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# Characterizing Student Interaction in a Learning Assistant Supported Biology Course: The Classroom as a Social Network

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## Introduction

Large enrollment undergraduate science courses often suffer from having little opportunity for student engagement. These courses are often taught in large, stadium style auditorium rooms with a great deal of distance between the instructor and most students, and the large number of students, most of whom do not interact with one another, creates an impersonal setting (Geske, 1992). Reform efforts that focus on active learning strategies or teaching for interactive engagement aim to target this problem (Froyd, 2008). But what does it mean for students in these courses to be engaged? And how can we characterize these engagements in the context of such reform efforts? In this paper, we offer an operational definition of student engagement and present an instrument and analytic method for characterizing that engagement in the context of adoption of one such reform effort- the Learning Assistant (LA) model (Otero, Finkelstein, McCray, & Pollock, 2006). We then use the resulting measure of student engagement (together with other independent variables) as a predictor of two student level outcomes in a large enrollment General Biology II class: final course grade and gain in conceptual understanding as measured by the Conceptual Inventory of Natural Selection (Anderson, Fisher, & Norman, 2002).

## Background

There is strong evidence that the implementation of *active learning* methods in undergraduate science courses can lead to increased student conceptual understanding and course achievement (Freeman et al., 2014). *Active learning* is a term generally used to describe interactive innovations in undergraduate science teaching, similar to the notion of *interactive engagement* (IE) used in physics education research (Hake, 1998). Wieman offers a definition of active learning, in which “students are spending a significant fraction of the class time on activities that require them to be actively processing and applying information in a variety of ways, such as answering questions using electronic clickers, completing worksheet exercises, and discussing and solving problems with fellow students” (Wieman, 2014). Consistent with such definitions, others have offered pedagogical approaches and strategies which could support active learning environments. For example, Froyd (2008) suggested teaching practices including cooperative group work, frequent formative assessment, facilitated active learning in class, use of electronic communication among groups outside of class, and use of pedagogically trained teaching assistants. Many studies have pointed to the value of peer interaction and active learning strategies for increasing student achievement and learning (Beichner, 2008; Freeman et al., 2007; Hake, 1998; Knight & Wood, 2005; Ruiz-Primo, Briggs, Iverson, Talbot, & Shepard, 2011; Smith et al., 2005; Udovic, Morris, Dickman, Postlethwait, & Wetherwax, 2002). But we also know that not all of these innovations in undergraduate science teaching practices (i.e., *active learning* or *interactive engagement*) contribute equally to student level outcomes (Ruiz-Primo, Briggs, Iverson, Talbot, & Shepard, 2011). Further, these practices and strategies can be difficult to implement in large undergraduate science courses because of high student-to-faculty ratios, limitations of classroom setup, and possible student resistance to non- traditional practices (Allen & Tanner, 2005; Felder & Brent, 1996). We posit that using Learning Assistants (LAs) in these classes can help support the implementation of such approaches. In fact, there is evidence that Learning Assistants (LAs), a practice embedded resource, can support the use of active learning methods in the large lecture science classroom and enhance student outcomes (Chasteen, Perkins, Beale, Pollock, & Weiman, 2011; Otero et al., 2006; Pollock, 2005; Talbot, Hartley, Marzetta, & Wee, 2015).

Much of research around active learning has focused on comparing the active learning classroom to “business as usual” or traditional instruction (Freeman et al., 2014). As many researchers have noted, it is time to move beyond these studies and move towards identifying the specific aspects and mechanisms by which active learning is successful (National Research Council, 2012; Wieman, 2014). Recently, some research has begun to examine the effects of active learning in a more fine-grained manner. For example, a recent study (Eddy & Hogan, 2014) examined the effectiveness of a specific intervention (increased course structure) on the achievement of students of different ethnicities. This move towards what has become known as “second generation educational research” (Freeman et al., 2014) is only just beginning, and promises to contribute much to the field.

Though we know that practice embedded resources such as LAs can help support the implementation of such strategies, we do not know what specific types of active learning contribute the most to these outcomes, or the mechanisms by which these activities work. A precursor to investigating these deeper questions is characterizing student interactions in the active learning environment, and the relationship between those interactions and student level outcomes.

## The Learning Assistant Model

The LA model was developed at the University of Colorado Boulder (CU Boulder) in 2003 and has since been replicated at over 60 institutions around the world (“Learning Assistant Alliance | Home,” n.d.). The LA program at the University of Colorado Denver (CU Denver) is a replication of the CU Boulder model. In general, LA programs seek to: (1) improve student learning in undergraduate STEM courses, (2) support the transformation of undergraduate STEM courses by facilitating more student-centered methods of teaching and learning, and (3) offer high performing science students an opportunity to learn about STEM teaching as a possible career choice. Learning Assistants are undergraduates who have succeeded in their STEM courses and expressed interest in helping other students learn. They are recruited by faculty in science and science education. Selection of LAs is competitive, and LAs typically receive a monthly stipend for their work. The foundations of the LA program are content, pedagogy and practice:

- *Content*: LAs must have successfully completed the course they support with high achievement. They meet weekly with their lead faculty to reflect on the past week's activities, plan for the next week's lesson, discuss the content under study, and analyze student work. These meetings help the LAs deepen their own content knowledge and provide a richer content-based context for the students in the supported course.

- *Pedagogy:* First time LAs take a pedagogy course while they are serving as LAs. In this course, they discuss learning theory, teaching strategies, formative assessment, promoting discourse, and students' conceptions, all in the context of their specific discipline and their roles in the classroom. LAs learn about teaching and learning, in large part through reflecting on their LA experience.
- *Practice:* An LA's primary role is to facilitate discourse and interaction among students in the supported course. This work occurs in different settings. During class, LAs facilitate interaction and discussion among groups of students during participation in active learning methods. Outside of class, LAs facilitate learning by holding drop-in office hours, answering emails from students, moderating discussion boards, and helping students develop study skills.

LAs help faculty to incorporate active learning methods in undergraduate courses, and support the development of increased classroom interactions. The use of LAs is generally well received by students in supported courses (Talbot et al., 2015). As mentioned above, research has also shown that learning gains of students in LA supported courses are significantly higher than those of students in non-LA supported courses (Otero et al., 2006), and that the use of LAs contributes to impact on curricular change in these courses (Pollock & Finkelstein, 2013). However, recent research has not specifically examined the role of LAs in classroom interactions.

**Framing**

Our framing for this work and our broader research agenda is both practical and theoretical, grounded in the existing research on active learning, and also drawing on more theoretical work in cognitive science. We contend that the existing research base can be better specified and understood with respect to the specific cognitive processes that are targeted and elicited by active learning methods. We also believe that learning occurs through participation as much or more so than it does through acquisition (Sfard, 1998), and that this participation occurs within a classroom community (Lave & Wenger, 1991). Interaction between individuals is the central element of this participation in a community. These interactions involve the social exchange of information, ideas, and dialog about that which binds the community (e.g., Biology). Engaging in these specific interactions is our operational definition of one aspect of "interactive engagement" (IE). With that in mind, the interactions themselves serve as an indicator of engagement in learning and are a proxy for IE within a classroom.

In order for this "second generation" of active learning research to have a substantial impact, we need to draw on what we know about student cognition and learning. For example, we have a good understanding about how more expert individuals differ from novices, and how they can transfer their learning to novel situations (Bransford, Brown, & Cocking, 2000). We also know that experts use (and know when to use) conditionalized knowledge to sift through a large amount of information, and then focus on the points that matter in that context (Glaser, 1992). The concept of "conditionalized knowledge" has implications for the design of curriculum, instruction, and assessment (Bransford et al., 2000). This concept might also help us interpret or better understand the effectiveness of interactions during active learning in context. For example, when afforded the opportunity to interact or discuss while engaging with a task, what do students ask? What do they offer to each other in discussion? Before delving into these fine-grained mechanisms of interaction, we must first have a sense of what kinds of (and how many) interactions takes place, and how that differs between individuals in the same classroom.

We assert that an overarching view of cognitive processes in general can help us to make better sense of student interactions during active learning. By cognitive processes we mean the mental action(s) that a learner engages in as they are participating in an activity, solving a problem, etc. These mental actions may involve memory, organization and application of knowledge schema, linking schema together to form mental models, and ultimately evaluating those models in light of new situations (Redish, 1994). One of the most straightforward and widely used frameworks for thinking about cognitive processes or various levels of demand on student cognition is Bloom's Taxonomy (Bloom, 1956). Originally developed in order to classify educational objectives and goals but widely used throughout K-12 education, Bloom's has seen recent use in Discipline Based Education Research (Crowe, Dirks, & Wenderoth, 2008). A more recent revised version of Bloom's Taxonomy (Krathwohl, 2002) separates the knowledge dimension from the cognitive process dimension, making application and interpretation cleaner.

Though potentially powerful and easy to interpret, Bloom's Taxonomy alone may not be appropriate for classifying interactions or observed activities in class. However, other recent work has focused on classifying overt activities and linking those activities to attendant cognitive processes. Chi's Interactive-Constructive-Active-Passive (ICAP) framework differentiates between these observable, overt activities and identifies their relationship to internal cognitive processes (Chi & Wylie, 2014; Chi, 2009). In that framework, "Interactive" (I) is associated with "deepest understanding, potential to innovate novel ideas." While this is not, of course, necessarily a highly probable cognitive outcome of every classroom interaction, it is nonetheless a potential outcome of such interactions. Knowing whether or not and how often such interactions take place is a first step towards interpreting those interactions in terms of a cognitive process framework.

In this work, our overarching question is: How can conceptualizing the classroom as a social network help to characterize student interaction and engagement? Our specific research questions address both the class and student level: What role do Learning Assistants (LAs) play in the active learning classroom network? How does the classroom network develop over the course of the semester? What is the relationship between the interaction characteristics of students and their achievement and learning? Our hypotheses are that LAs play a central role in the classroom network, that network will become more dense and interconnected over time, and students who play a more active role in the classroom network will exhibit higher achievement and greater gains in conceptual understanding.

**Methods**

This work was conducted in a large enrollment section of a General Biology II course at the University of Colorado Denver during spring semester 2014. Total student enrollment was 161, and eight Learning Assistants (LAs) were utilized during lecture time. The class was characterized as using many active learning strategies, such as posing questions via personal response systems (clickers), and group work on in-class question packets and other activities during lecture. The instructor for this course had utilized LA support for this course two times prior to this semester. Observations of her teaching using the Reformed Observation Teaching Protocol (Sawada et al., 2002) indicate a “reform orientation” to instruction.

To investigate our research questions we developed a simple survey for students. The survey is administered on paper during class time, and consists of one free response question:

> *Who do you communicate with about this course? Include all types of communication (in person, electronic, etc.). List other students, professors, TAs, LAs, etc. Please write first and last names if you know them.*

Students are prompted to list names in each of two columns: IN CLASS and OUTSIDE OF CLASS. This survey was administered at three time points during the spring semester of 2014 (weeks 3, 9, and 14) in a general Biology II class. In this paper, we discuss only the IN CLASS responses, analysis, and findings[1].

Student response data from each administration was cleaned using class rosters and then entered into a sociomatrix for analysis. This matrix is symmetrical, and denotes directional communications (“edges”) between individuals (“nodes”). For example, student A may report communicating with student B, but B may not report communicating with A. The matrix would not show a bi-directional communication in this case, only one-way communication (from A to B). Separate sociomatrices are created from the IN CLASS responses for each of the three administrations. Each of these serves as the basis for analysis using social network analytic methods (Wasserman, 1994). In our work, we conduct

[1] Responses from the OUTSIDE OF CLASS prompt have proven much more difficult to work with and interpret, as we cannot consistently identify listed individuals who are not rostered in the class.

these analyses using the UCINET software (Borgatti, Everett, & Freeman, 2002) and the igraph package (Csardi & Nepusz, 2006) in R (R Core Team, 2014).

## Results

### Class Level Network Characteristics

Our analysis of the in class networks at each time point show that the class level network is highly interconnected from early on in the semester, and that LAs are central nodes in these networks. Conceptually, these two findings are best illustrated by the sociogram in Figure 1. In this figure, unconnected nodes (isolated students) are visible on the outside edge of the graph. All nodes in the supergroup (main group) are connected by varying path lengths. Lines between nodes ("ties") represent these communication paths. These ties are directional, which is represented by arrows on the end of the ties. This is a graph-theoretic representation, in which the size of the nodes is weighted by the number of connections incident upon it (indegree). In other words, the more that people report talking to an individual, the larger that individual's node is on this graph. Nodes are colored to denote the group identity of the individual (yellow = professor, red = LAs, black = TAs, blue = students). Node position is based on connectedness within the network. In this sociogram, the largest nodes are LAs, and the more central nodes are placed nearer to the center of the graph. Note also that some students (e.g., S114) are larger and more central than many others.

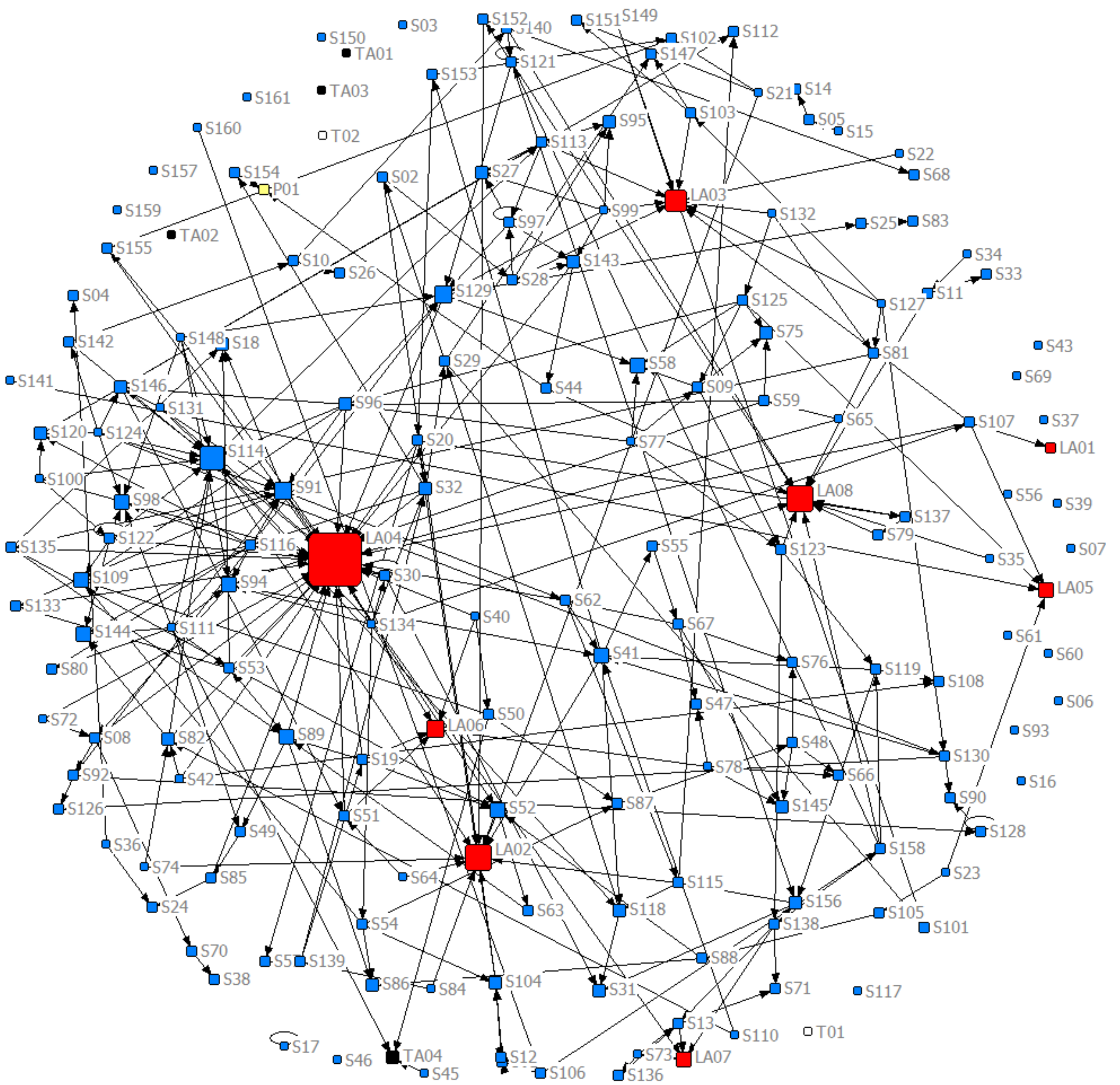


*Figure 1.* Sociogram from week 3 administration of social network survey. Nodes are labeled as students (e.g., S01, are blue), LAs (LA1, are red), TA's (TA1, are black), and professor (P01, is yellow). Node size is set as a function of indegree.

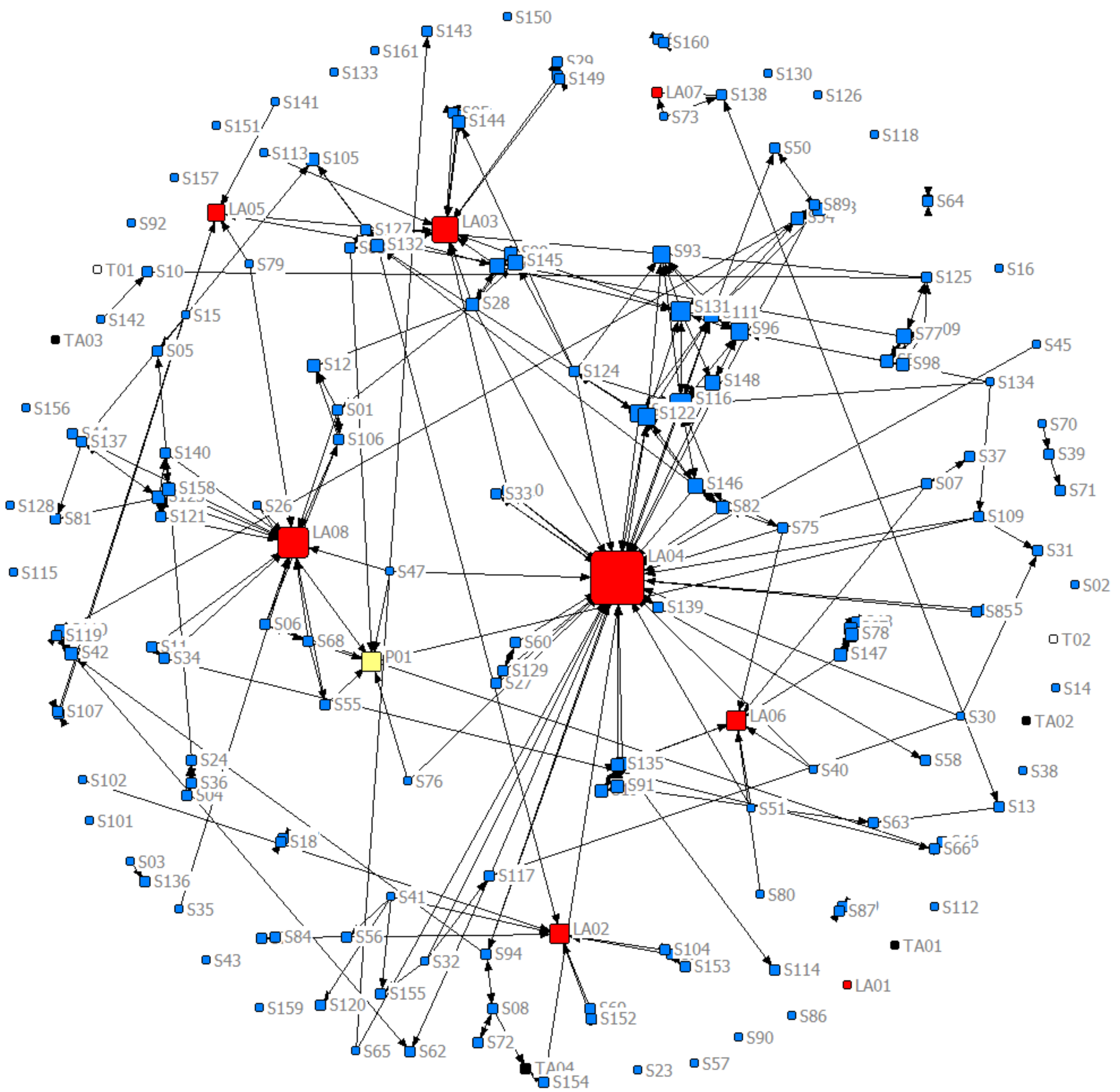


*Figure 2.* Sociogram from week 9 administration of social network survey.

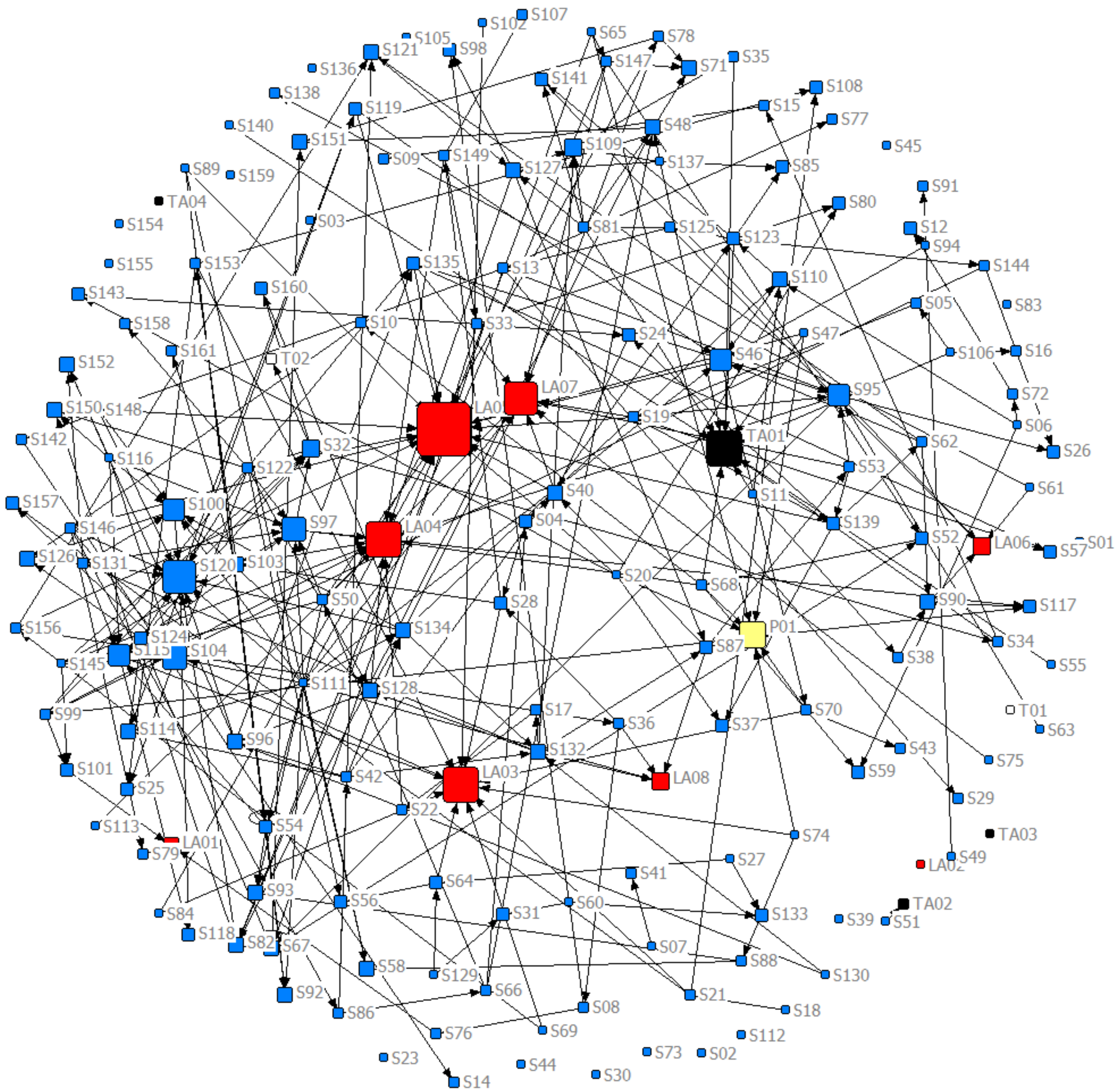


*Figure 3.* Sociogram from week 14 administration of social network survey.

Table 1.
*Network measures at each measurement point*

| Time | Number of ties | Avg Degree | Density | Connectedness |
|---|---|---|---|---|
| Week 3 | 317 | 1.767 | 0.010 | 0.110 |
| Week 9 | 323 | 1.972 | 0.011 | 0.052 |
| Week 14 | 314 | 1.773 | 0.010 | 0.197 |

Select class level network measures from each point in time are given in Table 1. The density of this network (the number of ties as a proportion of the number of possible ties) did not change from week 3 to week 9 to week 14. Similarly, the average degree (total of indegree and outdegree) for any individual in this network remained essentially unchanged over time. Connectedness (the proportion of pairs of nodes that can reach each other by any path) did increase slightly from the first to the last measurement points. These data refute our hypothesis about the increasing density of the network over time, and suggests that the role of the individuals was developed early on in the semester and maintained throughout. However, a visual examination of these graphs does show us that the LAs are indeed central figures in this network, providing support for the related hypothesis. Further, upon closer examination of individual centrality measures (specifically indegree and Bonacich power, both discussed below) by group, we can confirm that the centrality of LAs increases slightly over time which suggests that they indeed become more important actors in the network as time progresses.

**Student Level Characteristics and Outcomes**

For each point in time, the following centrality measures were calculated for each student in the class network: indegree, outdegree, Bonacich power, and betweeness. All centrality measures are reported as normalized values in Table 2. Below we describe the meaning of each of these measures, how they were calculated, and our hypotheses on how these relate to student outcomes.

Indegree is a measure of how many links are incident upon a node, or in the present case how many people report talking *to* a specific individual. Outdegree is a measure of how many links are outgoing from a node, or in this case how many people an individual reports talking *to*. We are interested in both, but from the perspective of predicting student outcomes we hypothesize that outdegree is related. If a student reports talking to many different people about Biology in class, one might assume that they are gathering a lot of information relevant to achievement and learning.

Bonacich power was calculated for each student at each point in time based on specifying Beta at 5% less than the reciprocal of the largest eigenvalue[2]. This centrality measure can be interpreted as the total amount of influence an actor in the network can have on others via both direct and indirect (longer path) channels. Positive values represent increasing power in communications networks such as the classroom.

Betweeness is a measure characterizing how often a student is on the shortest path between two other students. Students exhibiting high betweeness are in a position to filter

[2] for time 1 Beta was set at 0.815, for time 2 Beta was set at 0.204, and for time 3 Beta was set at 0.560

information as it is passed, and are also quite important to other students that they connect. For example, consider a student who is, quite literally, between another student and an LA. The “between” student is necessary to the other student in passing questions to the LA, passing information back. and potentially filtering or even distorting that information (imagine the “telephone game”). They occupy an important position in the network, and if removed it affects not only themselves but those whom they connect.

Table 2.
*Average student centrality measures*

| Parameter | week 3 | week 9 | week 14 | average |
|---|---|---|---|---|
| indegree | 0.008 | 0.009 | 0.008 | 0.009 |
| outdegree | 0.011 | 0.012 | 0.011 | 0.012 |
| Bonacich power | -0.108 | 0.311 | 0.432 | 0.212 |
| betweeness | 0.003 | 0.001 | 0.007 | 0.003 |

While average indegree and outdegree did not change over the course of the semester, Bonacich power and betweeness did increase slightly. This leads us to make the following Inference: while the number of communication ties did not increase between students (network density remained constant), the ability of students to influence each other and the information shared did increase. This could be due to an increasing strength or value of the communication links between individuals in the classroom network. Perhaps our hypothesis about increasing network density was not the best way to think about the situation. It might not be about increasing the number of ties, but rather about developing the strength or value of those ties over time. The observed increasing (though slightly) Bonacich power and betweeness suggest that this is happening, and may be a better way to think about network development in the classroom.

Other student level variables relevant to our modeling of student outcomes is presented in Table 3. One can see that on average, student attendance in this class was very high (91%), as were homework scores (88%) and in-class question scores (94%).

Table 3.
*Other student level variables*

| Variable | average | SD |
|---|---|---|
| Attendance | 0.91 | 0.12 |
| homework score | 87.67 | 11.77 |
| in class questions score | 94.23 | 10.48 |

| | | |
|---|---|---|
| CINS pre-test score | 10.34 | 3.47 |

Table 4 provides descriptive statistics for our outcomes of interest, namely final course grade and post-test scores on the Conceptual Inventory of Natural Selection (Anderson et al., 2002). For the overall class, the normalized gain on the CINS (<g>) was 0.42, which is in the high range of such gains and is therefore indicative of an interactive learning environment (Andrews, Leonard, Colgrove, & Kalinowski, 2011; Hake, 1998; Talbot et al., 2015).

Table 4.
*Student level outcomes of interest*

| Outcome | Mean | SD |
|---|---|---|
| Course Grade | 79.35 | 11.16 |
| CINS post-test score* | 14.38 | 4.08 |

*maximum score on this version of the CINS is 20

**Regression Modeling**

Our initial hypotheses led to specifying a regression model which predicted student outcomes (course grade or CINS post-test score) as a function of outdegree (how many individuals a student reports talking to), betweeness (how often the student is on a short connection between other pairs), average attendance, average homework score, and average score on in-class question sets (which include clicker activities). This hypothesized regression model is given in equation 1.

$$Outcome = \beta_0 + \beta_1(outdegree) + \beta_2(betweeness) + \beta_3(attendance) + \beta_4(homework) + \beta_5(in - classQs) + \varepsilon \quad (1)$$

Before running these models, we first examined the relationship between each hypothesized predictor (as well as related predictors) and the outcome variables of interest. Averages for each student are taken across all three measurements (weeks 3, 9, and 14). Correlations between these predictors and the outcomes of interest are given in Table 5 below.

Table 5.
*Correlations between predictors and outcomes*

| Independent variable | Course grade | CINS pos-test | CINS <g> |
|---|---|---|---|
| average indegree | 0.121 | -0.11 | 0.068 |

| | | | |
|---|---|---|---|
| average outdegree | 0.204* | -0.167 | 0.079 |
| average Bonacich power | 0.089 | -0.068 | 0.080 |
| average betweeness | 0.202* | 0.044 | 0.129 |
| average attendance | 0.608** | 0.057 | 0.093 |
| average homework score | 0.824** | 0.226* | 0.126 |
| average in class questions score | 0.709** | 0.159 | 0.047 |
| average CINS pre-test score | 0.260** | 0.473** | -0.475** |

*correlation is significant at $p < 0.05$
**correlation is significant at $p < 0.01$

When we run the hypothesized model in equation (1) above to predict course final grade (on 155 cases), we find that neither average outdegree or average betweeness are statistically significant or substantive predictors (when taken together with the standard errors; see Table 6). Model assumptions were verified through analysis of a P-P plot of expected versus observed cumulative probabilities, and plots of standardized residuals (which were observed to be normally distributed). This model accounts for about 70% of the observed variance in course final grade.

Table 6.
*Regression coefficients, standard errors, and significance for variables in the hypothesized regression model predicting course final grade (n = 155)*

| Model Variable | Unstandardized Coefficient | Standard Error | Significance |
|---|---|---|---|
| intercept | 2.492 | 4.592 | 0.588 |
| average outdegree | -42.548 | 59.394 | 0.475 |
| average betweeness | 174.942 | 110.875 | 0.117 |
| average attendance | -19.504 | 9.448 | 0.041* |
| average homework score | 0.646 | 0.065 | 0.000** |
| average in class | 0.401 | 0.120 | 0.001** |

| | | | |
|---|---|---|---|
| questions score | | | |

*significant at $p < 0.05$
**significant at $p < 0.01$

Not surprisingly then given the resutls of the hypothesized model, average homework score and average in class question score were the strongest predictors of final grade, and the best regression model predicting final grade from these data consists of only those two independent variables (see Table 7).

Table 7.
*Regression coefficients, standard errors, and significance for variables in model predicting course final grade from homework score and in class questions score*

| Model Variable | Unstandardized Coefficient | Standard Error | Significance |
|---|---|---|---|
| intercept | 3.466 | 4.544 | 0.447 |
| average homework score | 0.640 | 0.065 | 0.000** |
| average in class qeustions score | 0.210 | 0.073 | 0.005** |

*significant at $p < 0.05$
**significant at $p < 0.01$

When predicting CINS post-test score (on 111 cases) from the initially hypothesized set of predictor variables, we find that the model accounts for very little of the variance observed (about 14%) in CINS post score. Again, model assumptions were verified by examining the distribution of residuals and P-P plots. Regression coefficients, standard errors, and significance are shown in Table 8.

Table 8.
*Regression coefficients, standard errors, and significance for variables in the hypothesized regression model predicting CINS post-test score (n = 111)*

| Model Variable | Unstandardized Coefficient | Standard Error | Significance |
|---|---|---|---|
| intercept | -2.862 | 6.180 | 0.644 |
| average outdegree | -103.040 | 40.491 | 0.012 |

| | | | |
|---|---|---|---|
| average betweeness | 130.382 | 81.492 | 0.113 |
| average attendance | -13.571 | 8.018 | 0.093 |
| average homework score | 0.140 | 0.060 | 0.022 |
| average in class questions score | 0.188 | 0.114 | 0.102 |

*significant at $p < 0.05$
**significant at $p < 0.01$

In summary, none of our regression modeling provided insight into any relationship between student level network measures and student outcomes.

**Discussion**

This work in characterizing student engagement provides insight into the communications network at the class level. In one sense, we have verified an unstated (but motivating) hypothesis about the connectedness of the active learning environment compared to that which would be expected in a traditional lecture environment. In the latter, one might expect a single transmitter (professor) and 200 receivers (students) with little or no interaction between various actors in the classroom. What we found is a rich connection of links between actors in the active learning environment, with one set of actors (LAs) being rather important and central to those interactions. Recall our first stated hypothesis: *LAs are central actors in the classroom network*. In fact, the evidence shows that LAs exhibit high indegree and Bonacich power which both increase over time. This hypothesis was therefore supported.

Our original hypothesis about the classroom network was stated in terms of density (the number of ties as a proportion of the number possible). We originally thought that more communications links would develop over time, increasing network density. However, density was essentially unchanged over time. About 310 links among the 173 actors were observed at each measurement time. Therefore it would seem that this evidence refutes our second hypothesis.  However, we did observe that while the average student indegree and outdegree did not change much over the course of the semester, average student Bonacich Power and betweeness increased slightly. This leads us to make the following inference: while the number of communication ties (and therefore network density) did not increase between students, the ability of students to influence each other and the information shared did increase. Perhaps we were asking the wrong question and need to focus on the nature of the communication links rather than merely the number of links.

Finally, we had hypothesized that students who play a more active role in the network will exhibit higher achievement and gains in conceptual learning. However, we observed that outdegree and betweeness, while significantly correlated with outcomes of interest, were not substantive or significant predictors of achievement or learning gains in the regression models. It would seem that this hypothesis was refuted.

**Conclusion**

The findings and results from this work suggest many next steps. While we feel somewhat confident that we can characterize networks at the classroom level, we are less certain about the insight we can gain about student level network measures from this type of data. To that end, we are currently administering this survey again in the same LA supported context, but are also asking students to rate the value of each communication link that they report. In that way, we can weight the links by value and gain some traction in pursuing how the active learning classroom network develops over time.

With respect to linking student level network measures to student outcomes, we acknowledge the complexities inherent in different instructional settings and how that might impact student outcomes. We are beginning a multi-year project in which we examine these factors in a nested research design: students within different classes within different institutions. Using a multi-level approach, we will then be able to model student outcomes in terms of factors at all three levels. Based on the findings of our current work, we expect that different class level network characteristics might have an effect on outcomes at the student level. Comparing students from different classes which use varying degrees and different methods of active learning will add variance to our sample, something that was not present in this work.

We expect “second generation” active learning research to be a fruitful and rapidly developing endeavor. And further, we expect network analyses to play a part in that effort as it relates to making sense of classroom interactions. Our continued work in this area will build upon the present, and grow to address multiple levels of diverse contexts.

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