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Networks and Learning: A View from Physics

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Abstract

Like learning analytics, physics education research is a relatively young field that draws on perspectives from multiple disciplines. Network analysis has an even more heterodox perspective, with roots in mathematics, sociology, and, more recently, computer science and physics. This paper reviews how network analysis has been used in physics education research and how it connects to some of the work in this special issue. Insights from physics education research suggest combining social and interaction networks with other data sources and looking for finer-grained details to use in constructing networks, and learning analytics is promising for both avenues. The discussion ends by looking at the complications with incorporating gender into network analysis, and finally the possibilities for the future.

Keywords:

network analysis, physics education research, gender

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1. Introduction

Why do we care about networks? In physics education research (PER), they were taken up because of a growing interest in students' social ties and interactions during class. In a field founded on calls for "interactive engagement" (Docktor & Mestre, 2014; Hake, 1998), it makes sense to seek tools to measure that engagement. (Also, complicated diagrams are a good way to entice other physicists to look at your work.) In PER, networks fit into a larger constellation of methods for trying to make learning visible: concept inventories (Madsen et al., 2017), attitude and epistemology surveys (Elby, 2010), science or physics identity questions (Hazari et al., 2010), analysis of representation use (Kohl & Finkelstein, 2008), problem-solving rubrics (Hsu et al., 2004), and more. Representing how learners engage with one another by using networks is different from these methods, since here representations are not tied directly to the physics content. Instead, they look at interactions in physics classes or elsewhere in the department but may not necessarily be about physics. Physics education researchers value peer engagement and collaborative knowledge construction in active learning classrooms, and recent studies on self-efficacy and identity development in physics further support the need to better understand these interactions (Hazari et al., 2010; Sawtelle et al., 2012). In some cases, and in keeping with research on persistence and retention, building student community may be an explicit goal that the instructor wishes to assess in its own right (Goertzen et al., 2013; Whitten et al., 2003).

In addition to social network analyses, a separate branch of network analysis in PER has looked at concept networks. Studies have examined the structure of participant-generated concept maps to contrast knowledge coherence of experts and novices (Koponen & Pehkonen, 2010), or the web of ideas and reasoning in student explanations of problem-solving (Bodin, 2012). Others have looked at the structure of students' incorrect ideas by partitioning answer co-occurrence networks of distractors on physics concept diagnostics (Brewe et al., 2016; Wells et al., 2020). Here, I focus on student interaction networks, which in PER are primarily gathered through self-report surveys.

Connecting the "background" factor of a social network with the "foreground" of learning or persistence outcomes poses a measurement challenge that network researchers have been grappling with for decades, and which physics education researchers are struggling with fresh. Compared to other tools of PER, networks add a layer of remove, taking a step back from the specifics of force diagrams or electric field integrals to look at the fuzzier social fabric in which these details are embedded. It is rarely possible to connect the outcome of a single conversation to greater understanding of the subject material, especially when most measures of that understanding are summative and encompass many individual moments of realization and practice. There are many potential confounding factors, such as varying levels of student prior knowledge about the class material. Effects such as student preparation can be included via supplemental data like pretest scores (Bruun & Brewe, 2013), but quantifying the often-indirect influence of networks is a persistently tricky problem.

In this commentary, I will give context on PER's history as a field, which is not that long and which still very much shapes how networks are used in research. Then I will circle back to how points raised in this issue may inform those studies, and to unresolved tensions between network analysis and the other major strand of my research, gender in physics education. I will end with a few "what if" thoughts on future combinations of learning analytics and network analysis.

2. Network Analysis in Physics Education Research

2.1. Development of Physics Education Research

The history of physics education research (PER) rooted in "interactive engagement" calls for better understanding of student social interactions. For much of PER's history, however, this attention to the social setting has been implicit rather than explicit, and the vocabulary is not well developed for defining and distinguishing meaningful social interactions (in contrast with, e.g., Woo & Reeves, 2007). University-level physics education research in the United States grew out of discoveries that even students who were fluent in solving quantitative problems could often not reason qualitatively with the underlying concepts. In other words, mathematical fluency was not a reliable indicator of deeper understanding. Many of the key early studies focused on conceptual understanding of foundational concepts such as velocity and acceleration or current in electric circuits (Trowbridge & McDermott, 1980; McDermott & Shaffer, 1992). After uncovering common patterns of flawed understanding or misconceptions, researchers developed curriculum materials to address these issues. These curricula often involved extended sense-making activities where students' misconceptions were elicited, confronted, and eventually resolved through Socratic dialog and guided reasoning (McDermott, 2001).

Though much of the misconceptions research came from individual student interviews, the curricula developed in response relied heavily on students working in groups (McDermott et al., 1998). In large-scale survey work on conceptual understanding, Hake (1998) defined interactive engagement methods as "those designed at least in part to promote conceptual understanding through interactive engagement of students in heads-on (always) and hands-on (usually) activities which yield immediate feedback *through discussion with peers and/or instructors*" (emphasis mine). Over decades, evidence mounted that classes using interactive engagement could produce conceptual gains far beyond those in passive lecture (Hake, 1998; Freeman et al., 2014; see also Chi & Wylie, 2014). Student–student interactions are a key feature in physics pedagogies developed from this research base, whether they focus on conceptual understanding, problem-solving skills, or other aspects of learning physics (Meltzer & Thornton, 2012).

Learning can be measured as a set of individual state changes in students, but it is situated at least partly in the social environment (Otero, 2003). This theoretical commitment long predates PER, going back at least to the work of Piaget and Vygotsky. While learning can happen in isolation, with a single student studying a textbook, the possibilities expand dramatically when students can draw on their peers (and community is inextricable from learning in some theoretical frameworks, such as Lave and Wenger's communities of practice). Nonetheless, measuring student outcomes is typically an individual-focused task, such as the extensive studies of conceptual gains (Docktor & Mestre, 2014, Sec. II). This focus on individual outcomes is somewhat true to life — to certify that a particular student understands the material, it is important to have a measure of what that one person can do. However, it is much less established how to quantify group problem-solving processes versus single-person exam scores, even if the former task is more authentic to many real-world situations. So, although social learning processes have been key to PER since its inception, they are far less studied than quantitative individual outcomes.

Most PER studies that focus on social interactions are qualitative, targeted at small groups. Sometimes the interactions are secondary to an end-product within the study, as is the case, for instance, in research mapping different epistemic games played by students solving physics problems (Tuminaro & Redish, 2007). Other times the social moves and cues are the primary target of analysis, such as work on negotiating the epistemological framing of problem-solving arguments (Bing & Redish, 2009), or studies of the social roles adopted by students in lab classes (Doucette et al., 2020). These qualitative results give rich insight into group dynamics, but are labour-intensive to analyze, so they typically must focus on small subsets of larger classes. An obvious challenge comes out of this: if student interactions are a key aspect of learning physics, how can we assess them class-wide the way we do conceptual understanding or epistemology shifts?

2.2. Networks and Physics Education Research

Network analysis entered PER to address this challenge and quantitatively capture class-level interactions. Many of the studies to date have been exploratory, mapping snapshots of social structure at one or more points in a semester. One influential example was provided by Brewe et al. (2010) where they contrasted early- and late-semester networks in lecture- versus studio-format physics classes, finding dramatically more network growth in the interactive class. Related work includes studying students' out-of-class interactions in a departmental student study lounge (Brewe et al., 2012), or mapping students' ego

networks as part of a more holistic understanding of success in the physics major (Goertzen et al., 2013).

Another wave of studies has looked at how student interaction networks are related to other information. This strand of work provides empirical insights into how peer engagement in physics classes may unfold but struggles with generalizing or explaining these observed patterns. Here, networks may be constructed from electronic sources such as records of online discussion posts and replies, but most often come from surveys asking students to recall their conversation or study partners. Outcomes examined for correlation include course grades (Vargas et al., 2018; Traxler et al., 2018a; Yang et al., 2015), self-efficacy (Dou et al., 2016), or success in the next course in the sequence (Bruun & Brewe, 2013). These correlations are typically small or moderate in effect size and are context dependent. For example, Brewe et al. (2010) found that both a lecture and an interactive engagement course had very few network links at the beginning of the semester, but that the interactive course developed a high-density network by the end — a result that might have been anticipated. However, due to institutional demographics or prerequisite courses, students may enter their first physics course with no connections or with an elaborate pre-existing social structure (Traxler, 2015). A correlation between students' grades and their late-semester network centrality might be very evident in a class where those network connections were formed during the class, but harder to detect in a different setting with a well-developed network prior to the semester. The density and development of the network can be influenced by many factors outside the classroom, e.g., residential versus commuter colleges, or how tightly grouped students are into cohorts for their progression of courses they are taking. When looking to relate network features or position to learning, these additional factors complicate claims about how the pedagogy may have been responsible for the network, or how the network may have contributed to student success.

Many network studies in PER construct self-reported networks of student engagement, for instance, by using a single survey question to generate links (for example, "who do you work with to learn physics in this class?"). More recent work often uses multiple prompts or time points to separate topics or activities of interest. For example, work by Bruun and Brewe (2013) generated distinct networks for problem solving, concept discussion, and in-class social interactions. These surveys were given weekly, allowing further study of how student groups stabilized and segregated over time (Bruun & Bearden, 2014). A study by Vargas et al. (2018) examined homework collaboration networks across three courses and found correlations between centrality scores and homework grades (and weaker correlations with exam grades). Analysis of networks constructed from these finer-grained questions offers insights that differ from what was observed through more general surveys reporting who interacts with whom. For example, Bruun and Brewe (2013) found that it was students' centrality in the in-class social network, not in problem solving or concept discussion, that best predicted their combined current and next course grades. Or work by Zwolak et al. (2018) found that centrality in the out-of-class social network was not a significant predictor of class persistence for students at the top or bottom of the grade distribution but was for those in the "middle of the pack." The number of studies looking beyond the timeframe of a single semester is still small, but a longer-term view is needed to understand how students' network placement may connect to larger issues of community and belonging, such as retention in the major.

Future directions for networks in PER should include connecting network growth or features to the learning environment and pedagogy (Commeford et al., 2021). Also, studies that consider multiplex relationships between the students to represent different student activities would be beneficial, to enable comparisons between network structures and student positions within them. However, a major challenge of collecting more detailed network data has been low response rate on surveys. Missing data can seriously disrupt many network measures (Smith & Moody, 2013), and longer or more frequent surveys increase respondent fatigue (or burden instructors who allow researchers access to their classes). Domains such as learning analytics offer great contributions towards overcoming this problem as technologies and digital data instruments can be used to help tracking fine-grained actions and interactions.

3. Connections between PER and Learning Analytics

3.1. Connections to this JLA Issue

In "The curious case of centrality measures" (Saqr & Lopez-Pernas, 2022, this issue) the authors address one of the many difficulties of doing network studies — the question of how to compare the complicated, often messy snapshots provided by networks, and how best to simplify them to look for replication of results. If students' node centrality is correlated with class outcomes, these correlation values provide one way to summarize and compare network effects between classes. But what centrality measure is best? Each one makes a slightly different claim about which processes are important in the network (Vignery & Laurier, 2020) — whether it is raw number of connections (degree centrality), brokerage between groups (betweenness centrality; Freeman, 1978), the predictable flow of information among actors (Sneppen et al., 2005), or others.

The authors take the route of correlating a suite of centrality measures with individual student grades across dozens of course sections enrolling several thousand students. All courses analyzed were at the same university and all had collaborative

problem-based learning discussions, though it should be noted that no other decision was taken to address potential selection bias. Of the tested centrality types, degree was the most commonly useful measure, being both correlated with student grades and relatively stable across different courses. Eigenvector and betweenness centralities were also good indicators, albeit with weaker correlations and more heterogeneity of results. Closeness fared the worst, with high heterogeneity of results and a correlation prediction interval that included zero.

The authors' commentary on this centrality meta-analysis is interesting, making the point that in different class setups, different network topologies may change the relevance of centrality measures. In some classes, a tightly connected single component might be both achievable and useful (Brewe et al., 2010). In others — for example, a MOOC — it might be more useful to have smaller "pods" of connected students, with a dense whole-class network not feasible or helpful. But across a wide range of geometries, the number of immediate neighbours (degree centrality) is almost always relevant.

3.2. Comparison with Evidence Observed in PER

All the centrality measures examined in the meta-analysis by Saqr and Lopez-Pernas (2022, this issue) appear often in PER studies, together with others such as harmonic centrality (a measure similar to closeness), PageRank (an eigenvector-based method and the original basis for the Google search algorithm), or other variants. Sometimes these choices are closely informed by theory, as in the study by Brewe et al. (2012) that grounds its use of Bonacich centrality in Rogoff's theory of learning as transformation of participation. But in many network studies, the selection of centrality measures is more idiosyncratic, influenced by the researchers' particular reading base or a prior study that serves as a comparison point.

Recently in physics education research, there is a growing push to move on from the question "Is active learning better than (passive) lecture?" and onto questions of which curriculum features promote particular types of learning. One way of asking this question is to look at different types of network structures that arise in different pedagogies. This comparison is the goal of the Characterizing Active Learning Environments in Physics (CALEP) project, where my collaborators and I collected classroom observation and network survey data from six prominent research-based pedagogies in physics. In this pilot study, we found some tendency for networks to show coherent subgroups in block models that identify network positions with similar linking behaviour (Traxler et al., 2020). The prevalence of the coherent subgroups pattern contrasts with other positional analysis studies, where hierarchy or core-periphery block structures are common. We also found marked differences in the whole-class networks of pedagogies such as Peer Instruction, SCALE-UP, or Modelling Instruction (Commeford et al., 2021). Peer Instruction (Mazur, 1997) is designed for large lecture classes, where students discuss clicker questions with their neighbours, and long chains appear in the collaboration network (Commeford et al., 2021). SCALE-UP (Beichner et al., 2007) is a studio-format pedagogy, where lecture and lab are combined, and students work in groups of three at tables of six or nine students. Modelling Instruction (Brewe, 2008) is another combined lecture/lab pedagogy, where students work in small groups but regularly gather as a class to present and discuss results. The SCALE-UP networks we observed had more clustered structure, while the Modelling Instruction network had a more densely connected large component where it was not possible to infer group placement by inspection. Though these two classes were very similar in size, they would likely have very different distributions for betweenness and closeness centrality, even though their average degree values were similar.

It is not clear if there is a "best" kind of network that most effectively spreads knowledge among students, but "The curious case of centrality measures" suggests that future studies linking centrality to success measures should include degree along with any more complex centralities that may be of interest. Clarity about research questions and theoretical frameworks is key because social network analysis in education is fundamentally about modelling what processes the researchers think are important for student engagement. If a particular type of interaction is fundamental to a pedagogy (such as problem-based learning sessions or discussing how to design a model-testing experiment), network data should be gathered and analyzed with an eye to capturing those signals.

4. Perspectives from Studying Gender

Network analysis is only half of my research focus; the other half is gender in physics education. Where these strands cross, my life as a researcher becomes more complicated. A large part of my work has been doing review and synthesis of gender in PER studies and looking for common themes and points of comparison to neighbouring fields such as science education or gender studies (Blue et al., 2019; Traxler et al., 2016). This work calls into question some of the simplifying assumptions commonly made in quantitative studies (including network analyses), so I will briefly outline this issue in hopes of gifting this confusion to a wider audience.

In physics education research, gender-based studies tend to be quantitative, most often following a pattern of looking for performance gaps on exams or other standardized assessments (Traxler et al., 2016). This body of work is valuable, but raises several tensions, such as the question of test fairness with instruments developed without checking their validity for various

populations (Traxler et al., 2018b). These standardized assessments that studies had examined tend to be developed and validated in calculus-based physics courses, normally in large research universities with stringent selection criteria for student admission. In terms of gender and racial or ethnic demographics, as well as math level, these courses often skew male and are broadly not representative of the national population of students taking college-level physics (Kanim & Cid, 2020). While these issues may be skirted by developing better tests, other tensions remain — such as the nearly ubiquitous practice of treating gender as a strict male/female binary, usually extracted from school records. These records are often out of date or institutionally inflexible for transgender students, and few if any universities recognize (or would have accurate records of) identities such as agender, genderfluid, or other shifting or nonbinary gender roles.

These difficulties extend to network studies that include gender as a node attribute — which is often desirable to do if researchers or teachers want to know whether benefits of network position are equally distributed among the class. However, drawing this information from school records will inevitably misclassify some students for the reasons noted above. Other workarounds such as automatic name classifiers are not recommended by members of the affected communities (Rasmussen et al., 2019). Surveying students directly is the obvious alternative but comes with decisions about how to ask the questions (Fernandez et al., 2016) and then what to do with the data for less-common gender identities. These "small N" elements in the data set can be difficult to include in quantitative analyses (Slaton & Pawley, 2015), and may also jeopardize anonymity depending on how the information is reported.

I do not see an easy way out of this quandary, and I do not know that there is one. Looking for network effects by gender (or race and ethnicity, or other identity groups) is critical if researchers and instructors want to know whether success outcomes are equally distributed, whether gender affects access to network benefits, and similar questions. Where disparities exist, documenting them is a key first step to fixing them. However, the abstractions of neat categories and quantitative models can obscure important complexities of identity. If results are only reported in binary, male/female terms, it reinforces the idea that this is all gender can ever be. Though I do not think this question will be solved anytime soon, I do think it can benefit from researchers being more explicit — in both the study design and reporting phase — about the assumptions they make about gender and other identity categories, and what trade-offs go with those assumptions.

5. Future Directions

From decades of accumulated PER (using networks or otherwise), it seems to matter both that students are talking at all, and what the nature of their physics conversations is. This is worth exploring further both in physics and in other educational network studies, where the social structure is more the focus of inquiry than the specifics of the material being discussed. The results from PER suggest that it may be illuminating to untangle the different conversational strands — not because only the "physics talk" matters, but because both "on-topic" and "off-topic" interactions can be important in interleaving ways. Learning analytics research has already made strides in investigating some elements of this but more empirical work, especially in relation to various designs, is required (Wise & Cui, 2018). Moreover, the domain of learning analytics enables us to record even more granular types of networks by capturing diverse student actions (Bruun, 2016). Alternately, where transcripts of student talk are available, text mining tools provide ways to incorporate the character of these conversations in the network structure, as learning analytics has also adopted (Joksimović et al., 2018, 2019). However, providing empirical and generalizable evidence that explains the relationship between course design with discourse quality and student positioning in multiplex networks is a step to be made.

Earlier when discussing future directions for networks in PER, I mentioned that types of interaction can be analyzed separately. Learning analytics systems could support making this process more seamless than data collection through survey questions, if class software can have record traces of students' homework conversations (Kortemeyer, 2006), forum interactions (Gavrin & Lindell, 2017), and other incremental acts of participation. This granularity of interaction would allow for more studies of the time development of networks, focusing on how they stabilize (Bruun & Bearden, 2014) or possibly connecting network changes to course events such an exam or a group-forming activity. Building networks from many small interactions opens more questions when circling back to the centrality analysis of Saqr and Lopez-Pernas (2022, this issue). For example, many centrality measures were created for binary social ties, and do not consider edge weight (which typically indicates interaction strength or frequency). How to incorporate edge weight in these measures is not always transparent (Opsahl et al., 2010). This question becomes very salient if we have the data to treat interaction as a spectrum rather than a binary, also observed as an issue in LA studies (Poquet et al., 2020, 2021).

Finally, the potentially rich data streams available through learning analytics open exciting and complicated possibilities for using multiplex networks to study learning. Student discussion of homework, group projects, other class topics, or even "off-topic" socializing could be separated as different link types, generating a multi-layered network (De Domenico et al.,

2015) for the same set of student nodes. This analysis is time-costly to do manually, though still fruitful. But a growing number of tools are applied to automatically code text in education research, such as sentiment analysis (Kelley et al., 2018), recurrence quantification analysis (Myers et al., 2019), latent semantic analysis, and others. One avenue of exploration is to use these text-processing tools to generate multiplex, time-dependent networks showing complex social structure and how it evolves over a course.

Network analysis has its roots in important exploratory studies, but as it continues to spread in various subfields of education research we are seeing new variations on how to connect interactions with learning and how to capture more nuances of interaction in networks. I think it is important to be cautious about the (over)simplifications that arise when classifying students for quantitative models, as discussed above. But it is possible to be thoughtful about that and still reach into the network tools made available by learning analytics.

Declaration of Conflicting Interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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