A Network Model of Distributed and Centralized Systems of Students

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Abstract – The body of knowledge in active and cooperative learning lacks an analytical model to determine the emergent patterns of distributed (active, student centered) and centralized (traditional, teacher centered) networks of students. To address the complexity of learning systems a network modeling approach based on Social Network Analysis and Ecological Network Analysis is proposed as an appropriate scientific construct for developing analytical techniques for studying and understanding learning systems. Models were developed, designed, and interpreted for two configurations, one with four actors and another with 16 actors. A preliminary analysis was performed on a 12 actor model to determine the optimal cluster size to maximize indirect effects within the system. In the future, network models can be utilized to further understand learning systems through network properties that are not directly observable. It is the aim of the authors to provide an additional lens to view, assess, and optimize student learning.

Index Terms – Active learning, Distributed cognition, Social Network Analysis, Ecological Network Analysis

INTRODUCTION

This paper is nested within the sociocultural perspective of learning. The sociocultural perspective does not separate the mind from the environment; learning is a composite of the person and their environment. The social constructivist perspective differs in that it separates the cognitive activities and the environment of a person [1]. This work is an extension of research based in the disciplines of education, general systems theory, sociology, and ecology. In particular this work is based on existing theories of distributed cognition, graph theory, Social Network Analysis, and Ecological Network Analysis. Modeling a network of learners will reveal patterns that are not directly observable. It is the aim of the authors to provide an additional lens to view, assess, and optimize student learning.

The authors have developed a Distributed Cognition Network Analysis model. This model will be helpful in further understanding learning amongst students, their tools, and their environment. In the context of this paper, a model is "a simplified representation of a situation that contains some, but not all, of the elements of the situation it represents" [2]. The development of a Distributed Cognition Network Analysis model adds the following to the current body of knowledge:

- A level of formality and rigor in the study of educational systems, and
- The capability to be modified for a large subset of social systems as modeling is an appropriate language to communicate and integrate disparate information across various disciplines.

Research focused on the interactions of people such as cooperative learning and distributed cognition could benefit from a network perspective that takes into account the flows of information through an open system. Similar network perspectives have been taken in sociology within Social Network Analysis [3]. This early version will include people exclusively, later versions will include tools and the environment.

I. Distributed Cognition/ Cooperative Learning

Active learners seek to understand complex information and are better prepared to transfer what they have learned to new situations [4]. In an active learning environment, the students teach each other, the students teach the professor, and the professor teaches the students, i.e. distributed cognition. Ed Hutchins and colleagues are credited with the formal development of distributed cognition in the mid to late 1980's. Distributed cognition has its roots in the cognitive sciences, cognitive anthropology, and the social sciences. According to Dorothy Winsor, distributed cognition "treats thinking not as an action that takes place wholly inside an individual's head, but rather as an activity that is distributed among the individual, other people, the physical environment, and the tools the person uses" [5]. The learner's knowledge construction process is aided by an environment of distributed cognition in which participants at all levels (experts, mentors, accomplished novices, and novices) teach and learn from each other [4].

Cooperative learning is similar to distributed cognition; however it includes interactions amongst people exclusively. Much research has been conducted on the effectiveness of cooperative learning environments in college and adult settings. Smith et al. describe the effectiveness of cooperative learning in their meta-analysis of 305 empirical studies [6]. Their results found cooperative learning to be valid, reliable, and applicable across a large cross section of people. This meta-analysis demonstrates that cooperative learning is an

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effective method of learning and discusses ways to implement it. In the overview section of their paper, Smith et al. describe the two models of learning processes as the "pour it in" model and the "keep it flowing" model (Figure 1). This metaphorical model is qualitatively descriptive and provides a critical first step in the development of rigorous models of educational systems.



METAPHORICAL MODEL OF THE "POUR IT IN" MODEL AND THE "KEEP IT FLOWING" MODEL (ORIGINALLY DRAWN BY LILA SMITH IN 1975, TAKEN FROM [6]).

II. Network Analysis

Social Network Analysis has its roots in the social and behavioral sciences in the 1930's. Since that time it progressed slowly with an adoption of network analysis in systems ecology in the 1970's. Around 1990 network analysis took root in many different areas of study such as organizational studies, physics, and epidemics [7]. The main difference between a network analysis and a non-network analysis is that a network analysis focuses on the relationships between different objects while a non-network analysis focuses on the objects [8].

Social Network Analysis arose from the need to move beyond the analysis of the characteristics and attributes of an individual person to an understanding of the environment in which a person situated (socially, culturally, economically, politically) and how this influences the characteristics and attributes of that person [8].

There are three notation schemes with Social Network Analysis: graph theoretic, sociomatrix, and algebraic. When conducting a Social Network Analysis, the boundary and the structure of the network must be specified. This involves determining the measured ties between the actors. A graph showing the actors and their ties to one another is called a sociogram. The sociogram can be analyzed visually or it can be represented by a matrix that can be analyzed quantitatively. Graphs often include nodes and nondirectional ties between the nodes. A digraph is a type of graph that has directional ties between the nodes. A trivial graph is one that contains only one node and an empty graph is one that contains nodes but no lines.

Recently Social Network Analysis has been applied to a study of networked learning/ computer-supported collaborative learning within a distance education, graduate level course at Sheffield University [9]. The researchers had

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previously conducted research within this context through content analysis and interviews, which provided them with static data. However, de Laat et al. felt that they needed a more dynamic way to analyze the data. Using Social Network Analysis, de Laat et al. studied the network and determined how dense the participation was, the extent to which the participants were active in the discourse, and how these changed over time.

Other studies that used Social Network Analysis as applied to network learning/ computer-supported collaborative learning will be briefly summarized to show the diversity of analysis and the patterns that emerged through a network analysis of data [9]. The presence of a teacher on an online discussion board was shown to affect the density of the network [10]. Students in a highly structured learning network reached a higher level of critical thinking than those in a less structured learning network [11]. Cho, Stefano, and Gay determined the influential students within a class and found that other students were more likely to follow recommendations made by these influential students [12].

Ecological Network Analysis differs from Social Network Analysis because it has an open system boundary. Each actor or actor has inputs and outputs to the environment in addition to links between the actors or actors. Additionally, Ecological Network Analysis determines different system properties than Social Network Analysis. These properties will be discussed in the Model Output section of this paper.

Recent work in the area of Ecological Network Analysis has involved modeling the flow of nitrogen through the Neuse River Estuary [13]. The Neuse River Estuary was modeled using two seven compartment models. Of the intercompartamental flows, only 45% were empirically observable. The results show that indirect effects are dominant within this system. The majority of the total system throughflow (37.6%) is accounted for by indirect flows between three compartments in the model. This confirms the results of previous empirical research that there is a greater contribution from indirect flows than from direct flows in well connected systems [14-16].

There are fundamental differences between modeling the flow of mass or energy through an ecosystem and modeling the flow of information through a learning system, and as such this paper will be devoted to the design and development of a Distributed Cognition Network Model. This model will be grounded in the Social Network Analysis and Ecological Network Analysis theory and methodology, and will add to the current understanding of distributed cognition. Following the design and development of the model, preliminary results will be discussed briefly and a discussion will follow.

MODEL DESIGN AND DEVELOPMENT

The purpose of this research is to develop a network analysis model that demonstrates the flow of information in a classroom and to determine the properties of these systems that are not directly observable. Centralized and distributed learning system models for systems of four students and systems of 16 students are presented. The design and

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development of the model will be discussed in the following sections: model structure, model variables, and model output.

I. Model Structure

Preliminary models were developed and analyzed in different configurations representing a set of four students and a teacher in a centralized classroom (traditional, lecture type classroom) and in a distributed classroom (active, cooperative, student centered classroom). Two types of configurations tested involved including the teacher inside and outside of the system boundary. After these preliminary models were developed and analyzed, it was concluded that the teacher needed to be outside of the system boundary so that the model could run correctly. This is due to the lack of inputs and outputs when the teacher is within the system boundary. A study of a longer period of time could include the teacher within the system boundary, because then there would be interactions between the students and others in the community.

The four actor digraphs consist of a boundary, actors, and arrows. The arrows represent pathways along which information flows. Pathways labeled as z_n represent information input from outside of the system (including the teacher), pathways labeled y_n represent the output of each student beyond the system boundary, and the pathways labeled f_{ij} represent the flows of information within the system to one actor from another (to i from j).

The centralized model with its corresponding pathways is shown in Figure 2. In this empty model, there are no network pathways between the students (f_{ij}) . This is representative of a centralized, teacher-centered classroom in which the teacher lectures to the students and the students passively receive the information. This centralized model is an idealization, because there is always some interaction amongst students even when it is not planned. Setting up the model for extreme cases (no interactions between students and interactions between all of the students) will show the largest possible difference between the models, although neither case may be realistic. The centralized model corresponds to Karl Smith's metaphorical model in Figure 1a.



The distributed model with its corresponding network pathways is shown in Figure 3 and is representative of a distributed, student-centered classroom in which the students are actively engaged in learning through working with one another and with the teacher. The distributed model corresponds to Karl Smith's metaphorical model in Figure 1b. The distributed model is a completely connected model because all students are connected.



Network structure is mathematically described using matrices. Within each matrix a "0" reflects that there is an absence of direct flow between the adjacent network compartments and a "1" reflects that there is a direct flow between the adjacent network compartments. For example a flow to actor one from actor two, a_{12} , has a value of "0" in matrix AC and a value of 1 in matrix AD. The corresponding four actor matrices, AC and AD are shown in (1) and (2)

The 16 actor models with their corresponding pathways are shown in Figures 4 and 5. The variables f_{ii} , z_n , and y_n are the same for this model as they were for the four actor model. The 16 actor model in Figure 4 is a centralized model with no connections between the students. The model in Figure 5 is a more distributed system as some links between the students have been established. Note that this system is not fully connected, i.e. not every possible pathway has been developed. However, it is distributed since there is a connection between all of the actors in the system although many of these connections are indirect. For example, actors 10 and 13 are directly connected while actors 10 and 14 are indirectly connected through the relationship between 10 and 13. A completely connected system would have links between all of the actors in the system.

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DISTRIBUTED 16 ACTOR DIGRAPH.

II. Model Variables

Information is the currency of the flows but it is not synonymous with learning or knowledge. While information can be shared between people, tools, and the environment, acquiring knowledge (or learning) depends heavily on what happens to the information within the individual as, or after, the information is received by the individual.

The **initial stock value** represents student understanding of fundamental concepts prior to the class (or subject or unit) and ranges in value from 0 to 10. A student with a misunderstanding will be assigned a 0, a student with a low level of understanding will be assigned a 5, and a student with a very high level of understanding will be assigned a 10.

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The **inter-student flow coefficients** (f_{ij}) represent the likelihood that a particular student will share information with other students within the system. This is dependent on the personality of the student and their understanding of the material. This variable will range from 0 to 1 with 0 representing 'no chance' that a student will share information (introvert personality type and/or low understanding of the material) and 1 being a very high likelihood that a student will share information with another student (extrovert personality type and/or high level understanding of the material).

The **input flow coefficients** (z_n) represent the information that is input to the system from outside of the system boundaries. All of the students are exposed to the same information (or input from the teacher) so the value of this coefficient is the same for all actors.

The **output flow coefficients** (y_n) represent each student's output beyond the system boundary. The students present information to the teacher in the form of tests, assignments, homework, quizzes, projects, papers, or projects. A student who conveys a misunderstanding of the subject to the teacher will have a value close to 0 while a student who conveys a high level of understanding of the subject will have a value close to 1.

Within the systems there are relationships between the actors and within the actors:

A simple **cycle** is a pathway of information flow having the same originating and terminating node. Cycles describe different ways to transfer information from one actor to another within a system. For example in the four actor distributed model (Figure 3) there are many different cycles that could be taken to get from student 1 and back to student 1 (1-2-1, 1-2-3-1, 1-2-4-3-1, 1-2-4-3-2-1, ...).

A **reflexive tie** (or loop) describes a cycle of length 1 and is also referred to as a loop or a self-loop [8]. This occurs within the individual when or after information is presented to the individual and they either learn (store it in long term memory or short term memory) or forget the information. This is the internal process that has the capability of turning information into knowledge.

III. Model Output

The strength in these models is the ability to detect patterns that would have otherwise been undetected. These models will be analyzed for the following system characteristics. The first two characteristics were developed in the Social Network Analysis research.

- Centrality: Describes how central an actor is within the system. Typically applied to individual actors, but can be applied to groups to determine' the most influential group. It is a maximum when at least one actor in the group is connected to every actor outside of the group [7].
- **Density**: Describes the number of links in a system. It is often normalized so that the totals can be compared (number of links in system/total possible number of links) [9].

The following characteristics were developed in the Ecological Network Analysis research [17].

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- Indirect Effects: Describes the effects between two actors that are not directly linked. For example, in Figure 5 there is an indirect pathway from actor 1 to actor 12 through actors 4 and 10. In ecological systems these effects have been shown to have larger effects on the system's overall function than do the direct effects. It is these indirect effects that give a system the characteristics of resiliency, stability, and flexibility [18].
- **Synergism**/ **Mutualism**: The effects of network organization convey positive benefits to each actor within the system. In the distributed model the network organization conveys positive benefits to each actor within the system [15].
- **Amplification**: The effects of cycling on the actors. For example, in the four actor distributed model (Figure 3) information is input to the system at actor 1, z₁; student 1 could share that information with student 2 by pathway f₂₁; student 2 could share that information with student 4 by pathway f₄₂; student 4 could share it with student 1 by pathway f₁₄, which would result in an increase in the knowledge base of student 1 although it was instigated by student 1. In other words, the total knowledge of student 1 is greater than it was when the student initially processed the input information (i.e. it has been amplified). This results in the distributed system network deriving more than face value from the inputs. [19].

Each of these model characteristics will show emergent patterns within the system. These can be theoretically modeled or can be modeled based on empirical data.

PRELIMINARY RESULTS

An interesting finding emerged from the model design and development. In ecological systems the centralized model would not survive. However, in engineering education practice the centralized (or traditional) model has been effective. The strength of the reflexive tie within each actor of a centralized and distributed system is critical (x_c in Figure 7 and x_d in Figure 8), but with the distributed model the reflexive tie is significantly strengthened because of the connectivity of the actor with other actors. If the reflexive tie in the actor within the centralized system is low, the reflexive tie can only be self-strengthened, it cannot be strengthened by interactions with other actors.



FIGURE 7 Actor 1 with Feedback in Centralized Model.



FIGURE 8 Actor 1 with Feedback in Distributed Model.

A preliminary analysis was performed on a 12 actor model to determine the effect of clustering on indirect effects. Digraphs were developed for four configurations of a 12 actor The first was a 12 actor model with random model. connections between the actors. The additional three digraphs were 12 actor models that were clustered in two groups (six actors each), three groups (four actors each), and four groups (three actors each). The links between clusters and within clusters were randomly determined using Microsoft Excel. Each model configuration was run in Eco-Net, an online dynamical simulation and network analysis software. The number of indirect links was determined for a case of 12 direct connections and for 24 direct connections (See Table 1). It was found that the indirect effects were maximum for the random group (15.2% and 50% respectively) and the group with two clusters (5.3% and 42.4% respectively). This preliminary analysis is not conclusive, because more iterations with random numbers would need to be run in order to ensure that the results are accurate. However, this does demonstrate that the indirect effects can dominate the direct effects, especially in a highly connected system.

 TABLE 1

 Preliminary Results Determining Indirect Effects for Varying Sociomatrix Structures

BOCIOMATRIA DIROCTORES							
	Direct			Indirect Density			
					2 clusters	3 clusters	4 clusters
Possible				Random	of 6	of 4	of 3
Links	Links		Density	Group	actors	actors	actors
132		12	9.1%	15.2%	5.3%	6.8%	3.0%
132		24	18.2%	50.0%	42.4%	25.0%	34.1%

DISCUSSION/ CONCLUSION

There are limitations to this model. In the Model Output section there are a number of system properties that are described as having positive effects to the overall system. This may be accurate, but there is a possibility of negative effects to the overall system. For example if an actor in a system has a misunderstanding about a concept that he/she believes he/she understands. Incorrect information could flow around the system and someone that had a firm grasp on the information could end up with a lower level of understanding. When the results of this model are compared to actual systems of students, the researchers should carefully pay attention to the 'good' and 'bad' information. Another potential limitation to this model is that in actual sets of students there will likely be irrelevant information in the system. An example of this would be students discussing weekend plans. This leads to the

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question of whether the relevancy and accuracy of the information should concurrently be analyzed. When this model is run based on data collected from systems of students more limitations may arise. For example, it may not be realistic to find a learning environment in which there are no interactions amongst the students or in which there are interactions between all of the students in the class. However, there will be classrooms of varying degrees of interactions amongst the students and these classrooms can be compared. A final limitation is gathering the data from the students. The amount of information that flows between students will need to be determined prior to running the model. Additionally, their understanding of the content prior to and after the learning activity will need to be determined. Measuring student learning will be a critical part of this research and if not accurate this could skew the results of the analysis.

This paper presents the development and design of a network analysis model of learning systems and the interpretation and implications of these models are discussed. The next step in the research is to rigorously analyze the model in the four actor and 16 actor configurations, to optimize the number of connections, and to eventually expand the model to include not only people, but tools and environment as well. After the theoretical analysis, it will be imperative to connect these models to actual classrooms through direct observation. For example, classes could be video taped and analyzed to determine how often and for how long information is exchanged within the system of students. This could occur over the course of a semester to assess the network properties. These results could then be compared to existing research on learning within the Social Network Analysis field (such as the network learning/ computersupported collaborative learning that was presented in the introduction section).

While the initial scope of the application of this model is small, the model can be used to predict the degree of cognitive distribution in other environments (expand it to other classrooms, study groups, service learning projects, extracurricular activities, and teams in industry). Future iterations of this model can be expanded to help educational researchers further understand effective learning theories. Determining these characteristics for systems of students will provide analytical rationale for many classroom practices such as group formation, classroom structure (time in lecture vs. group work), and effective methods for active learning. Future models will also include tools (books, computers) and the environment. This addition to the model can lead to an optimization of the tools to be used in the classroom (or availability of tools outside of the classroom).

The addition of Ecological Network Analysis will provide insight to existing Social Network Analysis models. The Distributed Cognition Network Analysis model that was introduced in this paper will be helpful for educators to understand why distributed learning environments improve student learning. Additionally the models developed will provide insight into how a student-centered classroom should be structured.

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