The Roles of Engagement: Network Analysis in Physics Education Research

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Abstract:

Network analysis is a method and theory for analyzing relational data and complex systems. Learning and education are complex systems built on interactions, and thus are ripe with relational data. This article argues that network analysis is a productive approach to addressing the complexities inherent in education and learning. It begins by providing a brief overview of network analysis and the existing applications to physics education research. The article then explores how I came to adopt network analysis through a confluence of research needs, theoretical commitments, and interpersonal interactions. I end with proposals and speculation for future directions of network analysis in PER.

1. Introduction

Network analysis has a relatively short history in physics education research. One might not even consider it a research tradition. However, it is fairly distinct from other statistical approaches and has a unique set of methodological and theoretical commitments that distinguish it from other research traditions. Many, though not all, of the projects I have been involved in over the last ten years have included network analysis. During this time, my thinking about data and the role of relationships in education have co-evolved. The article will detail some of the ways that I have come to consider networks and how network thinking has changed my views about education as a complex dynamical system. The goal of this paper is not necessarily to encourage people to use network analysis, but instead to provide some perspective on how adopting network analysis as a methodology has influenced my conceptualization of education. This paper begins with systemic causation as a theoretical motivation for using network analysis (section 2), then section 3 introduces network analysis. Section 4 details my adoption of network methods, and the article concludes by cycling back to systemic causation and how network analyses can contribute to addressing issues in education that are systemic (section 5). Finally, this article is uncomfortably autobiographical. My perspectives on education have developed in large part due to the relationships and interactions with collaborators during this time frame. I do not intend to speak for them, or diminish their contributions, but hope to draw on their input to characterize network analysis as a burgeoning research tradition in PER.

2. Systemic Causation

George Lakoff argues that scientists fear making statements about causality. In *"Don't Think of an Elephant"* he argues that scientists fear framing their work in terms of causal claims and that this fear is holding science back.[1] In cases of a preponderance of evidence such as global warming, scientists should frame the discussion by making claims such as "Global warming caused Hurricane Sandy." This claim is problematic for scientists as there is no singular direct causal link that connects climate change with a specific hurricane. However, he points out that climate is a complex dynamical system with multiple, probabalistic, interacting causes instead of direct causal claims and we should be making systemic causal claims based on a preponderance of correlational evidence. Climate change *caused* Hurricane Sandy, but the causation is systemic rather than direct.

Systemic causation is equally applicable to learning. No one thing - a curriculum, a pedagogy, a teacher, a lesson, or an interaction - causes learning directly. As a result, few articles across education research make direct causal claims. Two prominent articles[2,3] make claims about active learning that are systemic causal claims; active learning *causes* conceptual learning. Active learning is an umbrella term that describes a collection of interacting elements including instructor, pedagogy, context, classroom environment, curriculum and others. A large number of articles make correlational claims about different aspects of active learning and conceptual understanding. Yet, as education researchers we tacitly accept the claim that active learning causes improvements in conceptual understanding. This is a case of using a preponderance of evidence to establish systemic causation. Further, framing the results in terms of causation will strengthen and empower education researchers to make inroads on transforming educational systems.

Learning happens as a result of a complex system of influences. The causes for learning are multiple, probabilistic, and interacting. Classes are made up of different students with varied backgrounds, beliefs about learning, and preparation. Instructors have varying degrees of experience with and attitudes about teaching.[4] Institutions impose constraints through the availability of classrooms, policies, and established practices.[5] Further, these features interact. For example, the institutional policies about promotion and tenure influence instructional decision making. If instructional quality is a component of tenure and promotion, then faculty will likely attend to and prioritize instruction differently than if it is not. These are only a few of the systemic features that influence the implementation of a curriculum and pedagogy. Other salient educational outcomes (e.g. identity development, retention and persistence) are similarly systemic and thus subject to systemic causal claims.

My interest in using network analysis and social network analysis to analyze learning (broadly defined) in physics stems from a notion that is elegantly described in Lakoff's systemic causation. When I arrived at Florida International University (FIU) in 2007, the physics department was in the middle of a period of rapid growth in terms of the number of declared and intended physics majors. (See Figure 1.) A number of plausible explanatory variables were available: FIU had been implementing Modeling Instruction successfully for a few years, the Society of Physics Students chapter was active, there were faculty who were promoting physics as a major, a number of high school teachers were encouraging students to attend FIU and connect with the Physics Education Research Group, and physics majors had access to the Physics Learning Center.[6] Not one of these efforts could be established as directly causing the growth in the number of physics majors. But as a system, I was of the opinion that they were all contributing in an interconnected way. We came to the conclusion that *community* was the unifying theme of these influences. As a primarily quantitative researcher, I became determined to measure community as the systemic cause of the growth in numbers of physics majors. This led me to social network analysis.

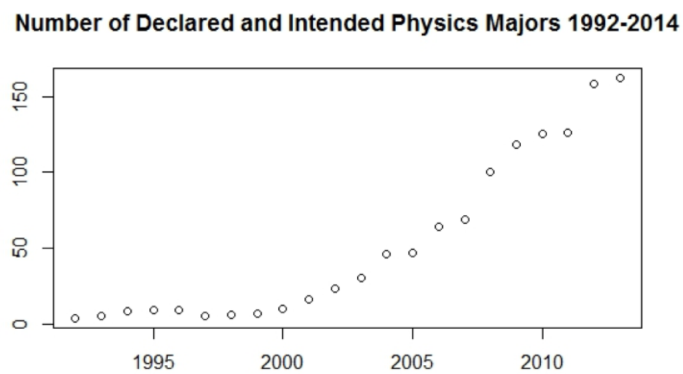


Figure 1: Number of declared and intended physics majors at Florida International University

3. (Social) Network Analysis

Social network analysis is a subset of a broader field, network analysis.[7] Network analysis is both a methodology and underlying theoretical framework about analyzing relational data or networks.[8,9] The relational nature of network data is unique, in part because networks defy the fundamental assumption of inferential statistics which is that measurements are independent. In a network, measures are by definition interdependent.

Networks consist of nodes and connections between nodes known as edges. I tend to think of nodes as objects (or at least object-like). In PER work, nodes have included students,[6,10–12] faculty members,[13] concepts, epistemic elements,[14] responses to multiple choice questions,[15] representations,[16] stages in a problem solving chain,[17] and others. Edges connect nodes. I think of edges as verb-like descriptions of relationships. Table 1 illustrates sample networks formed by node and edge pairs. Networks can be analyzed to investigate structure, test hypotheses, and numerically model situations. Longer, more detailed reviews and resources for those interested in network analysis are available,[18] but a brief overview will make later sections of this article more sensible.

Table 1. Networks formed by node and edge pairs

Nodes	Edges
Students	Study together
Faculty	Talk about teaching
Epistemic Elements	Adjacent in problem-solving discussion
Authors	Co-authored scientific paper

Social network analysis has roots in quantitative sociology from as far back as the 1920's and primarily developed in the social sciences where it was used to investigate social networks.[19] Beginning in the early 1990s a number of physicists, computer scientists, engineers, and mathematicians began to take up investigations based in graph theory that included social phenomena as well as other phenomena such as the Internet, electric grids, airline hub structures, disease spreading, and many many others. The two histories developed side-by-side and often failed to communicate, thus anyone exploring network analysis should know that there are two traditions, Social Network Analysis and Network Science, which is the source of some acrimony.[20] They have their own vocabularies, and own approaches to analyzing data. Social Network Analysis developed from the social sciences and thus tends to use statistical approaches of hypothesis testing. The network science community developed on the basis of graph theory and thus tends to use numerical modeling and simulation to draw conclusions. My work blends the two traditions, though I typically use the language from network science: nodes, edges, and use both network or graph. Over time, the two communities have overlapped.

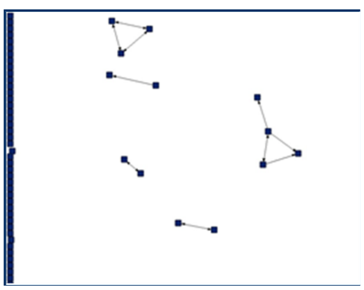
Regardless of tradition, there are two basic levels of analysis in network analysis: node level analysis and graph or network level analysis. Node level analysis tends to look at the position of each node within the network and to characterize the node. Work such as Brewe et al.[6] and Bruun and Brewe[21] used this approach. Brewe et al. considered whether individual attributes (gender and ethnicity) contributed to a student's centrality (relative importance) within a network. Bruun and Brewe used an individual's centrality in a network to predict grades in a future class. Both of these articles focused on features of the nodes to develop insight.

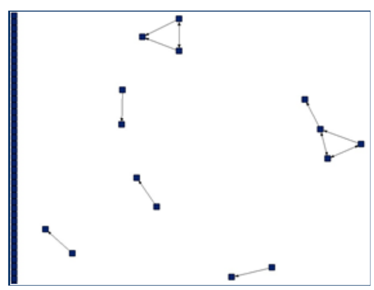
Graph level analysis tends to try to characterize the network as a whole object or to break the network into smaller groups - clusters or modules.[14,17,22] For example, Bodin coded transcripts of student interviews about computational physics. These codes were transformed into epistemic networks by considering the individual codes as nodes, then nodes were linked if they occurred next to each other. Then different epistemic networks were compared using density (a whole network metric that measures the proportion of links that exist within a network that are possible).

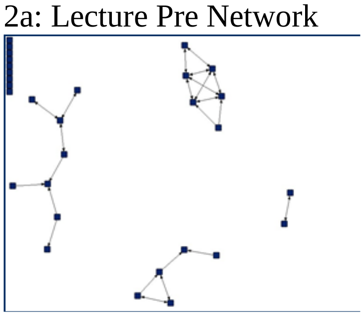
With both node-level and network-level analyses, metrics such as centrality or density can then be used in hypothesis testing, such as linear modeling, or in numerical modeling, such as generating random graphs as comparisons.

3.1 Social Network Example

To illustrate how network analysis can be applied, along with the types of interpretations that are available, I include an example network from previous work. Brewe et al. included a comparison of Modeling Instruction and lecture-format introductory physics classes.[23] The networks were constructed using pre-post surveys of students, asking them to report, "Who have you worked with to learn physics?" The nodes in this network are students in the introductory physics classes and the edges connect two students who report having worked together. The networks are represented in Figure 2. A node-level analysis might focus on the average degree of each of the nodes, where degree is a simple count of the number of connections to other nodes. In the Lecture Post Network (Fig. 2b) the average degree is much lower than in the MI Post Network (Fig. 2d). One interpretation is that any given node has less access to other nodes in lecture. Thus, if a student in the lecture network had a question about a homework problem, the student would have less opportunity to get help from other students. Then degree for each student could be included in a regression model to predict final grades or other outcomes.


2a: Lecture Pre Network


2b: Lecture Post Network


2c: MI Pre Network

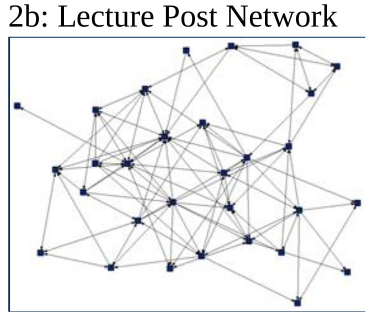

2d: MI Post Network

Figure 2: Pre and Post Networks from Lecture and Modeling Instruction. Reprinted with permission of the author.[23]

Network-level analyses would focus on characterizing the whole network. Density is one metric that characterizes networks; it is the proportion of possible edges. For example, the density of the Lecture Pre Network (Fig. 2a) is approximately the same as the Lecture Post Network (Fig. 2b), whereas the density of the Modeling Pre Network (Fig. 2c) is much lower than the density of the Modeling Post Network (Fig. 2d). This difference in density suggests that the two instructional modes differentially promote student interaction. Node-level and graph-level analysis can be combined. For example, one could first try to partition the network into communities (which is a graph-level analysis) and then begin to identify features of the nodes that make up the community (which is a node-level analysis). Such an approach might help to understand the structure that is present in the MI Pre Network (Fig. 2c).

3.2 Network Analysis Resources

This article does not aim to serve as a primer on network analysis, because a number of useful resources already exist. Grunspan et al. is a good primer for network analysis in education.[18] Wasserman and Foust is the seminal text in Social Network Analysis.[8] Scott and Carrington is a very useful handbook for many practical aspects and background.[24] Hanneman and Riddle[25] is an online text that is written to use the software package UCINet.[26] From a graph-theoretic perspective, Newman is the seminal work.[9] Barabási is focused on network science, and has an online version.[27] Both the Social Network Analysis and Network Science communities have their own journals (*Social Networks* and *Network Science*), their own professional societies (International Network for Social Network Analysis and Network Science Society) and their own conference series (Sunbelt for INSNA and CompleNet and NetSci for Network Science Society). From a software perspective, a number of programs have been developed for doing network analysis, as well as packages written for R and Python. Some of the best known freestanding programs are UCINet,[28] Pajek,[29] and Gephi.[30] Many write their analyses using common packages, particularly igraph[31] which works in R[32] or Python.[33] This is not an exhaustive list, but provides a foothold for those looking for options for beginning in network analysis.

4. Toward a Dynamic Systems View of Education

The tools of network analysis are commonly useful in studying complex dynamical systems. Although this was not my initial impetus for using network analysis in educational settings it is a compelling reason to continue. Regardless of research perspective, education has multiple facets including - but not limited to - cognitive, epistemic, affective, linguistic, sociocultural, policy. Each of these facets interacts with others. For example cognition is influenced by affect, as can be seen in research on self-efficacy,[11,34] impostor syndrome,[35] and stereotype threat.[36] These affective states are in turn influenced by culture, history, policy, and economics. Studying educational data from a network perspective attunes the researcher to interactions of this nature. Adopting a systems view of education is not revolutionary. As I have adopted a network analytic perspective, I have focused on how education can be considered from a systems perspective. Studying systemic elements does not require the use of network analysis - other methodologies are relevant and applicable - but when designing studies, the relational, systemic nature of education and learning should be considered. This section details my adoption of network methods, and how network methods met my needs (Sec. 4.1), fit with existing theoretical commitments (Sec. 4.2) and was supported by interactions with collaborators and friends (Sec. 4.3).

4.1 Network Analysis Addresses Need to Study Relational Data

Because network analysis is useful in situations with relational data, I found it to be particularly useful for looking at community. Doing so required a number of shifts in how data are collected and analyzed, but also challenged my thinking on the role of interaction in learning. Adopting this perspective on research drew on my own network of influences which I have identified retrospectively.

The first social network analysis study we undertook looked at the interactions of students in the Physics Learning Center at FIU. Looking back on the article, three things stand out: 1. my recollection of the small dance I did when I first was able to plot a network diagram, 2. the fact that we had unwittingly written from a Social Network Analysis perspective, and 3. the way in which the paper re-framed success. All three are relevant to the evolution of my research work in network analysis. First, the small dance is the result of a near complete sea-change in terms of data collection, handling, analysis and assumptions related to doing social network analysis. Adopting a network analytic framework required learning new vocabulary and new software, changing assumptions, and treating the data differently. In our first paper, the network was composed of students (nodes) and the edges connected students with whom they had talked to learn physics. At the time, we used pre-packaged software UCINet and NetDraw.[26,28] As a starting point this was particularly useful since there were resources that supported the analysis and representation of network data.[25] From there, we needed to identify how to use the network to generate results that informed us about the community of students who collaborated in the Physics Learning Center and how to interpret the results of that first analysis. For this we drew on our background in doing inferential statistics, which unwittingly meant we were coming down on the statistical tradition of Social Network Analysis. We decided to use linear modeling to determine if participation in the network was predicted by gender or ethnic background. The results of this first analysis, that neither gender nor underrepresented status predicted centrality in the Physics Learning Center served two purposes. First, it showed that network measures held real promise for helping to understand learning and being viable for educational research. Second, and more importantly, it caused me to re-frame the way I thought about success. Previously, success in learning was about earning good grades, making gains in knowledge, or problem solving, or earning degrees - perhaps not a surprising framing of success from a cis-gendered straight white man in physics. Instead, I was forced to re-think how success might also mean being a member of a community that is engaged in the processes of physics. From that analysis, I saw that students who had a large number of connections – and thus were important members of the community of physics learners at FIU - did not all fall into the category of students normally considered high-achieving. Communities need people in a variety of roles; fulfilling these roles within a community is another way of thinking about success.

4.2 Coherence between Network Analysis and Theoretical Commitments

Because of the success of the first analysis, I found motivation to continue using network analysis, in part due to the coherence between network thinking and other theoretical commitments, which I describe in this section. As Wasserman and Faust point out, network thinking conceives of the network as representing lasting structure of a social setting and that structure is inherently relational.[8] This notion of lasting relational structure fit nicely with other theoretical commitments, particularly Modeling theory,[37] Vygotskian Social Constructivism,[38,39] and Tinto and Nora's frameworks of retention and persistence.[40–43] It is congruous with some of the prevailing research on active learning in that the various forms of active learning all rely on the interactions of students with others.[2,3]

Certainly, other theoretical perspectives also fit with network thinking. Other researchers have drawn on distinct frameworks. Bodin drew on epistemology heavily,[14] Forsman et al. drew on complexity,[44] Quardokus and Henderson drew on institutional change.[13] As more people adopt network analysis more theoretical influence will come to bear. Yet, there is a common theme across these studies of network analysis providing methodological tools for addressing complex phenomena. But because there are theoretical elements that accompany network analysis as a method, it has been productive for me to consider how network thinking complements other theoretical commitments.

4.2.1 Modeling Theory

My primary work prior to taking up network analysis was developing curriculum and investigating the implementation of Modeling Instruction.[45–47] Network thinking overlaps significantly with Modeling theory[37] in that we have defined models as being formed from a set of interconnected representations and that models exist in the shared discourse of a community.[48] These mutually reinforcing theoretical perspectives have prompted further work. Some of this work includes using network analysis to investigate how the use of representations are integrated in problem solving and how students from a modeling class use these representational tools differentially.[16]

4.2.2 Social Constructivism

Constructivist thinking including its various offshoots has been the predominant epistemological framework for the bulk of the 20th century. Vygotsky in *Thought and Language* argues that thought and language are intertwined and thus, learning inherently involves interaction.[38] His famous concept of the Zone of Proximal Development describes how interactions functionally promote learning. This view on learning was particularly influential in the development of the structure of the Modeling Instruction curriculum and pedagogy.[45,49] The role that interaction plays in Vygotsky's framing of teaching and learning inspired a focus on student-student dialog, using whiteboards and centering the discussion around the process of developing models for physical phenomena. From a network thinking perspective, this also greatly influenced the approaches to measuring educational outcomes such as retention and persistence and considering how a student's role within a network contributes to retention and persistence.

4.2.3 Research on Persistence

Retention and persistence are key educational outcomes, particularly as it pertained to physics majors at Florida International University. The prevalent theoretical frameworks for understanding retention and persistence were Tinto's[40,41,50,51] and Nora's[42,52] theories of academic and social integration. Both of these theories emphasized that students, and in particular Hispanic students, need to be integrated into the fabric of the university through classroom interaction, mentoring relationships, extracurricular activities, and other sanctioned departmental activities. These theories focus on how interactions among students, students and mentors, students and faculty, and students and department members help to form the academic and social integration that lead to retention and persistence decisions. The overlap with network thinking is obvious. Other studies, particularly Treisman,[53] were similar in their influence. A consistent theme of student-student interactions contributing to positive educational outcomes suggested that using network analysis to study educational systems had strong theoretical and empirical value.

4.3 Interpersonal Relationships promoted and fostered network thinking

Perhaps unsurprisingly, academic and social interactions with other researchers contributed to my adopting a study of relational data through network analysis. It was through these relationships that I was introduced to principles of network thinking and methods for carrying out investigations of the roles of social interactions in social phenomena.

My first exposure to network thinking was through a colleague at Hawaii Pacific University, Scott W. Campbell, primarily during training sessions for the Honolulu Marathon. He studied mobile telephony and was able to show in the early years of adoption that peoples' perceptions and uses of the technology are significantly related to those in their social circle.[54] Aaron Warren was the first to use Social Network Analysis in Physics Education Research, publishing a PERC proceedings article in 2008 studying lab groups.[10] From these two I was able to see both the value in considering the role of interaction in the social construction of understanding and to learn preliminary tools for designing and carrying out an investigation using social network analysis.

My understanding of network analysis and capability to carry out network studies has been influenced most by my collaborator Jesper Bruun. In 2010, Jesper spent six months visiting the FIU PER Group from University of Copenhagen. During these six months we worked on developing our first paper together.[21] Jesper's input was particularly important for me as he brought a different perspective on network thinking. To that point, I was primarily influenced by the social network analysis tradition of using network metrics to carry out hypothesis testing. Jesper held a more information-theoretic view of network analysis, focusing on how information can be transferred across a network.[22] I primarily conceptualized networks as structures that provide opportunity or constraint within a social system - for example, students in a class with greater numbers of connections with other students have a greater opportunity to get help should they become stuck on a homework problem. Jesper primarily conceptualized networks as structures that allow or inhibit flow probabilistically. In the same homework example, a flow perspective would consider how information passes through the network and then students who handle a larger number of messages are more important to the network. This flow perspective is more aligned with a graph theory view, draws more heavily on probabilistic views of interactions, and borrows concepts from statistical physics.

Beyond conceptualizing networks differently, Jesper pushed me to move away from pre-packaged software to using the statistical programming language R for data cleaning and analysis. I believe it was important that for my first efforts at network analysis we used UCINet software, but moving forward the flexibility and power that R (or Python) provides is essential. This transition to using a programming language for data analysis is one that researchers interested in doing network analysis eventually make.

With Jesper, I encountered different perspectives on data analysis and network conceptualization. We also were able to negotiate the analysis of a large data set and to write a paper that resulted in a second satisfying result, particularly one that would not have been feasible without using network analysis. We found that the best model for predicting student grades in a future class included a measure of how isolated the students were socially in an in-class network.[21] This result, that students' social isolation impacts grades, is interesting and important because it shows how Tinto's theory of academic and social integration impacts academic performance. It also provides an example of how network analysis illustrates student integration into the social fabric of a class.

Relationships, both personal and professional, have been a strong influence on adopting network analysis in my research. They have driven both my foundational conceptions of networks and the methods for analyzing them. A variety of results and theories support the notion that persisting is related to the ways in which one is integrated into a field, both socially and academically. So, while these personal and professional relationships will be different for each individual, they should not be ignored in adopting a different research tradition.

5. Conclusions: Role of Beliefs in Adopting Research Perspectives

My belief systems have clearly influenced my perspective on taking up network analysis. These stem from being sufficiently privileged that I have had the time, resources, opportunities for relationships, and support of a number of colleagues and friends to consider these questions.

I believe that change in humans takes time. Thus, I prefer educational research that does not focus on short interventions. This comes from my belief that making lasting changes within humans rarely takes place on a time frame of hours or days. The issue with this belief is that many research design courses aim to closely link interventions with outcomes so that the researcher can work toward causal claims. One way of doing this is to constrain the research setting using smaller time frames. To be clear, this is appropriate research design. Yet, one of my goals is to be able to make causal claims on larger timescales. For example, Modeling Instruction is a curriculum and set of pedagogical practices that contributes to student successes. Research into curricular effects have one semester as a lower bound on the time scale (appropriately in my mind). Yet, from a research design perspective this is an impossible situation in which to make causal claims. We can identify a number of positive and negative outcomes from students who have participated in Modeling Instruction classes, but cannot attribute any one of these outcomes directly to the curriculum or pedagogy.

Research at the curriculum level should proceed with correlational studies, using principles of educational research design. And, armed with a number of inter-related correlational studies, I am willing to allow researchers to make systemic causal claims about a curriculum. This framing of research results allows for research to be impactful by attributing outcomes to systemic causes. Network thinking supports and reinforces this view by focusing attention on how related studies contribute to a broader outcome.

I have argued that student success is a complex networked outcome. It includes opportunity, identity, grades, participation, self-efficacy, and many other features which are related in a probabalistic manner. As Lakoff[1] points out, this is a complex dynamical system, which appropriately should be studied from a systemic causation perspective. Learning is a social process inherently involving interaction. Brain organization, activation, recruitment, and inhibition are complex dynamical systems; connecting these to social processes and learning will be challenging. Ultimately, connecting outcomes across large scales - societal, individual, and neural - will not be done with direct causal effects. Instead these complex systems yield networked effects. Education research will need tools which are equipped for such complexity. Kopponen et al. provide one set of quantitative examples, using agent-based modeling to simulate learning.[55,56] Qualitative work provides another avenue.

Network analyses provide a set of tools which are designed for relational data. Developments in method, data collection, and analysis in network analysis hold some promise to span scales of outcome and to coordinate research efforts to allow for systemic causal claims. Developments such as multiplex networks - where multiple layers of relationships are then related - are promising in terms of handling complex dynamical systems. Time-evolution of networks provide promise for investigating dynamics of the systems that underpin education.[57] Network models based in epidemiology have promise for understanding how information flows through an educational system or how access to educational systems provides opportunity or imposes constraint on students. Using tools developed for non-linear systems such as phase diagrams might identify tipping points at which cascading outcomes emerge. Linguistic networks may help transform the ways in which large qualitative data sets are analyzed. These are but a few of the directions that I envision network analysis evolving in educational spaces.

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