Mapping Literature with Networks: An Application to Redistricting

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Abstract

Understanding the gaps and connections across existing theories and findings is a perennial challenge in scientific research. Systematically reviewing scholarship is especially challenging for researchers who may lack domain expertise, including junior scholars or those exploring new substantive territory. Conversely, senior scholars may rely on long-standing assumptions and social networks that exclude new research. In both cases, *ad hoc* literature reviews hinder accumulation of knowledge. Scholars are rarely systematic in selecting relevant prior work or then identifying patterns across their sample. To encourage systematic, replicable, and transparent methods for assessing literature, we propose an accessible network-based framework for reviewing scholarship. In our method, we consider a literature as a network of recurring concepts (nodes) and theorized relationships among them (edges). Network statistics and visualization allow researchers to see patterns and offer reproducible characterizations of assertions about the major themes in existing literature. Critically, our approach is systematic and powerful but also low cost; it requires researchers to enter relationships they observe in prior studies into a simple spreadsheet—a task accessible to new and experienced researchers alike. Our open-source R package enables researchers to leverage powerful network analysis while minimizing software-specific knowledge. We demonstrate this approach by reviewing redistricting literature.

Keywords: qualitative methodology, networks, redistricting

1 Introduction

The first step in any scientific research is understanding the state of relevant existing knowledge. “Literature reviews” range from simple expositions of past work, to critical analysis, to identifying intellectual communities or schools of thought. No matter the style, the goal is typically the same: identifying what is known, assessing what is unknown, and suggesting paths for productive research (Knopf 2006). As central as literature reviews are to the research process, there is surprisingly little guidance on how to write them in political science (Knopf 2006). What constitutes a good summary of prior research?

1.1 What a Review Should Include

Ideally, a scholar draws on expert knowledge and a systematic search of published work to identify a literature (McGhee 2020), sifting through and identifying all relevant prior studies, organizing them using a schema (perhaps conceptual, theoretical, empirical, or chronological), distinguishing what is known from what is unknown or disputed, and ending with research questions.

More commonly, however, literature reviews are *ad hoc*, with writers unconsciously applying heuristics such as familiarity, citation patterns, and author prestige to signal relevant work. Such methods can reproduce existing biases that can exclude work written by women or minorities (Dion, Sumner, and Mitchell 2018). While transparency in inclusion criteria is essential (Snyder 2019), few papers in political science discuss methods of literature review, much less inclusion criteria.

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Motivated by a need for transparent approaches and methods to uncover broad patterns in literature reviews, we offer a network-based framework for reviews. The core components of a classic social network are simple: a set of actors (*nodes*: e.g., individuals and organizations), any two of whom can be connected through a social interaction (*edges*: e.g., friendship and co-occurrence). As social networks help conceive of actors and their relationships with one another, so too can a body of scientific knowledge be organized as a network of concepts (nodes) and theorized relationships among them (edges); importantly, social networks are analyzed for their entire structures and patterns across them, which map nicely to questions we can pose about patterns of studied concepts and their relationships.

This framework is helpful on several fronts. First, it provides greater transparency in the choices of work comprising the "universe" of relevant prior knowledge—that is, defining a network clarifies the population, sampling approach, and sample the review includes. Second, network graphs can display *broad and complex patterns* among concepts that may not appear to human imagination alone. We show that network visualization and simple network statistics clarify gaps in theory and theory testing. Third, our approach makes evidence for assertions about prior knowledge easy to produce, critique, replicate, and extend. Fourth, a network of concepts is an accessible first step toward causal graphs used in causal identification.

Any review of research is as biased as the sample of work that comprises it. While our approach cannot estimate biases, clarifying standards for inclusion may diminish the role of heuristics based on familiarity and prestige. Moreover, patterns revealed in a network may draw attention to new research areas. Explicating assertions about gaps in knowledge may also reduce reliance on conventional wisdom and the likelihood of overlooking contributions from less cited or well-networked research, including work by underrepresented minority and junior scholars. While quantifications of human biases in reviewership are inherently difficult to measure, we conduct an illustrating set of experiments of biased sampling drawn from a fixed corpus and present descriptive findings on preserved and lost aspects of network structure in such a process in Section B of the Supplementary Material.

1.1.1 *Questions Asked in Classical Literature Reviews.* We begin with common questions asked in literature reviews, summarized in Table 1. We show how these questions correspond to features of networks (shown in column 2, *network questions*) captured by *network statistics* (column 3), and distinguish questions that *identify and assess* literature, *explore* possibilities to contribute, and *isolate and control* conceptual relationships for causal theory-building.

1.1.2 *Assess and Identify.* This group of questions includes summaries of research and offers a sense of existing knowledge—key parts of a literature review identified in Knopf (2006). Summarizing pairs ("dyads") of studied concepts is straightforward. Global patterns of connections are harder to contemplate without visual aids. Visualizing a network constructed from concept dyads offers a useful "global summary" of prior literature. Identifying key concepts similarly translates to finding *central nodes*. Finally, identifying clusters of related studies is to discover "network communities," the aim of community detection algorithms (Yang, Algesheimer, and Tessone 2016).

1.1.3 *Explore.* Reviews often aim to identify "gaps in the literature:" under-theorized relationships among concepts or theorized relationships that lack empirical validation (Table 1, "Explore"). *Exploration* questions are difficult to answer without systematic accumulation and organization of the literature, as they inherently require isolating "missing" links. A network framework makes finding missing links straightforward. Exploring network components that lack theoretical ties reveals opportunities to link communities of concepts—and the scholars who study

Table 1. Literature review questions as network questions.

	Literature question	Network question	Network statistic	Example
Assess and Identify	What is the global summary of the current research on this topic? How complete is it?	What does the network look like?	Network graph	See Figure 2
	What are the key concepts that the literature has focused on?	What are central nodes?	Centrality (*local* degree centrality, *global* vertex centrality)	*Partisan advantage* (degree=14), followed by a three way tie of *communities preserved, partisan gerrymandering,* and *compactness* (each degree=5) are the most "globally central" concepts covered in the recent redistricting literature.
	What are communities of work that have developed?	What are communities in the network?	Community-detection algorithms; densely connected subgraphs (via random walk)	Largest community centers around *partisan advantage* and *district competitiveness*; rich related community of literature on how voters are affected.
Explore	What are areas for theoretical exploration? • What bodies of work can/should be connected to each other? • What are unconnected causal concepts?	Where are unconnected communities? Where are potentially unclosed triangles?	Unconnected communities; A->B, B->C, but no observed A->C	Discussions about how campaign spending can result in elite/corporate bias disconnected from implications of social networks. Redistricting commissions are related to partisan gerrymandering, which has been studied as affecting donors and government interest, though direct impacts of redistricting commissions on the latter are understudied.
	What are areas that are under-empirically validated?	What are edge differences between two networks with the same nodes?	Exact comparisons of two networks for differential types of edges.	Summarized in Figure 2 as *solid edges* for theoretically and empirically explored connections, while *dashed edges* connect theoretically connected but not empirically validated concepts.
Isolate and Control	What are causal pathways related to a theorized concept?	What does the neighborhood of a node look like?	Visual inspection	See Figure 3(a)
	What are confounding concepts to a hypothesized causal relationship?	What are nodes with directed edges towards independent and dependent concept nodes?	Visual inspection	See Figure 3(b)

them—together. Similarly, if prior work theorizes that concept A affects concept B (an edge between A and B), and other work demonstrates that B affects C (edge from B to C), but no work exists that discusses the effects of A on C, this appears in the network as a missing edge between A and C, suggesting opportunities for theorizing.

1.1.4 *Isolate and Control.* Finally, a network approach can clarify causal relationships and potential confounding pathways. In a network, existing bodies of scholarship form the local *neighborhood* of a given concept (node). Scholarship on causal relationships among concepts linked to both independent and dependent concepts may reveal confounding causal pathways.

We next present an example application reviewing the literature on redistricting guided by questions drawn from Table 1.

2 Application to Redistricting

To illustrate the method, we imagine ourselves as a researcher new to studying redistricting and conducting a literature review. Figure 1 summarizes steps we take as an example for researchers interested in this approach. Redistricting following the 2020 U.S. Census attracted the attention of courts, politicians, and the public, to the prior decade of academic work, highlighting the importance of district boundaries to political outcomes. Understanding this literature poses a challenge for new scholars. We focus on work over the last 10 years as a way to demarcate the "latest research" (Dion *et al.* 2018).

What constitutes the relevant literature? We recommend selection criteria based on predefined and replicable rules. Our criteria prioritize *recent* and *impactful* work on redistricting, indicated by journal rankings and citations. We select six highly ranked political science journals broad enough in scope to cover the topic of redistricting (Scimago 2020), two journals specifically from the American politics subfield, and finally, *Election Law Journal*, which has systematically published redistricting research cited by courts, expert witnesses, and government entities. Within these journals, we conduct keyword searches among articles published since 2010 containing any of the following phrases in either title or abstract: *efficiency gap*, *gerrymander*, *partisan symmetry*, and *redistrict*. To capture relevant work outside these journals, we search Google Scholar for any post-2010 peer-reviewed article with 50 or more citations that included a key phrase in the title/abstract. One hundred fifteen articles matched these criteria, constituting the

Algorithmic steps to creating a literature network

Step 1 **Select**: select studies, perhaps using topic-associated keywords by soliciting suggestions from domain area experts and iteratively searching and selecting a few articles highly related to the topic phrase(s) — the seed keyword(s) — to snowball-sample related keywords. Finalize a shortlist of keywords. Decide and implement criteria for a) time-frame, b) outlets, c) extent to which outlet features keywords. Finalize a set of works that constitute the body of literature to review.

Step 2 **Input**: for each work, input a single row in spreadsheet with information on the study (*title, author, etc.*), concepts studied (*nodes*), their connections (*edges*), and information pertinent to nodes or edges (*attributes*).

Step 3 **Questions**: refer to Table 1 for questions that can be asked of the literature network and visualize patterns in related network/network components.

Figure 1. Steps to creating a literature network. Application to redistricting demonstrated in italics.

corpus of studies for this review.[1] Keyword selection necessarily affects article selection. For a comprehensive search that balances exploration and "starting values," we recommend an iterative process of selecting seeding keywords to survey the literature and snowball-sample highly related keywords (e.g., searching articles with keyword *redistricting* returns articles that regularly speak of *gerrymandering* and *efficiency gap*) and soliciting keyword suggestions from domain area experts.

For each article, network data is input through familiar steps: reading the work and identifying the main concepts and connections posited between concepts. We select concepts representing the main causes and effects investigated, often concepts discussed in the abstract or theory sections. We enter this information into an *edgelist* spreadsheet—such that concepts constitute *nodes*, and their connections are *edges*, often hypothesized with directions so the edge can be drawn as an arrow from cause to effect.[2] For example, the two main concepts in Cain *et al.* (2017) are "independent redistricting commissions" and "partisan advantage." The authors further posit that such commissions are unlikely to produce extremely partisan maps, which we record as a directed edge. Information pertinent to this edge—such as whether the effect is positive or negative—and the number and identity of works that address this same connection are *edge attributes*. Attention must be paid to the important process of defining nodes and edges—no surprise to regular users of network analysis or analyses that rest on well-measured concepts—how and what constitutes a node that represents a concept and whether it relates to another is ultimately an interpretive process by the researcher from research piece to row in an edgelist.[3] Authors may use different language in referencing the same concept (i.e., *partisan bias* and *partisan advantage*); in these cases, we employ an iterative concept-naming process. We add terms used by each author to the spreadsheet, then visualize the draft network to identify similar terms. After consulting the relevant articles, we consolidate terms referring to the same concept under an umbrella term in the spreadsheet.

In this example, the final spreadsheet contains 57 concept nodes and 69 edges describing relationships among concepts.

Figure 2 shows the resulting redistricting literature network. A global summary of the literature begins with describing the network itself—57 theoretical concepts studied, as causes or effects,

1 Here, we focus on political science redistricting literature as our universe of interest; we could easily see an interdisciplinary approach to defining a universe, whereby literature is drawn from social sciences and mathematics for instance. A pattern that could be explored might be the extent to which disciplines tackling the same topic aren't "speaking" to one another. The nature of the representation of networks (identifying few or no connections can prompt pursuing research directions) can bring scholars together in a scientific sense.

2 Though researchers might represent literature based on other theoretical connections that are of interest—for instance, whether concepts share measurement methodologies—then we suggest coding edge types separately, and representing resulting networks separately for visualization/analysis.

3 This can result in variation across researcher output; Section C of the Supplementary Material presents an exercise comparing several researcher outputs on the same corpus of literature to evaluate similarities across the resultant network structures.

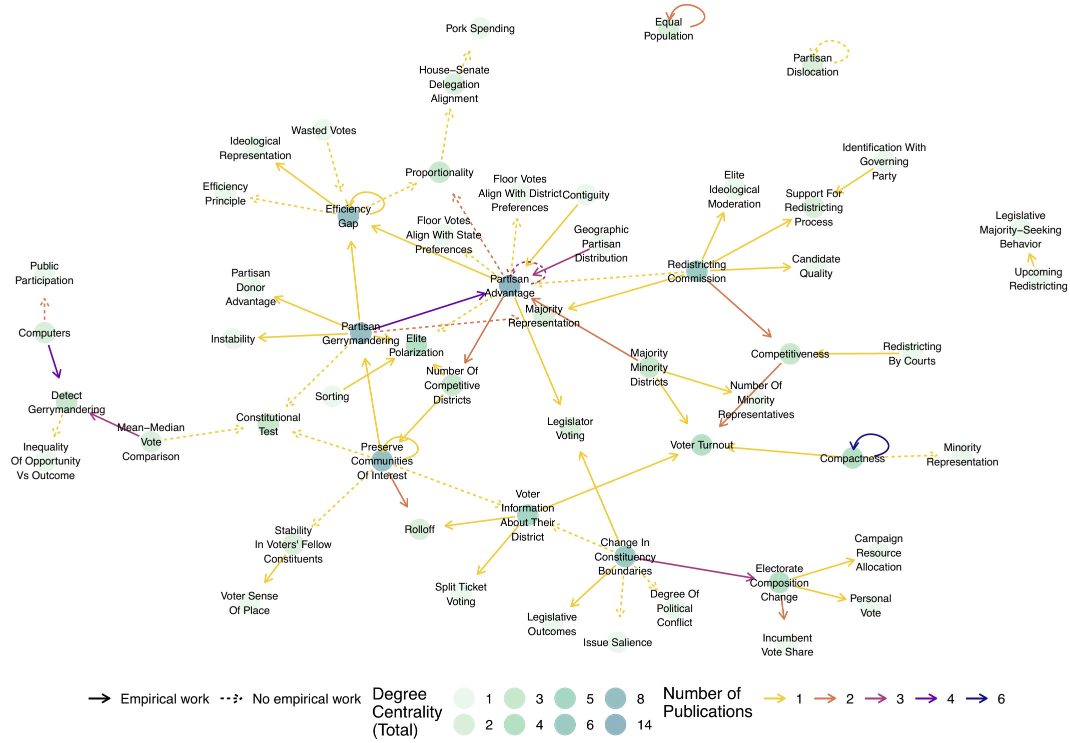
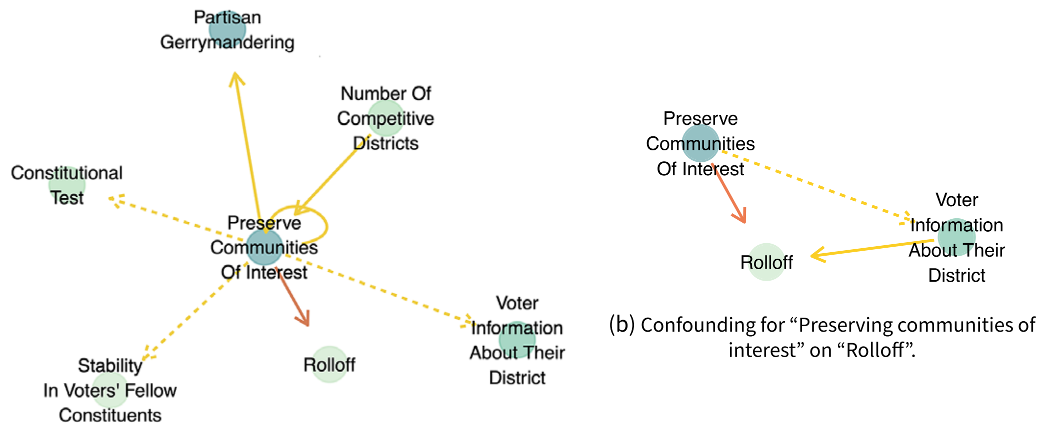


Figure 2. Redistricting literature network. Nodes represent theoretical concepts, shaded by total degree centrality. Arrows connect concepts theorized as directional relationships in works, colored by number of works (and can be both directions—such as might indicate an endogenous relationship). Solid edges indicate empirically studied connections; dashed are relationships that have been theorized but not studied empirically. The *netlit* vignette walks through production of network graphs, using the *graph* object returned by the *netlit::review()* function as the input to network graphing functions from packages like *ggnetwork*. The vignette illustrates how *nodelist* and *edgelist* objects provide required inputs for other network visualization packages, for example, *ggraph* or *visNetwork*.

shaded by the node's total degree centrality.[4] Sixty-nine edge arrows show each directional relationship explicitly theorized in our corpus, colored by number of publications addressing that relationship. Edge colors can illustrate attributes of relationships supplied as an additional column in the input spreadsheet (here representing the number of citations that theorized the edge relationship). The *netlit* vignette presents attributes that one may wish to highlight, including edge statistics (e.g., edge betweenness) produced by *netlit::review()*. Literature discussing the measurement of a single concept appears as *self-ties*. For example, measuring the concept of *compactness* (right-hand side of Figure 2) has inspired a series of works (Barnes and Solomon 2021; Chen and Rodden 2015; De Assis, Franca, and Usberti 2014; Magleby and Mosesson 2018; Saxon 2020; Tam Cho and Liu 2016).

What are key concepts in redistricting literature? As posed in Table 1 "Assess and Identify," a natural translation of this question to a network is "what are the central nodes?" The concept of *partisan advantage* is most central with 14 total edges. *Efficiency gap*, *partisan gerrymandering*, and *preserve communities of interest* each have degree centrality of eight. We define *preserve communities of interest* as an umbrella term covering the broad goals of preservation of minority areas and political subdivisions within districts, and core district retention (Figure 3a). It is unsurprising that this predominantly legal concept scores high in total degree (five out edges, one in-edge, and one self-tie) as it is both a traditional redistricting criterion and widely studied.

4 Degree centrality and other network statistics describing nodes are produced when the spreadsheet of theorized relationships is provided to the *netlit* :: *review*() function.



(a) Neighborhood of “Preserving communities of interest”.

(b) Confounding for “Preserving communities of interest” on “Rolloff”.

Figure 3. (a) Redistricting literature directly related to the concept of *preserving communities of interest*. Nodes represent theoretical concepts (shaded by total-degree centrality). Arrows connect concepts explicitly theorized as directional relationships, colored by number of works. Solid edges indicate empirically studied connections. Dashed edges indicate theorized relationships that aren’t studied in the empirical literature reviewed. *Preserving communities of interest* is often studied as a cause to *rolloff* and *partisan gerrymandering*, and has been theorized to affect voters’ information and fellow constituents; ways to measure it (self-ties) have also been explored. (b) Confounding concepts for the effect of *preserving communities of interest* on *rolloff*.

Are there communities of work that have developed recently? In network terms, we can ask: “what are communities in the network?” A distinct community (Figure 3a) of scholars has investigated how changes in the electorate’s composition (*change in constituency boundaries*) can affect downstream campaign resource allocations and vote power, highlighting the effects that redrawing of maps might have on political environments for individual candidates.

Beyond assessing the state of the literature, two defining tasks in research are finding areas for theory building and identifying where theory has yet to be empirically tested; that is, finding the “gaps” in knowledge. A visual approach to the first question looks for areas in the literature network where two concepts are discussed separately and where a researcher might posit a connection. For example, recent work (Ansolabehere and Snyder Jr. 2012; Carsey, Winburn, and Berry 2017; Hood and McKee 2013; Limbocker and You 2020) has shown that redrawn lines that change the composition of the electorate exert an exogenous effect on the vote, but less attention has been paid to how such changes affect minority representation; there exists an opportunity for research concerned with political consequences of constituency boundaries to engage more directly with scholarship on minority representation.

Answering questions about empirical gaps is a simple matter of analyzing edge characteristics in the network—whether concepts that are linked in theory are also linked in empirical work. In Figure 2 edges drawn as dashed lines indicate a theorized but not empirically validated relationships. Solid lines represent empirically demonstrated connections between concepts. *Partisan advantage* is hypothesized to affect whether *floor votes align with district/state preferences* (bottom of Figure 2)—both through connections that remained untested empirically until recently (Caughey, Xu, and Warshaw 2017). Likewise, Figure 2 suggests *equal population* and *partisan dislocation* are concepts that are important to measure (visually verified with self-ties). Measuring *equal population* has been discussed more often than *partisan dislocation* (Gatesman and Unwin 2021; Magleby and Mosesson 2018), which is reasonable given that equipopulation is a long-standing and firm legal rule in redistricting; whereas the latter concept is relatively new (DeFord, Eubank, and Rodden 2021).

For researchers interested in causal relationships, a network approach offers two tools for *isolating and controlling*, potentially the first step toward a more complete directed analytic graph.

To answer the question "what causal pathways are related to a theorized concept?", we inspect the neighborhood of nodes and edges. Consider the node *preserve communities of interest*. Exploring its neighborhood (Figure 3a) reveals hypothesized downstream effects on preserving community interests, including changes at the voter (*voter information about their district* and *stability in voters' fellow constituents*) and district levels (*partisan gerrymandering* and *rolloff*). It also suggests that *preserving communities of interest* is a prominent confounding concept that affects how *voter information about their district* contributes to *rolloff*.

How does a network approach differ from a traditional expert-guided review? As a thought exercise, one of our team members (Mayer)—a redistricting scholar and experienced expert witness in gerrymandering litigation—prepared a traditional review. We compare our approach against his and McGhee (2020)'s recent redistricting literature review. Mayer and McGhee separately identify three key themes in the recent redistricting literature that parallel our network findings: developing metrics, automation of redistricting methods, and exploring downstream effects of gerrymandering. The network approach brings some nuance to each of these themes, however, by allowing quick identification of metric-oriented works, avoiding over-inflating the importance of growing communities of work, and allowing us to develop more complex directed acyclic graphs from the literature around the effects of gerrymandering.

Specifically, Mayer and McGhee note that recent work has focused on developing metrics to propose a legal standard for federal courts to place limits on partisan plans (and which Justice Anthony Kennedy appeared to request in *LULAC v. Perry* 584 U.S.399 (2004)).[5] Our network approach also identifies scholarship on metrics, represented as nodes with self-ties. Further, it parses out where scholarship on metrics is more or less likely to contribute to theories of redistricting. For example, measures of *compactness* versus *equal population* both have self-ties, but the network shows that only the former has been recently theorized to affect political outcomes such as voter turnout.

Similarly, Mayer notes that automated redistricting methods have captured substantial attention recently (Chen and Rodden 2013; Cho and Liu 2018; Liu, Cho, and Wang 2016; Magleby and Mosesson 2018; Vanneschi, Henriques, and Castelli 2017). One method draws large numbers of maps with different decisions rules and initial conditions, with the resulting maps used to identify outliers that indicate partisan gerrymanders or possible "natural" gerrymanders (Cain *et al.* 2017; Chen 2017; Chen and Cottrell 2016; Chen and Rodden 2013, 2015; Fifield *et al.* 2020; Ramachandran and Gold 2018; Tam Cho and Liu 2016). The network figure shows these studies with self-tying nodes and node connections, including the relationship between *geographic partisan distribution* and *partisan advantage*. Both expert reviews emphasized methodological advancements. While this strand of work is prominent in the full network graph, it is a *minority* of scholarship that is still primarily concerned with political science theories related to redistricting. Thus, we see our approach as avoiding the conflation of overall patterns of scholarship with popular and highly discussed work. The latter would be better captured with a citation network than a causal graph.

The third insight of a traditional literature review is that recent work has continued exploring the effects of gerrymandering on various outcomes including incumbency advantage (Henderson, Hamel, and Goldzimer 2018); electoral competition (Cottrell 2019); candidate quality and emergence (Williamson 2019); roll-call voting and state policy (Caughey, Tausanovitch, and Warshaw 2017); political parties (Stephanopoulos and Warshaw 2020); campaign contributions (Crespin and Edwards 2016); and constituent access (Niven, Cover, and Solimine 2021). Our network also captures these relationships as dyadic connections, but can further illuminate downstream causal chains, confounding concepts, and multiple causal paths.

5 In *Rucho v. Common Cause* 588 U.S.—(2019), the Supreme Court found partisan gerrymandering to be a nonjusticiable political question, closing the door on future litigation in federal court.

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3 Discussion and Conclusion

We present an organizing framework based on network representations to conduct literature reviews. Our application focused on redistricting, but the approach is general; where research builds on complex combinations of prior work, a network approach might prove especially fruitful.

We highlight several helpful features of networks as a way of uncovering patterns in scholarship. Beyond assessing prominent themes and communities of work, the network representation most importantly lends itself to theoretical exploration and identification of relationships that have yet to be studied empirically. Finally, the directed graph representations in this framework can be used to inspect causal pathways related to a concept or to identify confounding relationships (see, for instance, discussion of causal interpretations in regression models in (Keele, Stevenson, and Elwert 2020)).

Our approach may also lower barriers to entry: while substantive expertise always improves exercises like these, the input units to the network require summarizing concepts and identifying posited relationships between them within single research works, repeating this over the list of works, and submitting this information into a spreadsheet. This process is accessible to newcomers to a literature. Illustrated in the *netlit* vignette is another pattern-discovering tool for reviewing literature evolution—by subsetting the input data to prior periods and comparing the generated literature network to the most complete and up-to-date network.

In emphasizing the importance of clearly delineating inclusion criteria for work included in a literature review, our approach may also limit unintentional biases in the process of assembling "relevant" works for literature reviews (e.g., favoring personal or institutional social networks, running the risk of over-representation of well-connected works at the expense of research from underrepresented scholars (Lalanne and Seabright 2022)). While our approach does not eliminate systemic under-representation, we hope that clear criteria and full visualization of included work can sidestep under-representation and under-inclusion.

Ultimately, the proposed framework still relies on researcher choices—including the universe of sources, selection criteria, and identification of main concepts—choices that are still undertaken in traditional reviews of literature. By clarifying choices and utilizing our network framework to visualize the resulting network, we expect it to be easier to evaluate such choices and how sensitive assertions about gaps in the literature are to these choices.

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Data Availability Statement

Replication code for this article is available and has been published in Code Ocean, a computational reproducibility platform that enables users to run the code, and can be viewed interactively at the following DOI: `10.24433/CO.0502881.v1` (Lo *et al.* 2023a). A preservation copy of the same code and data can also be accessed via Dataverse at https://doi.org/10.7910/DVN/NV66YN (Lo *et al.* 2023b). A copy of the R package, code, and data can also be accessed via Github at https://judgelord.github.io/netlit.

Supplementary Material

For supplementary material accompanying this paper, please visit https://doi.org/10.1017/pan.2023.4.

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