align with earlier discussions.

Social Psychology

Meltem Yucel and colleagues studied the sociocentric network of a forty-five-member, college-level crew team to better understand how gossip spreads and impacts friendship.[30] Teammates with many group connections were found to spread more positive gossip and less negative gossip; the opposite held true for less connected members. An online survey asked each team member to identify friends and whether they gossiped (positively and negatively) about each of their teammates. Sociograms were created for each of the networks studied: friendship, positive gossip spread, and negative gossip spread. In these visualizations, color was used to denote gender and edges were both bidirectional and weighted, allowing the viewer to observe reciprocity and frequency within dyadic pairs. The lead author deleted personally identifiable information before sharing the data collected with other team members.

Human Resources

Claire Gubbins and Thomas Garavan studied the egocentric networks of 300 human resource (HR) professionals to uncover the role social connections play in career advancement and success.[31] An online survey solicited names of five to ten individuals who had "helped you at any point in your career" and asked if the contacts were similarly positioned on the career ladder, along with whether they worked in the same unit or organization. Following common practice and aligned with research goals, network metrics (e.g., percent of alters higher on ladder) were calculated and compared with personal characteristics (e.g., salary, career satisfaction) using advanced statistical tests. Results show HR professionals in other organizations and in higher positions on the career ladder are best positioned to offer the necessary support. Participant confidentiality was maintained by aggregating results. While sociograms were not used, deliberately chosen and anonymized examples might have aided reader comprehension of a narratively dense discussion—again illustrating the importance of defining the need for visuals within a project, especially in consideration of audience and sharing or publication methods as well as the project's intended purpose.[32]

Education

Yang Yang, Nitesh E. Chawla, and Brian Uzzi looked at the social networks of 700 graduate students in a STEM-based leadership program to determine the impact relationships have on job placement outcome.[33] While secondary data (i.e., e-mail) was used,[34] this example demonstrates the power of SNA to discover how homogeneous affiliations show up within social networks. Women needed an inner circle of other women to achieve the same placement levels as the men in their program, demonstrating how creators can use visuals to literally represent social or cultural identifiers like gender.[35] Results were again aggregated to maintain confidentiality. Unlike the missed opportunity in the previous example, model sociograms were leveraged to visually communicate insights. These exemplars allow the audience to easily see structural differences—number of nodes and level of connectedness—described within the text. With its ties to conversations on equity, this study serves as a good segue into the closing section on diversity, equity, and inclusion.

Diversity, Equity, and Inclusion

SNA can play a valuable role in uncovering inequity in social structures or measuring the impact of diversity and inclusion efforts over time, as in the previous example showing the impact of a STEM leadership program. Discussions about the diversity of one's social network can be challenging, and I *do not* advocate that anyone survey all their social contacts about what may be deeply personal information; however, relationship development includes acts of self-disclosure that allow us to learn more about one another over time. Additionally, consider your personal comfort with physically capturing diversity characteristics in any kind of qualitative research—you may opt to record data in a more general manner, keep your data and visualizations in a secure location, or limit whether and with whom you share this information. Regardless, the choices you make in collecting and sharing DEI data will have a direct impact on the meaning that your visual is able to convey.

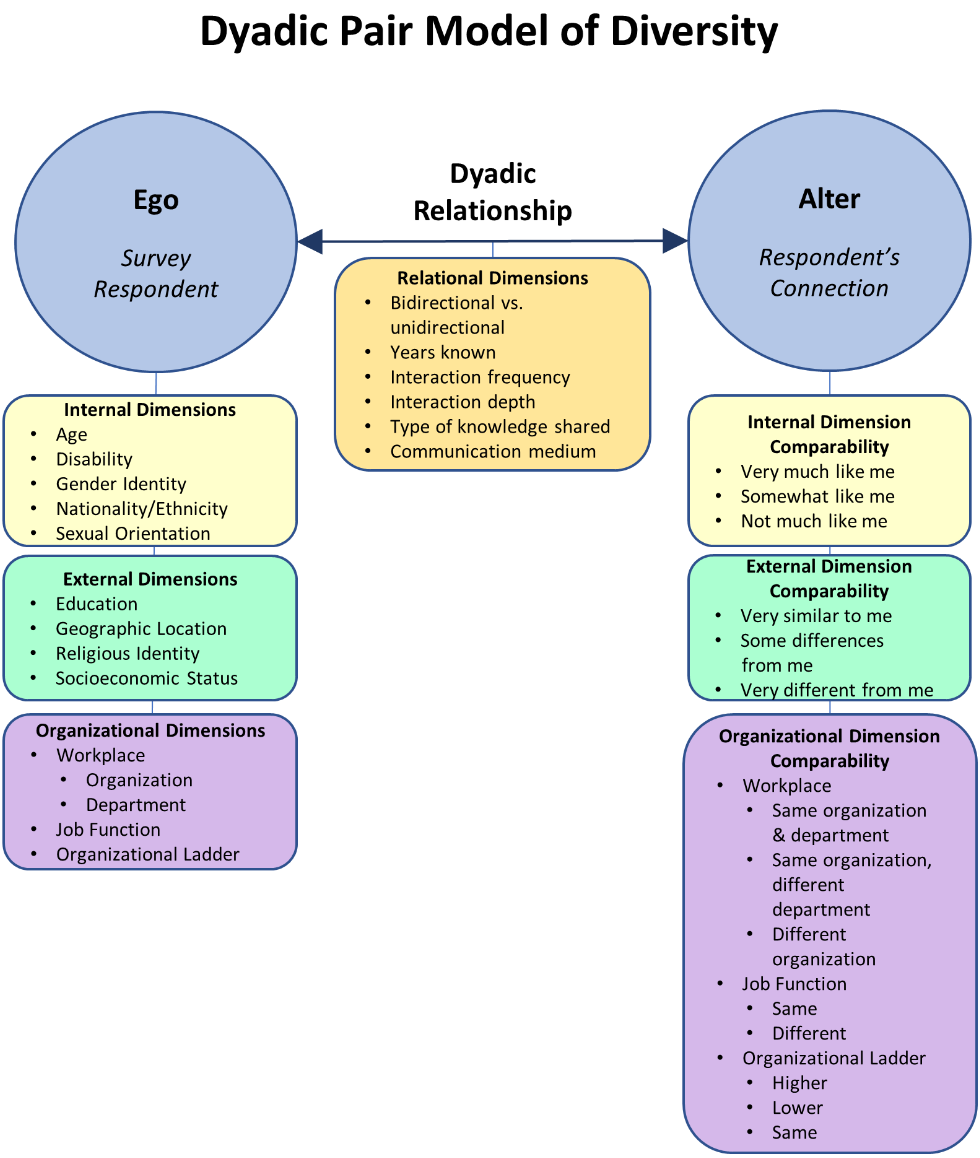

Figure 10.2

Mapping Diversity Wheel characteristics to sociogram components.

Researchers developed a Diversity Wheel (figure 10.2) that breaks diversity down into different categories—personality, internal, external, and organizational—giving us a starting point from which to evaluate network diversity.[36] Figure 10.2 extends their work by placing these characteristics into the context of a network dyad.[37] While internal dimensions most closely align with traditional views of diversity, other conceptualizations should not be overlooked. In particular, organizational dimensions tend to be publicly available and accessible via the internet, as well as more accurately recalled due to ease of observability.[38]

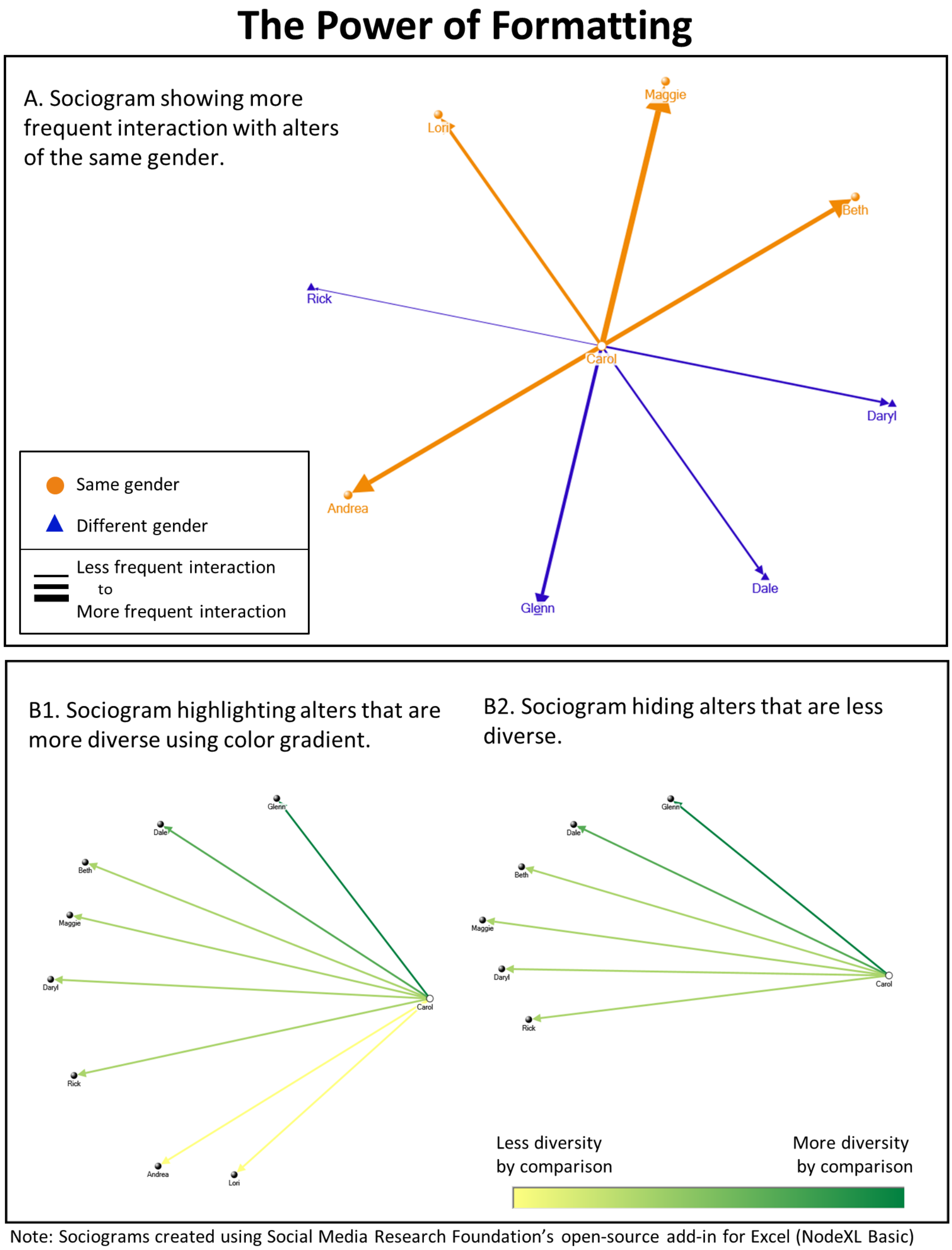

Figure 10.3

Using formatting in a sociogram to influence DEI choices.

Within a dimension, diversity can be operationalized in different ways. For example, the internal dimension of gender identity can be explicitly captured and shared (e.g., men, women, nonbinary or gender nonconforming people) as seen in the social psychology example, compared across individuals (e.g., same gender identity, different gender identity), as suggested by Rob Cross and Andrew Parker, or captured in the aggregate with other internal attributes (e.g., Do you feel that you and *alter n* have more or less in common when it comes to internal attributes such as gender, age, and ethnicity?).[39] Figure 10.3 shows different approaches for visually communicating network diversity data and highlights the need for researchers to experiment with formatting options to ensure a sociogram is communicating what they intend to convey.[40]

Final Reflections

Academic librarians will need to be conversant in SNA and sociograms as interest in data visualization services grows and university libraries work to stay competitive with peer institutions.[41] In addition to librarians being able to provide research support—such as reference materials, technology, and training—to library patrons, fluency in data visualization methods and tools can be leveraged internally for library assessment and marketing campaigns.[42] At the same time, students can reflect on the way "choices made in the production of visual communications" impact the way data is visualized in sociograms (whether their own or made by others), as well as consider the role of sociograms as visual communications in representing cultural and social identifiers within social networks.[43]

Notes

1. Also referred to as organizational network analysis (ONA) or the derivative knowledge network analysis (KNA).
2. Jennilyn M. Wiley, "No Librarian Is an Island: A Network Analysis of Career Motivation and Progression in U.S. Librarians" (PhD diss., Kent State University, 2019), 24–28, 54, ProQuest (27765870).
3. Hsuanwei Michelle Chen, "Information Visualization," *Library Technology Reports* 53, no. 3 (2017): 26–27; Atalay Kutlay, Cal Murgu, and Tammera Race, "Shiny Fabric: A Lightweight, Open-Source Tool for Visualizing and Reporting Library Relationships," *Code4Lib Journal* 47 (February 17, 2020), sec. "Background," https://journal.code4lib.org/articles/14938; Mahmoud Sherif Zakaria, "Data Visualization as a Research Support Service in Academic Libraries: An Investigation of World-Class Universities," *Journal of Academic Librarianship* 47, no. 5 (2021), 8, https://doi.org/10.1016/j.acalib.2021.102397.
4. Chen, "Information Visualization," 19–21; Zakaria, "Data Visualization," 4–7.
5. Shelia Corrall, Mary Anne Kennan, and Waseem Afzal, "Bibliometrics and Research Data Management Services: Emerging Trends in Library Support for Research," *Library Trends* 61, no. 3 (2013): 641, https://doi.org/10.1353/lib.2013.0005.
6. Jacob L. Moreno and Helen H. Jennings, "Statistics of Social Configurations," *Sociometry* 1, no. 3/4 (January–April 1938), 342, 345–46, https://doi.org/10.2307/2785588.
7. Chen, "Information Visualization," 7; Zakaria, "Data Visualization," 1.

8. Robert A. Hanneman and Mark Riddle, *Introduction to Social Network Methods* (Riverside: University of California, 2005), chap. 5, http://faculty.ucr.edu/~hanneman/nettext/index.html.
9. Association of College and Research Libraries, *The Framework for Visual Literacy in Higher Education*: Companion Document to the *Framework for Information Literacy for Higher Education* (Chicago: Association of College and Research Libraries, 2022), 6, https://www.ala.org/acrl/sites/ala.org.acrl/files/content/standards/Framework_Companion_Visual_Literacy.pdf.
10. Rob Cross and Andrew Parker, *The Hidden Power of Social Networks* (Boston: Harvard Business School Press, 2004); Hanneman and Riddle, *Introduction*; Derek L. Hansen, Ben Schneiderman, and Marc A. Smith, *Analyzing Social Media Networks with NodeXL* (Cambridge, MA: Morgan Kaufman, 2011).
11. Some researchers will use nodes to represent groups of individuals, organizations, or explicit knowledge sources such as databases, manuals, and reports; Remko Helms and Kees Buijsrogge, "Knowledge Network Analysis: A Technique to Analyze Knowledge Management Bottlenecks in Organizations," in *16th International Workshop on Database and Expert Systems Applications (DEXA '05), Copenhagen, Denmark, 2005* (New York: Institute of Electrical and Electronics Engineers, 2005), sec. 2.2, https://doi.org/10.1109/DEXA.2005.127.
12. Mark S. Granovetter, *Getting a Job* (Cambridge, MA: Harvard University Press, 1974), app. C; John Scott, *Social Network Analysis*, 2nd ed. (London: SAGE, 2000), 2–5; Cross and Parker, *Hidden Power*, 169; Helms and Buijsrogge, "Knowledge Network Analysis," sec. 2.2; Corey Phelps, Ralph Heidl, and Anu Wadhwa, "Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda," *Journal of Management* 38, no. 4 (2012): 1115–66, https://doi.org/10.1177/0149206311432640.
13. Granovetter, *Getting a Job*, app. C; Scott, *Social Network Analysis*, 2–5; Cross and Parker, *Hidden Power*, 169; Phelps, Heidl, and Wadhwa, "Knowledge, Networks."
14. Hansen, Schneiderman, and Smith, *Analyzing Social Media*, chap. 4.
15. Association of College and Research Libraries, *Framework for Visual Literacy*, 6.
16. Association of College and Research Libraries, *Framework for Visual Literacy*, 7.
17. Hanneman and Riddle, *Introduction*, chaps. 7, 10, 11.
18. Isidro Maya Jariego, "Why Name Generators with a Fixed Number of Alters May Be a Pragmatic Option for Personal Network Analysis," *American Journal of Community Psychology* 62, no. 1–2 (2018): 234, https://doi.org/10.1002/ajcp.12271.
19. Jennifer Merluzzi, and Ronald S. Burt, "How Many Names Are Enough? Identifying Network Effects with the Least Set of Listed Contacts," *Social Networks* 35, no. 3 (2013): 332–33, https://doi.org/10.1016/j.socnet.2013.03.004; Maya Jariego, "Why Name Generators," 235.
20. Frank J. van Rijnsoever, Laurens K. Hessels, and Rens L. J. Vandeberg, "A Resource-Based View on the Interactions of University Researchers," *Research Policy* 37, no. 8 (September 2008): 1258, 1260, https://doi.org/10.1016/j.respol.2008.04.020.
21. van Rijnsoever, Hessels, and Vandeberg, "Resource-Based View."
22. Peter V. Marsden, "Network Data and Measurement," *Annual Review of Sociology* 16, no. 1 (1990), 441–44.
23. Marsden, "Network Data," 441–44; Merluzzi and Burt, "How Many Names," 333.
24. Wiley, "No Librarian," 144.
25. Marsden, "Network Data," 440, 445.
26. Merluzzi and Burt, "How Many Names," 332.
27. Care should be taken with this approach because follow-up questions will be asked about each alter. While full names are often unnecessary to the practitioner, survey respondents must be able to recognize and differentiate their social contacts. When collecting information on large numbers of alters, this approach may prove impractical and data should then be anonymized after it has been gathered.
28. Association of College and Research Libraries, *Framework for Visual Literacy*, 7.
29. Association of College and Research Libraries, *Framework for Visual Literacy*, 7.
30. Meltem Yucel et al., "Being in the Know: Social Network Analysis of Gossip and Friendship on a College Campus," *Human Nature* 32, no. 3 (2021): 603–21, https://doi.org/10.1007/s12110-021-09409-5.

31. Claire Gubbins and Thomas Garavan, "Social Capital Effects on the Career and Development Outcomes of HR Professionals," *Human Resource Management* 55, no. 2 (2016): 241–60, https://doi.org/10.1002/hrm.21727.
32. Association of College and Research Libraries, *Framework for Visual Literacy*, 6.
33. Yang Yang, Nitesh V. Chawla, and Brian Uzzi, "A Network's Gender Composition and Communication Pattern Predict Women's Leadership Success," *Proceedings of the National Academy of Sciences of the United States of America* 116, no. 6 (2019): 2033–38, https://doi.org/10.1073/pnas.1721438116.
34. Research design excludes face-to-face social interactions from the analysis (i.e., those occurring during class time, in the moments before or after class, and outside the classroom) and might have impacted the authors' findings.
35. Association of College and Research Libraries, *Framework for Visual Literacy*, 6.
36. Lee Gardenswartz and Anita Rowe, *Diverse Teams at Work* (Chicago: Irwin Professional Publishing, 1994), chap. 2; Khalil Al-Jammal, "Student Leadership: Basic Skills and Appropriate Activities," *International Journal of Innovative Research and Development* 4, no. 13 (December 2015): 24, http://www.internationaljournalcorner.com/index.php/ijird_ojs/article/view/135936.
37. Gardenswartz and Rowe, *Diverse Teams*, chap. 2; Cross and Parker, *Hidden Power*, 169; Al-Jammal, "Student Leadership," 24.
38. Marsden, "Network Data," 456.
39. Cross and Parker, *Hidden Power*, 169; Yucel et al., "Being in the Know," 610–11.
40. Association of College and Research Libraries, *Framework for Visual Literacy*, 6. See "Learners who are developing their visual literacy abilities …anticipate that the process of visual creation is iterative and involves many phases, including inspiration, transformation, experimentation, synthesis, and refinement."
41. Zakaria, "Data Visualization," 4, 9.
42. Chen, "Information Visualization," chap. 3; Zakaria, "Data Visualization," 4–7.
43. Association of College and Research Libraries, *Framework for Visual Literacy*, 6.

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