

Investigating Student Communities with Network Analysis of Interactions in a Physics Learning Center

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Abstract. We describe our initial efforts at implementing social network analysis to visualize and quantify student interactions in Florida International University's Physics Learning Center. Developing a sense of community among students is one of the three pillars of an overall reform effort to increase participation in physics, and the sciences more broadly, at FIU. Our implementation of a research and learning community, embedded within a course reform effort, has led to increased recruitment and retention of physics majors. Finn and Rock [1997] link the academic and social integration of students to increased rates of retention. To identify these interactions, we have initiated an investigation that utilizes social network analysis to identify primary community participants. Community interactions are then characterized through the network's density and connectivity, shedding light on learning communities and participation. Preliminary results, further research questions, and future directions utilizing social network analysis are presented.

Keywords: Social network analysis, Physics education, Informal education, Learning community.

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INTRODUCTION

The Center for High Energy Physics Research and Educational Outreach (CHEPREO) at Florida International University has established a learning community within the physics department as part of a comprehensive effort to increase participation and success by traditionally underrepresented students in physics. The comprehensive reform effort rests on three interdependent foundations: 1. Reform of several sections of introductory physics by implementing Modeling Instruction, 2. Establishing, fostering and sustaining student collaboration through establishing Physics Learning Center, 3. Systemic faculty advocacy on behalf of students and institutional reform. The impacts of the Modeling classes on students' conceptual understanding [1] and attitudes toward science [2] have been established. However, these classroom-based measures are insufficient to account for increases in enrollment, retention, and persistence seen at FIU since the origin of CHEPREO. In an effort to describe and quantify the sources of the persistence and retention, we turn to Social Network Analysis (SNA). SNA provides a set of tools for visualization, quantification and hypothesis testing on networks of actors (in our case students).

PHYSICS LEARNING CENTER

Modeling Instruction engages students in the process of building, validating, and deploying models. This process of modeling replicates the central activity of practicing scientists and, therefore, strongly integrates an explicit Nature of Science theme throughout the curriculum. Modeling Instruction courses at FIU operate in a collaborative learning environment, with 30 students in a studio-format class with integrated lab and lecture. Inquiry labs and activities focused on conceptual reasoning and problem solving are the primary vehicles through which models are built, validated, and extended [3].

The implementation of Modeling Instruction at FIU was facilitated by the development of a dedicated studio-format, technology-enhanced classroom. Early in the lifetime of CHEPREO, students in the Modeling classes expressed a desire to have opportunities outside of class hours to extend the collaborative learning they experienced in the Modeling classes. The Physics Learning Center (PLC) incorporates the modeling classroom, a lounge, and a conference room. Students were granted access to the room and the portable whiteboards to work on homework outside of

scheduled classes. A select set of students were chosen to be CHEPREO fellows, these fellows were given open access (keys to the room and computer cabinets) and responsibility for the room (supervising open labs, where student learn and make use of technology).

We aver that the availability of the PLC has contributed to the persistence and retention of physics students. Research into participation in communities and collaborative learning environments like Modeling Instruction [4-7] indicates that students who experience a sense of academic and social integration are more likely to persist. Tinto [4] identified the classroom as the most likely entry point into a community and thus argued for the inclusion of interactive/collaborative pedagogy. In this paper we extend the research of Tinto incorporating Social Network Analysis to investigate interactions between students in the PLC and their impact on increasing retention and persistence.

SOCIAL NETWORK ANALYSIS

Social Network Analysis has been employed as one tool for investigating the collaborations, participation, roles, and interactions among students who work together in the PLC. Wasserman and Faust's 1994 text on SNA is the seminal work in this area [8]. They identify four basic assumptions when conducting SNA. They are: 1. Actors and interactions are interdependent. 2. Linkages allow flow (information, resources, etc.) between actors. 3. Network models on individuals both constrain and provide opportunity for individual action. 4. Network models conceptualize structures as representations of lasting patterns of relations among actors. SNA enables researchers to create visual representations of interactions and to quantify the interactions between actors in a network using a wealth of techniques. Wasserman and Faust should be referenced for greater insight into the various techniques available for SNA.

METHODS

Student users of the PLC completed an online survey which included background questions and asked them, "What are the names of people that you work on homework with in the PLC?" One challenge of investigating social networks is the effort to be comprehensive about collecting data from all actors in the network. As a result, we sought responses from students in Modeling classes, the Society of Physics Students (which meets in the PLC), physics majors, and by posted signage in and around the PLC requesting that students complete the survey. These efforts generated 107 responses, 99 students (from 7

different majors) completed the [entire](#) survey.

The 99 responses were then used to generate a 99x99 matrix of student interactions (1=interaction present, 0= not present). UCINet 6 [9], a standard SNA software package, and NetDraw [10], a network visualization package integrated with UCINet, were used to identify *isolates* (students who neither reported working with anyone in the network, nor did anyone report working with them). These isolates were then removed, leaving a 76x76 matrix of students. All analyses are conducted on this reduced matrix in an effort to characterize the students who are active participants within the network. The decision to use the reduced matrix for analysis has several consequences which should be acknowledged. First, there were several students who would have played a substantial role in the network but were not included because they did not complete the survey. A second consequence is that by removing the isolates we are not attending to students who may have been marginalized within the social network. These decisions are made in deference to page length and not importance.

Our first analysis is a simple visualization of the network of students, see Fig. 1. This helped us identify primary players within the network (shown on the right side of Fig 1), as well as identifying the approximate proportion who are weakly connected (on the left side of Fig. 1).

Because we are not comparing this network to other networks, our measures focus on the roles students play within the network. Social Network Analysis allows several measures of *power*, including *degree centrality* and *geodesic distance centrality*. Power can be thought of as a measure of the advantage/disadvantage resulting from an actor's position within a network. Degree is defined to be the number of ties any actor is involved in, a greater number of ties means greater opportunity, less ties means greater constraint, degree centrality is then a measure of how well connected an actor is. Geodesic distance is a measure of the number of ties between any two actors in the network; geodesic distance centrality is often calculated as the eigenvector of geodesic distance. This vector is made up of distance values for each actor within the network, in this study a 76x1 vector. We use descriptive statistics on degree centrality to characterize the overall student network and the eigenvector of geodesic distance centrality as the measure of centrality for each student as the basis for comparisons of students with different attributes (gender, ethnicity, major, time spent in the PLC, and Modeling class participation).

Finally, the basic assumption that actors within a network are interdependent means that standard parametric statistics are not appropriate. Instead,

bootstrap methods allow for hypothesis testing using modified t-tests and ANOVA [11]. To conduct the ANOVA a second matrix of student attributes (the grouping variables) was assembled based on student responses to the background section of the survey. We used ANOVA on the geodesic distance eigenvector to investigate the role that gender, ethnicity, major, time spent in the PLC (measured in days/week), and student participation in the Modeling classes on their centrality in the network.

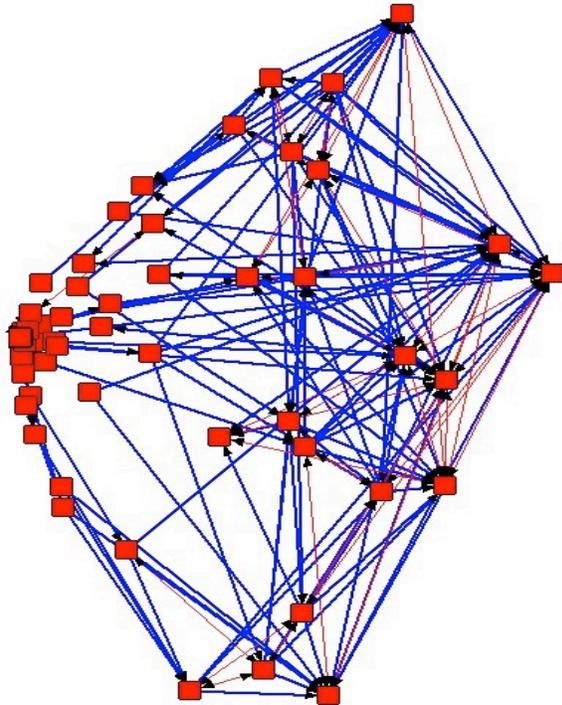


FIGURE 1. Social Network Diagram for students in Physics Learning Center. Squares represent students and lines represent interactions. Arrows indicate directional interactions: arrows out indicate a student listing other students as a part of an interaction, arrows in indicate students being listed in interaction.

RESULTS AND ANALYSIS

Figure 1 shows the network diagram for students in our study. Upon inspection, the central actors (students) in the network are not exclusively the strongest students academically, and in some cases are simply socially well established. This indicates that the network is sustained by the combination of social interactions and academic interactions. This qualitative finding supports Tinto's description of academic and social integration as being supportive of students' persistence, retention and participation.

Quantitatively, whole network measures of centrality allow us to infer whether the network has "positional advantage." Although it seems clear that

the PLC network depicted in Fig. 1 has some positions which are more 'powerful' than others, measures of *network centrality* confirm this observation. Hanneman and Riddle describe network centrality as a measure of the concentration of power across all actors in a network. In a network, like the one in Fig. 1, with substantial amounts of concentration or centralization, the power of individual actors varies rather substantially. For example, in our network the actors on the right side have considerably greater density of ties than the actors on the left. Thus, positional advantages are rather unequally distributed in this network. One way to identify a network with positional advantage is by comparing the centralization of outdegree (% of all possible ties going out from a node) to the indegree (% of all possible in ties going into a node). In our network, the Network Centralization (Outdegree) = 10.49% and the Network Centralization (Indegree) = 24.00%, which indicates that the 'power' is not equally distributed throughout the network.

Table 1 includes the ANOVAs conducted on the geodesic distance centrality eigenvector. Three of the attributes; gender, ethnicity, and Modeling (whether or not a student took a modeling course); were not significant. Thus there were no significant differences in a student's centrality within the network based on these attributes. Two attributes, time spent in the PLC and major, were significant. These two attributes each accounted for differences in the mean of a student's centrality within the network. The eta-squared of these attributes identifies that the differences in group centrality means account for 33% and 31%, respectively, of the total variance in eigenvector centrality scores among the students. In order to further account for the role that each of these five attributes play in determining how central a student is to the network, further analysis is needed including possibly structural equation modeling. These analyses are a future direction for research with SNA.

TABLE 1. Results of ANOVAs of students' centrality in PLC network by student attribute.

Attribute	Deg. Fr.	F	Sig.	Eta - Sq
Gender	1	3.73	0.059	0.048
Ethnicity	5	1.99	0.084	0.124
Modeling	1	3.60	0.058	0.046
Time Spent in PLC	3	11.74	<0.001*	0.329
Major	6	5.25	<0.001*	0.313

DISCUSSION AND CONCLUSIONS

Social Network Analysis holds significant promise

for the description and analysis of student learning communities and therefore has potential impact on methods of supporting students' participation, retention, and persistence in physics. Our analysis leads to three primary conclusions: 1. Membership in the learning community is equitably distributed, both in terms of gender and ethnicity. 2. Social, as well as academic characteristics, are valued in central actors within the network. 3. Three features, which did not factor into the centrality of actors, help us to understand characteristics of the network and how it can be sustained.

The ANOVAs suggest that membership in the PLC learning community is an equitable environment in terms of participation and students' centrality. Gender and ethnicity do not significantly account for differences in student centrality, indicating that the learning community is inclusive of students. This finding is in contrast with other classroom-based measures, specifically with gender learning gaps in introductory physics [1, 12, 13]. Further, these findings are consistent with socio-cultural and participatory views on learning [14 - 16].

Our qualitative analysis of the PLC network diagram (Fig 1) led to the tentative conclusion that social features contribute to the sustainability of a network as much as academic features. The outcome of this is profound: rather than attempting to limit student activities to academics in order to foster community, building social functions should also be integrated. It speaks to the vision of the faculty supporting the FIU PLC to have allowed students to hold movie nights, game nights, and even Thanksgiving dinners in the PLC.

Modeling Instruction, which is one foundation of the CHEPREO reform effort, is not a requisite for participation in the learning community. It clearly is a common entry point, but our results show that the PLC learning community is welcoming to all students, including those from traditional lecture classes and transfer students.

The significant ANOVA results, both time spent in the PLC and major, are also not surprising. First, greater investment of time by the student provides more opportunity to play a prominent role in the community. Second, because the data collection included requests to Modeling classes, the Society of Physics Students, and physics majors, (all of which include greater numbers of physics majors), and because the PLC is physics focused, physics majors are positively biased and likely influenced student centrality within this network.

We have illustrated how SNA provides a rich set of methodological tools for describing learning communities, identifying features unaccessible through classroom measures alone. Future directions

for SNA of the PLC includes using statistical methods to model the centrality in the network. Additionally, students who were isolates should be included, analysis of these students may reveal characteristics which inhibit their participation in the learning community.

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