

Network Analysis of Social Interactions in Laboratories

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Abstract. An ongoing study of the structure, function, and evolution of individual activity within lab groups is introduced. This study makes extensive use of techniques from social network analysis. These techniques allow rigorous quantification and hypothesis-testing of the interactions inherent in social groups and the impact of intrinsic characteristics of individuals on their social interactions. As these techniques are novel within the physics education research community, an overview of their meaning and application is given. We then present preliminary results from videotaped laboratory groups involving mixed populations of traditional and non-traditional students in an introductory algebra-based physics course.

Keywords: Social network analysis, Physics education, Laboratories, Group work

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INTRODUCTION

Physics laboratories enable students to interact with each other and with physical materials to achieve certain goals. These interactions trigger various types of activities within each lab group [1], the amount of which may be affected by the laboratory design [2]. Prior research has primarily utilized timelines of group activity to infer lab design principles that may excite or inhibit various activity modes. While certainly useful, this methodology has some limitations.

Within a group, members may participate in different activities simultaneously. Such parallel activity cannot be captured by timelines which treat the entire group as a single entity that uniformly engages in one type of activity after another. Thus, the true time of activity is likely greater than the clock time due to parallelization. Timelines also cannot quantify the strength or amount of activity within a group. The amount of lab time spent in one type of activity is often used as an indicator of how much the group engaged in that type of activity. However, the degree of engagement in an activity likely varies over time. Moreover, the importance of individual interactions as triggers for student activity and learning is probably highly variable.

In particular, qualitative analysis of lab group transcripts has been used to investigate the relative impact of metacognitive statements made within a

group [1]. This work showed that some metacognitive statements are more successful than others at triggering productive sense-making episodes. Measuring the total amount of metacognition was not enough to ascertain the ability of a lab design to induce sense-making because only a fraction of the metacognitive statements actually induced sense-making episodes.

SOCIAL NETWORK ANALYSIS

To deepen the study of lab group activity one may use social network analysis (SNA). SNA [3,4] provides a set of tools for quantitative analysis of the roles of individuals, TAs, and physical materials at a finer scale than possible with timelines alone. After introducing basic concepts and relevant quantities we will summarize a few illustrative results of SNA using data from videotaped lab groups.

Relevant Questions & Quantities

First, how can we characterize the overall structure of a network? One useful quantity is the *density*, measuring the cohesion of a network by summing the strengths of dyadic connections. It is given by the average strength all ties divided by the total number of possible ties, and gives a measure of a network's

general activity level. Another is the *clustering coefficient*, using the density for each node's local neighborhood to assess how tightly knit the network is.

Second, how can we characterize the importance of an individual within a network? To do this, one examines the centrality of a node. One appropriate measure of centrality for our data is *flow betweenness*. This assesses how much of the information flow between pairs of nodes was facilitated by a particular node. Another is the *Taylor influence measure*, computing the strength of a node's connectivity to other nodes by summing over all connecting paths and attenuating the strengths as path length increases.

Third, how can we characterize the degree of similarity between two or more networks? The *dyadic quadratic assignment procedure (QAP) correlation* tests whether the ties between nodes in one network are correlated to the ties between nodes in another network. This is also extended to an equivalent of standard linear regression, called *QAP regression*, to test the dependence of one network on several others. These procedures can therefore be used to test whether a lab group maintains a consistent relational structure when engaged in different modes of activity (e.g., sense-making or writing), whether their pattern of activity is consistent from lab to lab, and whether two different lab groups have similar patterns of activity.

Fourth, how can we characterize the degree of equivalence between different individuals within a network? *Structural equivalence*, *automorphic equivalence*, and *regular equivalence* each examine whether two nodes have similar patterns of connections to their local neighborhood. These measures differ by exactly how they define equivalence, with structural using the strictest definition and regular using the least. Nodal equivalence relations enable categorization of students and subsequent testing for causes and effects of such similarities.

Standard inferential statistical methods typically cannot be used for testing network structures because the individuals and ties are not independent of one another. Statistical tests can be adapted, though, via a bootstrapping method using random variations of the network to obtain more correct estimates of standard errors and significances. Thus one may use bootstrapping versions of T-test, ANOVA, and regression just as one would for more typical data. All the quantities and tests described in this section are performed by the UCInet 6 software package [5].

STUDY DESIGN & RESULTS

Two lab groups with three (Group A) and four (Group B) students in an introductory algebra-based

physics course were randomly chosen and videotaped for one laboratory. The students are quite varied, with four males and three females, ages ranging from 18 to 41 (average of 27), and a mixture of engineering majors (three) and life-science majors (four).

Data Formatting

The videos were used to create transcripts by coding each verbal and physical action by each group member, including the time the action began and ended. Our transcription uses the following coding scheme [2]; Sense-Making (SM), Writing (W), Procedure (P), TA help (TA), Off-Task (Off). Each sense-making action is then sub-coded depending on whether the action focused on the Design (SMD), Mathematical Model (SMM), Assumptions (SMA), or Uncertainties (SMU). The TA and physical materials are included as actors in the transcript. Transcripts are subjected to an inter-rater reliability check and revised as necessary. Agreement with one reviewer for the data presented here was 87% before discussion.

From this transcript various adjacency matrices are constructed. Directed actions, such as when group member i asks a question to group member j , are placed in the ij position of the matrix. Undirected actions, such as when group member i announces the result of a measurement to no one in particular, are placed in the ii position. The value placed in the cell may count the number of particular instances of an activity type and direction, producing a Count Adjacency Matrix (CAM), or may count the amount of time spent, giving a Time Adjacency Matrix (TAM). In general, we will have a CAM and a TAM for each category of activity. For example, we may have a TAM for sense-making actions only and another TAM for procedural actions only. Each adjacency matrix produces a distinct network of relations among the lab group members, TAs, and physical materials. For purposes of coding, we consider all physical materials to be one, instead of distinguishing between specific materials. It is important to remember that the methods here only operate at the level of external activity. Without evidence, such as from fMRI studies, they have no clear implication for internal cognitive activity.

Instead of coding the number or time of actions involving the actors, an alternative format is to code the number of transitions from one activity mode to another by actors within a group. Instances where activity i leads to activity j for any node are recorded in the ij position. This produces what we call an Activity Adjacency Matrix (AAM). Using the techniques discussed above this approach allows one to identify which activity types are most strongly

associated, how much one mode of activity facilitates the triggering of other modes, etc.

Data Visualization

Once the various CAM, TAM and AAM are established, they are graphically represented. A few examples are shown in Figures 1 thru 4 using the spring-KK embedding. The symbolism of the nodes and ties may be changed to illustrate different intrinsic and relational quantities. What is shown here is only a small hint at the range of representational possibilities.

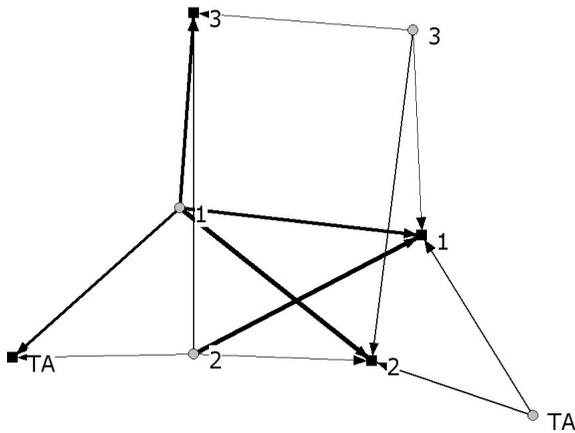


FIGURE 1. 2-Mode rendering of Group A sense-making TAM, tie size indicating relative strength. Each actor has two nodes in this representation, their in-node (black) and their out-node (grey), as indicated by the arrows. Notice the uniformly strong ties from student 1's out-node, while student 2 directs nearly all verbal sense-making activity at student 1. Student 3 makes relatively few sense-making verbalizations.

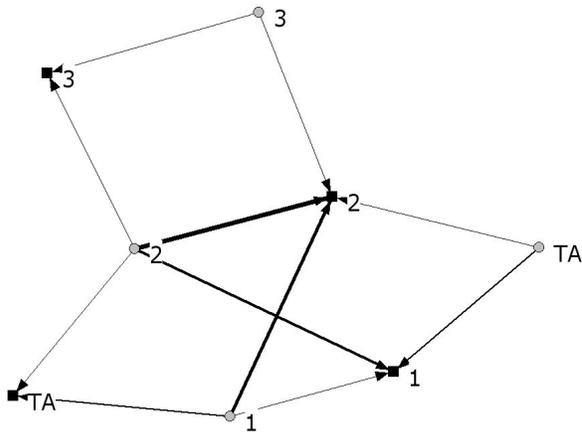


FIGURE 2. 2-Mode rendering of Group B sense-making TAM. In-nodes are black, out-nodes are grey. Student 4 is isolated, so is not included in the network. Students 1 and 2 perform the vast majority of sense-making activity, with much of it being non-directed verbalizations by student 2 (indicated by strong tie between student 2's in and out nodes).

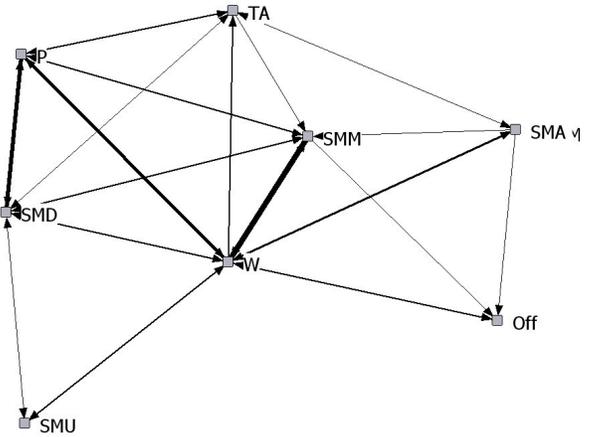


FIGURE 3. Rendering of Group A AAM, without reflexive ties. SMM is the strongest associate of W, while W and SMD are the strongest associates for P. SMA is primarily associated to W.

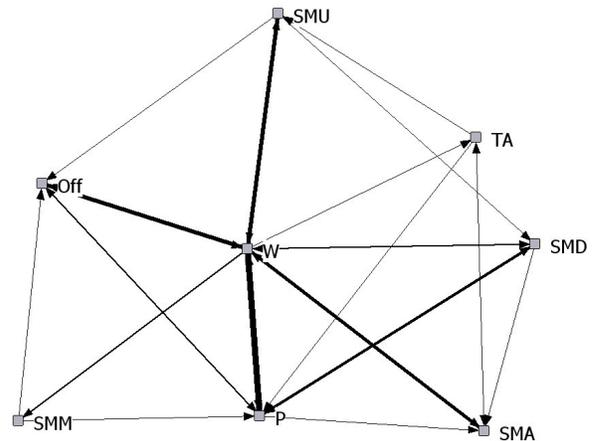


FIGURE 4. Rendering of Group B AAM. There is a relatively stronger relation between W and P, stronger relations with SMU, and weaker relations with SMM as compared to Figure 3. SMA is again primarily related to W.

Results

The purpose of the results presented here is primarily to illustrate the types of conclusions that can be reached with network analysis. More detailed results must wait for the completion of an ongoing study, as discussed below. The results reported here all have very weak external validity due to the small sample size and particular context of the laboratories.

Overall Structures: The densities for Group A & Group B's summed TAMs when confined only to ties between students are 356.8 ± 142.1 seconds and 56.4 ± 74.2 seconds, respectively. A Mann-Whitney U test indicates these are significantly different ($U_A = 2, z = 3.14, p = .001$). This indicates that, on average, any two students of Group A spent more time physically and verbally interacting than did any two students of Group B. Although Group B spent more clock time in

the lab (89m 13s versus 65m 53s for Group A) the density of activity among members of Group A was much higher. Due to parallelization, active times for the two groups were nearly equal (124m 40s for Group A, 129m 8s for Group B).

Sense-Making: Members of Group A spent 13.5% of their active time sense-making, while Group B spent 9.7%. Collapsing the transcript data to a serialized timeline by focusing on predominant modes of activity, we coded 24.4% of clock time spent on sense-making by Group A, and 21.4% by Group B. The differences again illustrate the effects of parallelization. Some members would write while others engaged in sense-making, for example, causing the timeline approach to overestimate the percentage of time spent sense-making.

Normalized flow betweenness scores for each group member are listed in Table 1 along with scores for the Abstract Conceptualization – Concrete Experience (AC-CE) and Active Experimentation – Reflective Observation (AE-RO) factors from the Kolb Learning Style Inventory (LSI) [6]. Although the general reliability of this LSI has been critiqued and is not established in the context of physics learning, it is the most appropriate tool available to assess learning style preferences. The LSI was administered at the beginning of the semester to all students in the class.

TABLE 1. Normalized Flow Betweenness for Sense-Making TAM and AC-CE & AE-RO Factors from Kolb’s Learning Style Inventory.

Group - Student	nFlowBtw	AC-CE	AE-RO
A-1	33.5	22	-10
A-2	19.9	14	-12
A-3	1.6	-1	9
B-1	13.9	18	-1
B-2	21.8	-1	-17
B-3	0.0	-2	11
B-4	0.0	6	0

A regression of nFlowBtw onto AC-CE and AE-RO indicates significant relations between nFlowBtw and AE-RO at the .05-level ($r = -0.814$, $p_l = .025$) and AC-CE at the .10-level ($r = 0.508$, $p_l = .089$). These results suggest that the importance of a student for facilitating sense-making within a group may be related to her preferences for information-inputting (AE-RO) and information-processing (AC-CE). There were no significant correlations of the LSI with students’ nFlowBtw scores for procedural or writing TAMs.

The point-biserial correlation between sense-making TAM nFlowBtw scores and gender was strong but not significant ($r_{pb} = 0.512$, $p_l = .120$). This suggests gender may have had some confounding effect. Other potential confounding factors, such as

personality traits, major field of study, age, and prior physics experience are not addressed here.

Activity Adjacency: Both groups’ activities centered on the writing of the lab report, as shown by nFlowBtw scores (Table 2). Procedural activity was a more important facilitator mode for Group B; sense-making of the design and model were more important for Group A. Dyadic QAP indicates the AAMs for the groups are structurally distinct ($p = .439$).

TABLE 2. Normalized Flow Betweenness for AAM data.

Activity	Group A	Group B
P	12.9	23.0
W	60.1	60.1
SMD	16.7	4.3
SMM	11.3	0.8
SMA	9.3	13.1
SMU	1.7	6.0
TA	6.5	6.6
Off	2.5	8.9

FUTURE WORK

A study is currently underway to collect more data with repeated observations of groups and more measures of intrinsic factors to parse out potential confounding factors. In the long run it would be useful to develop and use methods that can identify how specific knowledge elements are established or communicated by each action, for example. Such methods are currently being developed under the name of Dynamic Network Analysis [7].

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