Social Network Analysis and the Representation of Female Students in Introductory Undergraduate Physics

Sarah Teresa Hierath
Wright State University

SOCIAL NETWORK ANALYSIS AND THE REPRESENTATION OF FEMALE STUDENTS IN INTRODUCTORY UNDERGRADUATE PHYSICS

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science

By

SARAH T. HIERATH
B.S., University of Dayton, 2014

2016
Wright State University

WRIGHT STATE UNIVERSITY

GRADUATE SCHOOL

June 20, 2016

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Sarah T. Hierath ENTITLED Social Network Analysis and the Representation of Female Students in Introductory Undergraduate Physics BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science.

Adrienne Traxler, Ph.D.
Thesis Director

Doug Petkie, Ph.D.
Chair, Department of Physics

Committee on
Final Examination

Adrienne Traxler, Ph.D.

Jason Deibel, Ph.D.

Eric Rowley, Ph.D.

Robert E. W. Fyffe, Ph.D.
Vice President for Research and
Dean of the Graduate School

ABSTRACT

Hierath, Sarah Teresa. M.S. Department of Physics, Wright State University, 2016. Social Network Analysis and the Representation of Female Students in Introductory Undergraduate Physics

Physics Education Research has begun to focus on the learning habits, success, and connections of students in physics classrooms using Social Network Analysis (SNA). SNA is an important tool in studying classroom dynamics because it can be used to map the social structure of a classroom's interactions and to aid in understanding how students work and study together. This study presents network diagrams, statistics, centrality measures, and conceptual understanding correlations for 7 different sections of introductory physics. Centrality measures were determined from a first and last week survey in which students were asked to indicate their study partners within the class. Courses were then analyzed in aggregate and by gender to look for gender effects in network participation, which may take the form of different patterns of centrality, or different centrality shifts over the semester. These measures were then correlated with Force Concept Inventory (FCI) scores and gains.

Contents

List of Figures

List of Tables

To my family

and close friends,

for all of your love and support.

Chapter 1

Introduction

Physics Education Research seeks to improve instructional methods and enhance student learning and understanding in physics (Beichner, 2009). Researchers and teachers work together to give students a strong foundation while minimizing the potential struggles encountered by students, particularly women and underrepresented minorities (Gonzales et al., 2002). Social Network Analysis allows us to study, quantify, and visualize the relationships that students build throughout a course and can be used in order to better understand classroom dynamics in hopes (or as a means) of increasing student success (Brewe et al., 2012; Bruun and Brewe, 2013). Student connections can be evaluated using different types of measures, called centrality. Different types of centrality consider factors such as students' numbers of connections, their positions as "information brokers" between groups of others students, or an iterative estimate based on the importance of their network "neighbors." By correlating these centrality calculations with a success measure like the Force Concept Inventory (FCI), a common conceptual test, we may be able to examine how new methods of instruction affect student learning (Hestenes et al., 1992). The FCI lends itself to studying student success because of its reliability to measure conceptual gains, which can be slower to improve than students' ability to solve quantitative textbook or exam problems (Hake, 1998). Centrality values for students in several sections of introductory undergraduate physics will be reported, in addition to correlations of these values with FCI post scores and gains. Additionally, student rankings based on the different measures of centrality will be correlated to determine the effect of the centrality measure on the students position within a network. Finally, preliminary results will be reported for these analyses for women specifically, as their under-representation in physics means that they are sometimes lost in the overall data.

1.1 Purpose of study

Educational research is important because it works to improve the learning and understanding of students, and educating individuals in order to better prepare them for the workplace is one of the most important tasks that fall upon university faculty (National Research Council, 2012). Traditional modes of instruction have left students with less understanding than what was intended or expected, and educational research has sought to change this (Freeman et al., 2014). New modes of instruction like active learning and group cooperation have been developed in hopes of improving student understanding by implementing more hands-on, engaging activities. Additionally, women and students from underrepresented minority groups may struggle more in traditional passive lecture settings (Seymour, 1995), for many reasons that could potentially be addressed in an active learning environment. In physics, female students are exceptionally under-represented and their success rates are of particular interest to education researchers (Jovanovic and King, 1998; Seymour, 1995).

In order to better understand how of different instructional methods affect students, specifically females, social network analysis has been used to analyze and graphically display the connections that students make with one another throughout an introductory physics course. The aim of this study is to probe not just students' individual conceptual gains, but also how the social structure of the classroom develops over a semester, and how this may connect with conceptual gains. After analyzing this information, conceptual gains may be correlated with network information to explore the relationship between instruction, connection, and understanding. The purpose of this study is to examine the representation of female students in introductory physics courses, and how the connections they make are related to their conceptual gains.

1.2 Significance of the study

Female students are often underrepresented in the sciences, however the absence of female students is particularly pronounced in physics, with only about 20% of awarded bachelor's degrees going to female students [1]. At a university where many different forms of instruction exist, are any of these forms more conducive to the success of female students? While research indicates that active learning and group-based activities may improve student understanding, do classes that encourage group work also encourage interaction of females students with their classmates? Additionally, does interaction with classmates correlate with higher conceptual gains and successes in the course? By quantifying the interactions and successes of female students, perhaps more can be understood about this under-representation and how it can be changed. In order to better understand the learning habits, group interactions, and success of female students in physics courses, social network analysis and conceptual gains will be explored for several sections of introductory calculus-based physics and compared to the overall gains of the sections. These results may provide feedback to the department and university as a whole as the school implements more active learning classroom settings, and will add to the still-growing literature on network analysis in introductory science classrooms.

[1] This data can be seen at the APS website at http://www.aps.org/programs/education/statistics/womenphysics.cfm

Chapter 2

Literature Review and Background

2.1 Educational Research Importance

Education-based research has become an important aspect in preparing undergraduate students for the workplace. While it is critical for students to learn and understand the complicated topics of science and engineering, it is equally essential to ensure that the material is communicated in a way that is conducive to the students. The National Academy of Sciences (NAS) directed the National Research Council (NRC) to develop a committee to more closely examine discipline-based education research with the goal of improving the education of undergraduate science and engineering students (National Research Council, 2012). It is also important to note that while previous modes of education have relied on the communication and repetition of facts, more recent education research has focused on the importance of understanding, rather than memorizing material.

Assembled by the NRC in 2010, the Committee on Undergraduate Physics Education Research and Implementation began identifying and evaluating the goals and challenges of physics education. From this study, many important themes became apparent. These themes included how foundational and fundamental physics is, that systemic tensions, major challenges, and improvements exist, and that there can be a scientific approach to how physics is taught. Physics provides fundamental information about the universe while helping students to develop conceptual understanding and mathematical techniques to comprehend complicated processes. However, this is not without strain.

Many physics departments play an important role in educating many majors, but physics majors remain particularly scarce with serious under-representation of minority groups. Additionally, despite the large numbers of students required to take physics courses, pre- and post- testing conceptual testing indicate students struggle to understand core physics principles (National Research Council, 2013). In order to improve the undergraduate education of physics, new methods of teaching have been developed to incorporate (and sometimes correct) pre-existing knowledge and to promote active learning by encouraging group problem solving and metacognition as students determine what material they do or do not understand (National Research Council, 2004). More recently, education research has indicated that utilizing active learning style courses rather than traditional lecture courses may improve the success and understanding of students (Freeman et al., 2014).

Physics Education Research (PER) aims to understand and learn how students work with and apply physics material. PER comes in several forms, from more basic to more applied, in both qualitative and quantitative forms while also exploring socio-cultural issues like race and gender in addition to epistemology and attitudes about physics. Basic PER looks to explain how students learn and use physics while applied PER looks to analyze these results, induce instructional changes, and analyze the results of the imposed changes. Qualitative PER includes interview-based studies in which students may be asked to talk through their problem solving methods, in order to gain insight into how students approach and utilize physics in problem solving. Quantitative PER typically incorporates the Force Concept Inventory (FCI) or similar testing methods where results are statistically analyzed over large sets of data in order to identify the topics and concepts that students may struggle with (Beichner, 2009).

While Physics Education Research may appear to fall under the scope of education rather than physics, it is important to note that being able to understand the concepts being tested or explored is an important attribute the researcher must possess and explains why this research is typically conducted within a physics department rather than a department of education. The typical Physics Education Researcher is not simply a faculty member that teaches, they are faculty that conduct research that is focused on students and the education of physics. This is distinctly different from curriculum development because the focus on education is more about what students gain from physics, how instruction can be improved to help students understand, how students solve problems, and what students fail to understand (Beichner, 2009). Additionally PER looks at how instructional methods affect student knowledge development and understanding, while recognizing that both acquisition of information and participation are important to learning (Sfard, 1998). The investigation of discourse models and collaborative group learning would fall within the scope of PER (Beichner, 2009) and many researchers have begun to explore the effects of group-based activities on the understanding of physics concepts (Heller et al., 1992; Heller and Hollabaugh, 1992).

In the last 5-10 years, students' social interactions and collaborations in class have begun to be studied at a course-wide level using techniques from social network analysis (SNA) (Brewe et al., 2010; Grunspan et al., 2014). This is important because student-student interactions are foundational to many active learning techniques, but close qualitative studies (Alsop and Watts, 1998) are impractical to do at such a large scale.

PER also examines the under-representation of minority groups in physics education. Women in particular are seriously underrepresented in physics and at least some of this difference has been attributed to the classroom environment (Seymour, 1995).

2.2 Social Network Analysis

Social network analysis (SNA) is an important tool used by researchers to represent the flow of information within a network of individuals (Cook et al., 1983). The goal of SNA is to understand the relationships and structures that make up the network. In educational research, SNA is typically used within a class to map the connections that students make with others over the course of a semester as a means of improving the educational experience. Networks consist of students and the relationships between them and they are represented by nodes and edges. In a network, each student is represented by a node and the edges indicate the self-identified interaction between students within the specified network. Network data can be obtained using survey style questionnaires in which students may be asked to identify who they work or study with within the class (Marsden, 2011). Once a network is constructed, this information can be correlated with success measures (Grunspan et al., 2014)

In PER, SNA has been used to map the development of relationships within physics courses over a given period of time. In most cases, this time period is the length of one course (a semester), but in some cases data is recorded over longer intervals. The length and frequency of data collection is determined by the researcher and depends upon what type of information is sought. Additionally, PER has begun to incorporate SNA as a means of monitoring the effects of participation in learning communities as a measure of success, rather than just conceptual gains or course grades (Goertzen et al., 2012). This allows for researchers to better understand the role that participation plays in retention rates of physics majors, along with the interaction of students within the learning community (Brewe et al., 2012). More intricate applications of SNA aim to quantify the changes that large networks undergo (Rosvall and Bergstrom, 2010) and how groups within a network evolve, congregate, and stabilize over time (Bruun and Bearden, 2014). This study will utilize SNA to map the representation of female students in multiple sections of introductory physics as a measure to correlate with conceptual gains.

2.2.1 Network Diagrams

Each network object can be plotted as a visual representation of connections between people within the course. These network objects are constructed using data collected through a survey-style questionnaire that students completed at both the beginning and end of the course. The dots (also called nodes) in a network diagram represent students while the lines connecting them (also called edges) represent a connection in which at least one of the two students involved in the connection identified the other as someone they work with to learn physics. Our network objects are undirected, meaning that a connection from one node to another is present so long as one of the students in the connection identified the other. A directed network would typically have arrows connecting students in order to indicate which students were named by others, and a link could be two-way or one-way depending on whether both students reported the connection.

2.3 Centrality Measures

Once a network has been constructed, the nodes and connections of the network can be evaluated in a multitude of ways. One way to mathematically describe the nodes of a network is to use centrality measures. Centrality is a mathematical formulation with many forms that depend on the information sought by the researcher. The most basic form of centrality is degree centrality which is a measure of the number of connections a node makes to other nodes in the network. The higher the number of connections a node has, the higher the degree centrality of the node (Freeman, 1978). Another measure of centrality is betweenness centrality, which is related to the number of times a given node appears on the shortest path between two other nodes in the network. A node that is situated between two nodes that are otherwise limitedly connected would have a high betweenness centrality, while a node that is not situated between many nodes, or is not located on the shortest path between nodes would have a low betweenness centrality (Freeman, 1978). Eigenvector centrality is an additional measure of centrality, that depends on the connectedness of a nodes connections. A node with connections to other nodes that are largely further connected to other nodes, would have a high eigenvector centrality. A node that is connected to other nodes that have fewer connections would have lower eigenvector centrality (Bonacich, 1987). Other measures of centrality include closeness and PageRank, but are outside the scope of this project (Freeman, 1978; Page et al., 1998).

A network diagram will typically show the many nodes of the network presented as points, with lines (edges) connecting them, showing the connections identified between students. Different measures of centrality reveal different information about the network objects and each can be used to create different network diagrams (Cook et al., 1983). These constructions allow us to quantify how important an individual may be within the network, while also allowing us to characterize the nodes with various other pieces of information, like FCI scores or demographic information.

2.4 Force Concept Inventory (FCI)

The Force Concept Inventory (FCI) was developed by David Hestenes, Malcolm Wells, and Gregg Swackhamer in the late 1980s/early 1990s (Hestenes et al., 1992). It is a concept-based examination that can be utilized to gauge student misconceptions about the physics of force in introductory physics courses. The inventory consists of 30 multiple choice questions that probe students' understanding of Newtonian Mechanics by presenting a set of answers in which the correct, Newtonian choice is present in addition to the "commonsense" answer. Incorrect answers on the FCI are indicative of concepts where students allow their common sense thoughts, rather than knowledge of physics, dictate how they solve a problem or apply a concept. The test has shown exceptional reliability and reproducibility as diagnostic and an instructional evaluation tool (Hake, 1998).

Some concerns about the FCI include whether it should be used as a placement test, whether it is meaningful to students, and its pre-test use as an influence on its post-test scores. In short, the FCI alone should not be used as a placement test, but students do take the exam seriously whether it is graded or ungraded and administering the FCI as a pretest does not have a statistically significant effect on the posttest scores (Henderson, 2002). Other criticisms revolve around the authors' 6 broad categories of questions presented in the exam. The questions on the inventory fall into the categories of Kinematics, Impetus, Active Force, Action/Reaction Pairs, Concatenation of Influences, and Other Influences on Motion. While a physicist or educational researcher might agree with the developers' categories, a factor analysis suggests that students actually see these questions as unique items. They answer the questions mostly by applying bits and pieces of their conceptual knowledge rather than a broader understanding (Huffman and Heller, 1995). While correct answers on the FCI are not quite as revealing as incorrect responses, if we can decrease the number of incorrect responses on the FCI over the course of a semester, we can attribute this to student conceptual improvement.

Our goal in this study is to use the FCI as a means of measuring student success in introductory physics. We plan to correlate different network centrality measures with students' gain on the FCI. Using gain allows us to compare scores of multiple sections to each other because all courses were taught at Wright State University. The FCI is chosen as our success measure because it is typically administered to each course at the beginning and end of the first semester of physics. Another option would have been to use final grades or exam grades as a measure of success, however with multiple faculty members teaching these courses, the differences in syllabus structure, scheduling, and material influence may have led to larger disparities between courses. The FCI provides a consistent measure of success across multiple sections of introductory physics and can be paired with SNA to quantify the effects of student-student interactions (Bruun and Brewe, 2013).

2.5 Gender

While the number of women in the physics has continued to increased over the past several years, enrollment of females in physics is still the lowest amongst the sciences cite. The fraction of bachelor's degrees earned by women in physics is approximately 20% while in other science and mathematics majors this ratio is significantly higher (Biology >55%, Chemistry >45%, Math and Stats >40%, Earth Sciences >35%). The fraction of bachelor's degrees earned by women is >55%[1]. Research has focused on the pre college experiences of men and women in an attempt to discern when the retention rates begin to decrease and what may cause them. These disparities begin early as boys and girls receive different types of feedback and attention, and are observable by 9th grade. The actual college experiences of female students choosing science, math, and engineering majors is less known. It is possible that emotions play a large role in why undergraduate and graduate level female students leave science, math, and engineering disciplines with reports of depression or alienation (Seymour, 1995; Gonsalves, 2012). Educators hope that by preventing these feelings or by looking at the role of connections made by female students to other students in courses may help these students perform better and succeed

[1] See data from the American Physical Society `http://www.aps.org/programs/education/statistics/womenmajors.cfm`, APS graph: Fraction of Bachelor's Degrees Earned by Women, by Major, sourced from the IPEDS Completion Survey.

in science courses and as science majors.

Another important struggle facing women in physics is the idea of stereotype threat. Stereotype threat has three main components. The first requires the individual be aware of a negative stereotype about a group with which they identify. This could take the form of a female student being aware of the stereotype that women aren't as good at math as men. Second, the individual must be in a situation where the stereotype seems salient, like a female student taking a difficult, math-intensive exam. This is where the third piece comes in: because the student is aware of the stereotype and are in a situation where it may seem most noticeable, they experience additional cognitive load while attempting to perform well. As a result, a portion of the student's attention is divided into attempting to disprove the stereotype and they aren't able to fully focus on the task at hand, thus adversely affecting their grade or score (Aronson, 2004).

While any group can be subjected to stereotype threat (Aronson et al., 1999), female students are particularly susceptible to this Aronson (2004), and the effect can be compounded when female students belong to additional minority groups (Gonzales et al., 2002). In a physics classroom, small numbers of female students are enrolled alongside large numbers of male students. This setting in particular can lead to adverse performance effects by either directly or indirectly inducing anxiety (Aronson, 2004) and these adverse effects may play a part in the under-representation of females in physics and their success rates. Additionally, introductory physics courses are well known as so-called "weed-out" courses and this notion may emphasize the effects of stereotype threat by adding additional pressure to students, specifically female students (Gonsalves, 2012). In order to examine the centrality measures and success scores of female students, we will present data for our overall sections (including both male and female students) in addition to the data for the female students within those sections (Rodriguez et al., 2012).

Chapter 3

Methods

3.1 Introduction and Background

Network and conceptual data were collected at both the beginning and end of each semester. Students were asked to complete a survey, outside of class, in order to identify with whom they worked to learn physics. They were provided a roster and were able to choose classmates from this list. Conceptual data was collected using the FCI which was taken during the first week of classes either in-class or during lab. Pre data was obtained during the first week of class and post data was obtained during the last week of class. The network data allows us to graphically represent students within the course and study how their connections to other students change throughout the semester. The FCI allows us to measure conceptual gains students obtain by taking the course. We would like to compare the network and centrality data correlated with conceptual gains for both the entire class and the gender-differentiated network. Centrality data is calculated from the network/survey data and then each form of centrality can be used to correlate with conceptual data to track gender differences throughout the course.

3.2 Human Subject Research

One focus of educational research is how individuals are educated and how they respond to different modes of instruction. In order to research such a topic, human subjects must be used which comes with important guidelines and considerations. While the implications of educational research may appear as only beneficial, it is still important to protect the identity of the subjects of a study. In order to regulate how human subjects are researched, universities use Institutional Review Boards (IRB) which are responsible for monitoring the research that is conducted on human subjects by researchers at the university. To conduct research on human subjects, researchers must seek IRB approval by clearly stating the goals, methods, implications, and outcomes of the research they intend to conduct. This also requires not only the notification of the subjects in question, but also their consent to participate in the given study. The identities of the subjects in this study are anonymous, however the demographic and testing information used in our study is considered sensitive information by the IRB and is a key part of our analysis. The informed consent materials used for this study can be found in Appendix 6.2 (Antonellis et al., 2012).

3.3 Measures of Centrality

In social network analysis, centrality is a measure that is used to quantify the position of a node within a network. Centrality can be calculated in a number of ways, depending on the information that is sought from the network. Some measures of centrality include degree, betweenness, closeness, eigenvector, and PageRank. Different measures of centrality reveal different information about the nodes of the network based on different assumptions about what processes are important in network communication. This study will focus on degree, betweenness, and eigenvector centrality. Degree centrality is the number of connections that a given node has to the other nodes in the network. This centrality measure can be normalized by dividing the total number of connections of the node by N-1, where N is the total number of nodes in the network. Betweenness centrality is a measure of a nodes position between other nodes in the network, and can also be normalized, but with a different normalization factor than degree centrality. Eigenvector centrality is a measure of the connectedness of a nodes connections.

In this study, network centrality measures of interest include degree, betweenness, and eigenvector centrality. Each of these measures produces slightly different results and have varying indications about a network object. The formulas used for each of these centrality measures will be provided and explained below.

The adjacency matrix is a mathematical representation of the course network. Undirected networks, such as the networks in our data, will have symmetric adjacency matrices, where each student is both a column and a row, and a matrix entry of 1 indicates that one of the students (either column or row) identified the other on the survey as someone they work with to learn physics. An example adjacency matrix, A, is presented below.

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{pmatrix} \tag{3.1}$$

If students A through H had participated in the survey, this matrix would indicate that student A was connected to student B, student B was connected to students A, C, F, student C was connected to students B, D, E, and F, student D was connected to student C, student E was connected to students C, F, and G, student F was connected to students B, C, E, and H, student G was connected to students E and H, and student H was connected to students F and G. The graphical representation of this network would look like Figure 3.1.

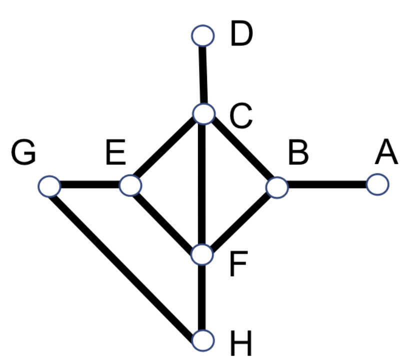


Figure 3.1: Toy Network A

Degree, betweenness, and eigenvector centrality mores will be described in detail and sample calculations will be shown for Toy Network A.

3.3.1 Degree Centrality

Degree centrality for node i is calculated by summing the ith row of the adjacency matrix, or:

$$C_D(i) = \sum_{j=1}^{n} g_{ij} (\mathrm{i} \neq j) \tag{3.2}$$

This measure is also sometimes used as a normalized value, in which the highest degree centrality a node may have is 1, indicating that it is directly connected to all of the other nodes in the network (Freeman, 1978). This calculation is accomplished by dividing the degree centrality of the node by n-1 (where n is the total number of nodes in the network), as shown below:

$$C_{D,normalized}(i) \frac{\sum_{j=1}^{n} g_{ij}}{n-1} (\mathrm{i} \neq j) \tag{3.3}$$

For the Toy Network in Fig. 3.1, the degree of each node is tabulated in Table 3.1.

Table 3.1: Degree Centrality for Toy Network A

Node	A	B	C	D	E	F	G	H
Degree	1	3	4	1	3	4	2	2
Normalized Degree	0.14	0.43	0.57	0.14	0.43	0.57	0.29	0.29

Degree centrality is simply the number of connections each individual student has. If a student is named by many and/or names many students within the course that they learn physics with, this student would have a high degree centrality.

3.3.2 Betweenness Centrality

Betweenness centrality measures the extent to which a particular node lies on the shortest paths between the other nodes in the network (Freeman, 1978). In more detail, it is expressed as the sum of the shortest paths (or geodesics), g, between node j and node k including node i, over the total number of shortest paths between node j and k, up to a total number of nodes, n.

$$C_B(i) = \sum_{j<k}^{n} \frac{g_{jk}(i)}{g_{ik}} \tag{3.4}$$

Betweenness centrality can be normalized by dividing by the number of node pairs excluding the node i, where n is the total number of nodes, as follows:

$$\frac{(n-1)(n-2)}{2} \tag{3.5}$$

Hence, normalized betweenness centrality would be calculated by

$$C_{B,normalized}(i) = \frac{\sum_{j<k}^{n} \frac{g_{jk}(i)}{g_{ik}}}{\left(\frac{(n-1)(n-2)}{2}\right)} = \frac{C_B(i)}{\left(\frac{(n-1)(n-2)}{2}\right)} \tag{3.6}$$

For the Toy Network in Fig. 3.1, the betweenness of each node is tabulated in Table 3.2. A student that is situated between large numbers of nodes, appearing on many paths between nodes, would have a higher betweenness centrality than a node with few connections, located near the exterior of a network.

Table 3.2: Betweenness Centrality for Toy Network A

Node	A	B	C	D	E	F	G	H
Betweenness	0	6	8.33	0	3.83	6.83	0.5	1.17
Normalized Betweenness	0	0.29	0.40	0	0.18	0.33	0.02	0.06

3.3.3 Eigenvector Centrality

Eigenvector centrality is a measure of the connectedness of a node's connections. It takes into account the entire shape and structure of the network, not just the connections of the ith node. A given node is represented as a row and column within the adjacency matrix. Connections to other nodes are indicated with an entry of 1, while an absence of connection is marked with an entry of 0. This matrix will typically be symmetric for an undirected network, and the main diagonal entries will be zeros (Bonacich, 1987). According to Bonacich, this centrality of node i may be calculated by:

$$\lambda e_i = \sum_i A_{ij} e_j \tag{3.7}$$

For a network of multiple nodes, the eigenvector centrality is calculated by solving the system of linear equations through the classic eigenvalue-eigenvector problem. After obtaining the eigenvalues, the highest eigenvalue is typically used in order to calculate eigenvector, which will then represent the eigenvector centralities of the nodes in the network.

$$det|A - \lambda \mathrm{I}| = 0 \tag{3.8}$$

Where I is the identity matrix, which will have dimensions n x n for a network of n nodes. For Toy Network A, this identity matrix would have dimensions 8 x 8 and would look like

$$I = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{3.9}$$

$$\lambda \mathbf{v} = A\mathbf{v} \tag{3.10}$$

The eigenvector centrality of Toy Network A, shown in in Fig. 3.1, is presented in Table 3.3. This was calculated using the highest eigenvalue of matrix A, which is 2.982.

A node with a high number of connections to nodes with high numbers of connections

Table 3.3: Eigenvector Centrality for Toy Network A

Node	A	B	C	D	E	F	G	H
Eigenvector	0.518	1.545	2.004	0.672	1.672	2.086	0.896	1

would have a higher eigenvector centrality than a node that is connected to nodes with few connections.

3.4 Participants and Course Logistics

Wright State University is a public institution located in Fairborn, Ohio. According to the Office of Institutional Research at there were 13,614 undergraduates attending in Fall of 2014. Of these undergraduates, there were 6,994 females and 6,620 males. In the Fall of 2015, there were 13,710 undergraduates, of which 7,079 were female and 6,631 were male [1].

In the last several years, Wright State University has begun to incorporate more active learning educational settings. The Physics Department has several types of instructional methods that have been used in recent semesters, mostly for the introductory physics courses. These methods vary from traditional lecture to heavily interactive. The traditional style courses typically involve an instructor lecturing and working problems during class, with students listening and taking notes. The heavily interactive courses, such as cooperative group problem-solving and SCALE-UP (Student-Centered Activities for Large Enrollment Undergraduate Programs) courses tend to incorporate less lecture and more student involvement (Beichner et al., 2007). Data collected for this study was collected over four semesters and consists of multiple course types and sizes of calculus-based introductory physics I (PHY 2400), taught by four different instructors, which are detailed below.

Our first semester of data (Section A) is for a large scale (~220 students), lecture-based instruction course that met three times for 55 minutes and incorporated a separate 55 minute recitation each week. This course was taught by instructor 1, with three additional

[1] This data can be seen at the WSU Institutional Research website at `http://www.wright.edu/institutional-research/publications-and-resources/student-fact-book`

instructors assisting with recitations. The second semester of data contains three sections of introductory physics. One section (Section B, taught by instructor 2) is a large scale (~200 students), traditional instruction course that met twice weekly for one hour and 20 minutes and incorporated an additional 55 minute recitation section taught by separate instructors, that met once each week. The other two sections (Sections C and D, taught by instructor 3) were small scale (~20 students), cooperative group problem-solving courses that both met twice weekly for one hour and 50 minutes. Our third semester of data (Section E, taught by instructor 1) is for a small scale (~30 students), SCALE-UP instructional course that met three times each week for one hour and 40 minutes. Our fourth semester of data includes two sections of introductory physics. One section (Section F, taught by instructor 4) was a medium scale (~100 students), traditional instruction course that met three times for 55 minutes and incorporated a separate 55 minute recitation each week. The other section (Section G) was medium scale (~70 students, taught by instructor 1), SCALE-UP instructional course that met three times for one hour and 20 minutes each week.

Table 3.4: Course Logistics

Section	Instructor	Class Size	Meeting Frequency	Class Length	Recitation
A	1	~220 students	4x per week	55 min.	Yes
B	2	~200 students	3x per week	80 min.	Yes
C	3	~20 students	2x per week	110 min.	Integrated
D	3	~20 students	2x per week	110 min.	Integrated
E	1	~30 students	3x per week	80 min.	Integrated
F	4	~100 students	4x per week	55 min.	Yes
G	1	~70 students	3x per week	80 min.	Integrated

3.5 Statistical Correlations

Correlations were used for two reasons in this study. The first use was to determine what, if any relationship exists between network/centrality data and conceptual scores/gains. The second use was to see how sensitive students' centrality rankings are to the centrality measure used (Kendall, 1938). Network data is inherently interdependent and because of this, permutation methods must be used when calculating correlation coefficients. In permutation methods, data is resampled over many iterations (n=10000) in order to calculate the correlation coefficient between the variables being correlated. Once statistical significance is determined ($p<0.05$), the correlation coefficient is compared to different effect size ranges in order to appropriately characterize the relationship between the variables (Fan, 2001). A coefficient of 0.1 is taken as a small effect, a medium effect is approximately 0.3, and a large effect is anything above 0.5 (Cohen, 1992). In order to detect a small effect, when using the correlation coefficient, the sample size must contain 783 participants while a medium effect requires 85 participants, and a large effect size requires 28 participants.

3.6 Procedures

Network data was collected in each course section using a survey in which participants were asked the question "Who do you work with to learn physics in this class?" Students were given the opportunity to complete this survey during the first and last week of the course and chose from a roster list in order to identify those that they work with (Marsden, 2011). In addition to the survey data, students also completed the Force Concept Inventory (FCI) during the first and final week of the course (Hestenes et al., 1992). Their scores on this concept test were used as a measure of learning gains in the course. The post scores and score gain on the FCI were used as correlating factors with the connectedness of each student at the beginning and end of the course, where the connectedness of a student depends on the centrality measure chosen.

The Flowchart shown in Figure 3.2 shows how data is collected and combined in order to conduct analysis and obtain results in this study.

This network data is inherently interdependent because it is built on relationships between students, so one students' connections are related to the other students in the network. This requires the use of a permutation method which resamples the data repeatedly in order to determine the significance of the correlations between data sets. In addition to correlation calculations, network objects were also constructed for the pre and

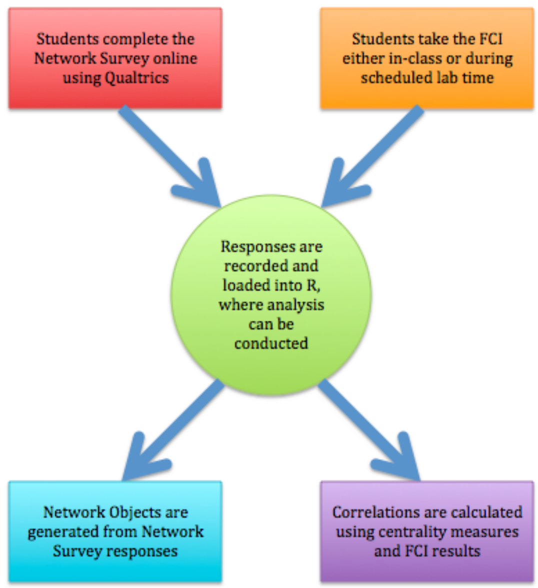


Figure 3.2: Data Collection and Analyzation Flow Chart

post networks to display how the networks evolved from the start of the course to the end, and to represent the proportion of females within the networks.

3.7 Instrumentation

Network analysis was conducted using the R Studio igraph package (Csárdi and Nepusz, 2006). Node lists (the students in the network) and edge lists (the connections between students) were constructed from survey data that was obtained using Qualtrics. Students were asked to take this survey at the beginning and end of the course as part of a longer survey that also included the CLASS (Colorado Learning About Science Survey). The network analysis portion of the survey provided students with the roster list of names of the other students in the course, and also provided students the opportunity to identify individuals they did not see on the list. Once this data was collected, student names and information were formatted and standardized to match roster information. Students also completed the FCI at the beginning and end of the course, which consists of 30 multiple choice questions. Student responses were recorded on scantrons, which were scored in order to calculate pre scores, post scores, and gains.

3.8 Data Analysis

Network data was analyzed in RStudio using the igraph package. Network diagrams were constructed from survey data and FCI results and demographic information from the IRB were imported and attached to nodes by matching UIDs.

Chapter 4

Results

Network surveys and the FCI were administered to each class (with the exception of Section B, which did not take the FCI). Network surveys were taken outside of class, while the FCI was taken either during class time or lab time. The class sizes and responses rates are presented in Table 4.1for Sections A-G. From the network surveys, network objects were constructed in R and graphical representations of the courses were created and are presented. Student positions within these networks were characterized using degree, betweenness, and eigenvector centrality. These centrality distributions of students are presented in histograms and boxplots and are then followed by the cumulative degree distributions. Cumulative degree distributions present the likelihood that a given student has a specific degree centrality. Following the network objects, FCI results are reported for each section of data, both for the overall class, and for the female students specifically. These results are then combined with network centrality measures in order to determine the relationship between student connections and conceptual gains.

4.1 Network Objects

The network object is a representation of the students in the classroom and the connections between them. Each node represents a student while the lines connecting nodes represent actual connections between them. The size of each node indicates a higher de-

Table 4.1: Response Rates

Section	Instructor		Class Size	FCI	Network Survey	FCI & Network Survey
A	1	Pre	203	94%	95%	88%
		Post	209	73%	63%	61%
B	2	Pre	193	–	85%	–
		Post	188	–	83%	–
C	3	Pre	26	92%	69%	65%
		Post	19	68%	84%	63%
D	3	Pre	30	100%	75%	70%
		Post	26	81%	69%	67%
E	1	Pre	36	69%	67%	66%
		Post	29	59%	72%	59%
F	4	Pre	118	81%	41%	40%
		Post	104	66%	28%	26%
G	1	Pre	70	80%	86%	57%
		Post	71	63%	61%	45%

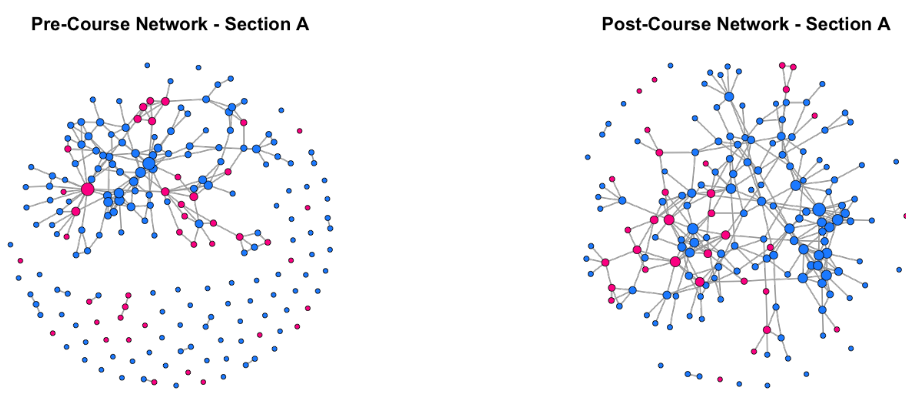
gree centrality. The network is undirected, indicating a connection regardless of which student specified it. The following network diagrams are color coded by gender, with male students colored blue, and female students colored pink. The size of the nodes also vary, depending on the degree centrality of the node. Students with higher degree centralities are represented by larger nodes. It is important to note that proximity of nodes in the network representation isn't their actual closeness (another form of centrality), nor does it indicate physical proximity within the class, as that was not documented or studied. Students with no connections to others are referred to as isolates and are identified on the network objects as solitary points at the periphery of the network. The network density is a measure of how densely connected the network is, and is calculated using the number of connections divided by the total possible connections (given by n(n-1)/2, where n is the number of nodes in the network). Table 4.2 contains a summary of the descriptive network statistics for each of the various sections.

Table 4.2: Network Descriptive Statistics

Section		Nodes	% Female	Edges	Network Density	% isolates
A	Pre	203	20.7%	213	0.010	34.0%
	Post	174	19.0%	304	0.020	8.0%
B	Pre	185	20.5%	288	0.017	11.9%
	Post	177	22.9%	327	0.021	7.9%
C	Pre	24	33.3%	28	0.102	4.2%
	Post	19	26.3%	17	0.099	15.8%
D	Pre	29	27.6%	47	0.116	3.4%
	Post	23	30.4%	27	0.107	4.3%
E	Pre	28	35.7%	28	0.074	10.7%
	Post	29	31.0%	47	0.116	3.4%
F	Pre	65	24.6%	41	0.019	32.3%
	Post	57	22.8%	56	0.035	12.2%
G	Pre	69	21.7%	69	0.029	15.9%
	Post	63	23.8%	70	0.036	11.1%

4.1.1 Section A

Section A was a large, lecture style course that met three times each week and incorporated peer instruction and group work. This course also had an additional recitation period in which students were encouraged to work together to solve problems. The pre and post network diagrams for Section A are presented in Figure 4.1. This was a large class that contains 203 people in the pre network and 174 in the post network. The nodes are colored by gender and the size of each node varies depending on its degree centrality. Together these networks show that the course became more connected at the end of the class (the percentage of isolates decreased from 34% to 8% and the number of connections increased from 213 to 304), which is expected as students meet each other and begin to work on physics together. It is important to note that this class began with a relatively high number of connections. This may be attributed to the fact that introductory physics is typically taken by second year students, whom may have already met some of the other students in the course in earlier classes.

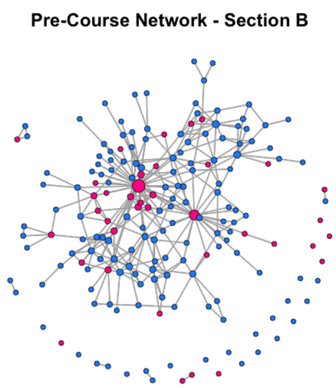


(a) Pre Network (b) Post Network

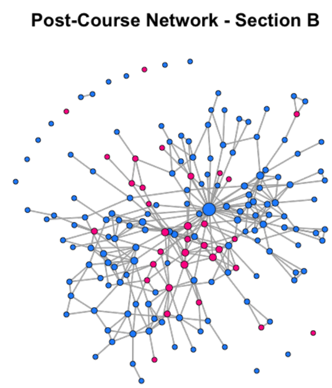
Figure 4.1: Section A Network Diagrams. These diagrams are color coded by gender (male students are blue, while female students are pink), and sized by degree centrality. Larger nodes have higher degree centrality.

4.1.2 Section B

Section B was a large, traditional lecture style course in which students attended class that met twice weekly for an hour and twenty minutes and also incorporated an additional 55 minute recitation period. The pre and post network diagrams are shown in Figure 4.2. This network, like section A, is a large course with 185 students in the pre network and 177 in the post network. This course became more connected from pre to post, as the number of isolates decreased from 11.9% to 7.9% and the number of connections increased from 288 to 327. The pre course network was 20.5% female and the post course network was 22.9% female. This class was also more connected at the beginning of the course than expected, which could be attributed to the required pre-requisites of the course (of Calculus I and/or EGR 1010), or that it was offered during the second term of the year.



(a) Pre Network

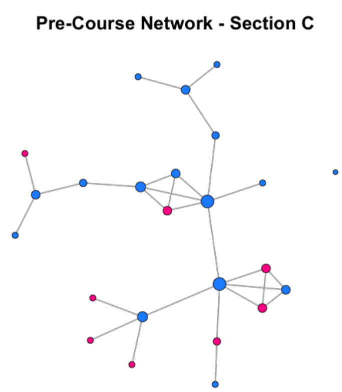


(b) Post Network

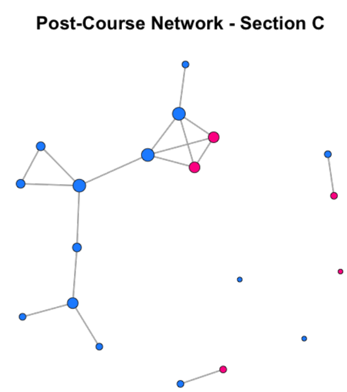
Figure 4.2: Section B Network Diagrams

4.1.3 Section C

Section C was a small, interactive course in which students worked through hands-on activities in order to solve problems and answer questions. The pre and post course network diagrams are shown in Figure 4.3. This was a small class with 24 students in the pre network and 19 in the post network. This course is a bit unusual because students began the course working with more people than was reported at the end of the course and the percentage of isolates increased from 4.2% to 15.8%. This decrease in connections from pre to post can be explained by two mechanisms. In this course, fewer people took the post survey in comparison to the pre survey, and the people who completed the post survey actually reported fewer connections at the end of the course.



(a) Pre Network

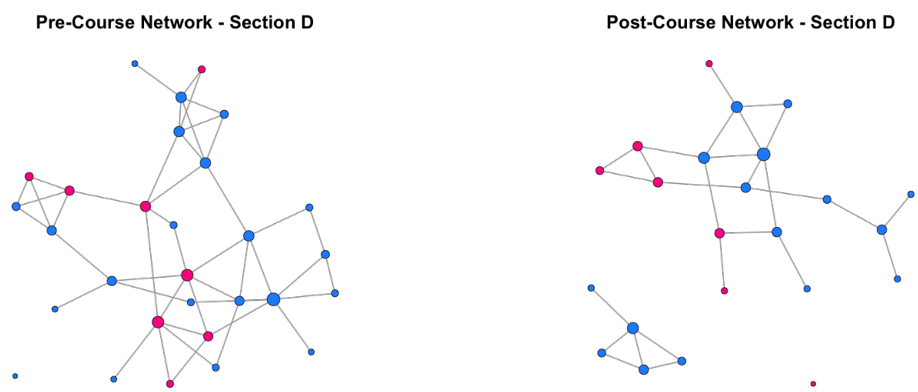


(b) Post Network

Figure 4.3: Section C Network Diagrams

4.1.4 Section D

Section C was a small, interactive course in which students worked through hands-on activities in order to solve problems and answer questions. The pre and post course network diagrams are shown in Figure 4.4. This class began with 29 students and ended with 23, with the number of connections decreasing throughout the semester and the percentage of isolates increasing (from 3.4% to 4.3%). This course began with 27.6% female and ended at 30.4% female. Initially the network was more connected than is typically seen and is less connected at the end. This is a result of people identifying less connections on the post survey than the pre survey.

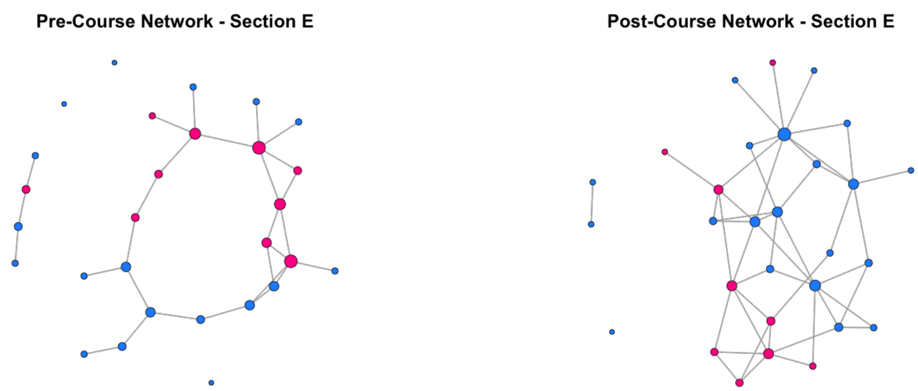


(a) Pre Network (b) Post Network

Figure 4.4: Section D Network Diagrams

4.1.5 Section E

Section E was a small, SCALE-UP style course in which students sat at tables in groups of 5-6 and worked together to complete activities. The pre and post course network diagrams are shown in Figure 4.5. There were 28 students in the pre network and 29 in the post network, with roughly 36% being female in the pre network and 31% in the post. This course began with a large group of students identifying others in the course as connections, and ended with a higher number of connections, which is expected, as the percentage of isolates decreased 10.7% to 3.4%.

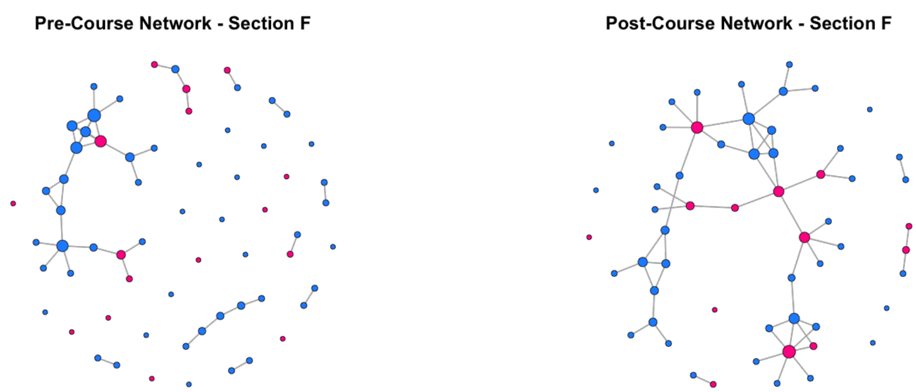


(a) Pre Network (b) Post Network

Figure 4.5: Section E Network Diagrams

4.1.6 Section F

Section F was a large, traditional lecture course in which the instructor presented material three times each week and students worked together on problem sets during an additional recitation period. The pre and post course network diagrams are shown in Figure 4.6. This course began with 65 students (24.6% female) in the pre network and 57 students (22.8% female) in the post network. The connections in this course increased from pre to post and the number of isolates decreased, indicating it was more connected as a whole at the end of the course. This course was actually larger than the network object due to a relatively low participation rate on the pre and post course survey (41% and 28% respectively), leading to a smaller network size than actual class.



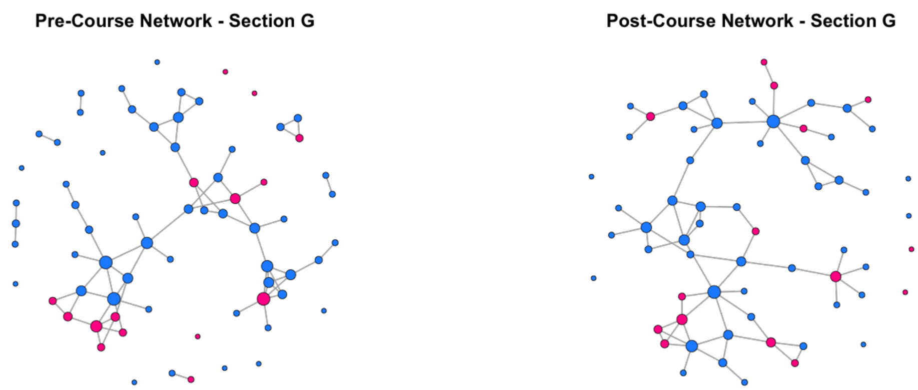
(a) Pre Network

(b) Post Network

Figure 4.6: Section F Network Diagrams

4.1.7 Section G

Section G was a medium sized, SCALE-UP course in which students sat at tables in groups of 5-6 and worked together to complete activities and solve problems. The pre and post course network diagrams are shown in Figure 4.7. This course began with 69 students (21.7% female) in the pre network and ended with 63 students (23.8% females) in the post network. The number of connections increased from the pre to post network and the number of isolates decreased, indicating the network became more connected over the semester.



(a) Pre Network (b) Post Network

Figure 4.7: Section G Network Diagrams

4.2 Centrality

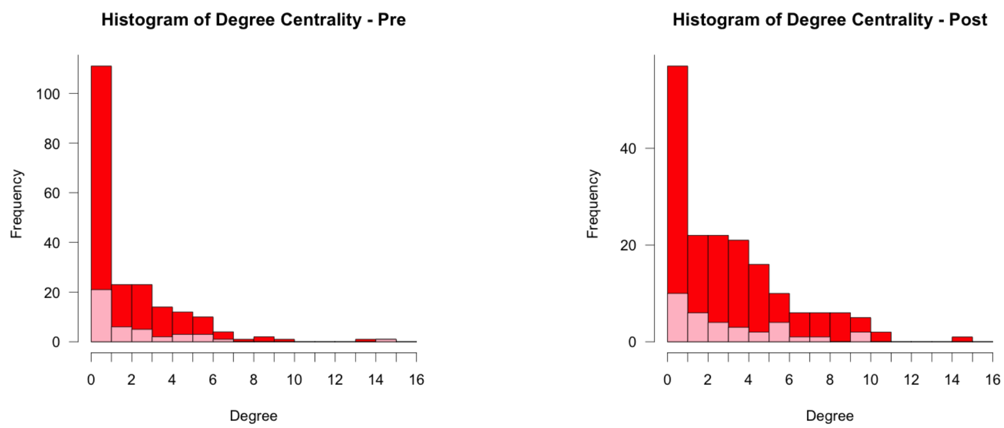
4.2.1 Section A

Figure 4.8 shows the histograms of the degree centralities for the pre and post course networks of Section A. Degree centrality is plotted along the x-axis, while frequency is plotted on the y-axis. The pre course histogram shows the frequencies of specific degree centralities of students at the beginning of the course, and the post course histogram shows the same information for the end of the course. The pink overlapping data set represents the female degree centralities for Section A. In the pre course network, over 100 students had degree centrality of 0 or 1, indicating that they worked with no other students in the course, or just one other student, and few students had more than 6 connections to other students at the beginning of the course. The post course network shows less than 60 students had degree centrality of 0 or 1 at the end of the course, and that more students had degree centralities of 3+, than at the beginning. For the female-specific data, approximately 20 female students had degree of 0 or 1 at the beginning of the course, with few having greater than 2+ connections. In the post course network, only about 10 female students have degree 0 or 1, with more female students having high degree centralities than the pre course network.

Figure 4.9 contains boxplots of the pre and post course degree centralities for the overall and female networks. Boxplots display the five-number summary of the data, including the minimum, first quartile, median, third quartile, and maximum values of the data set. Roughly 50% of the data falls between the first and third quartiles, with an additional 25% above the third quartile and below the first quartile. The median value is the middle number of the data set, indicating that 50% of the data falls below that number, and 50% is above it. The size of the boxplots are scaled by the size of the class, using a factor of the square root of the number of students in the class.

These histogram in Figure 4.8, in addition to Figure 4.9, indicate that the number of connections students made over the period of the course increased for the overall course and for female students specifically. Degree centrality values range from 0 to 15, with

69 students having degree 0 in the pre network and values range from 0 to 15, with 43 students having degree centrality of 1 in the post network. Figure 4.9 also shows that outliers exist in both the pre and post network. In the pre network, 50% of the course (overall or female) has degree centralities between 0 and 3, while in the post network, 50% have degree centralities between 1 and 5.



(a) Pre Network

(b) Post Network

Figure 4.8: Section A Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

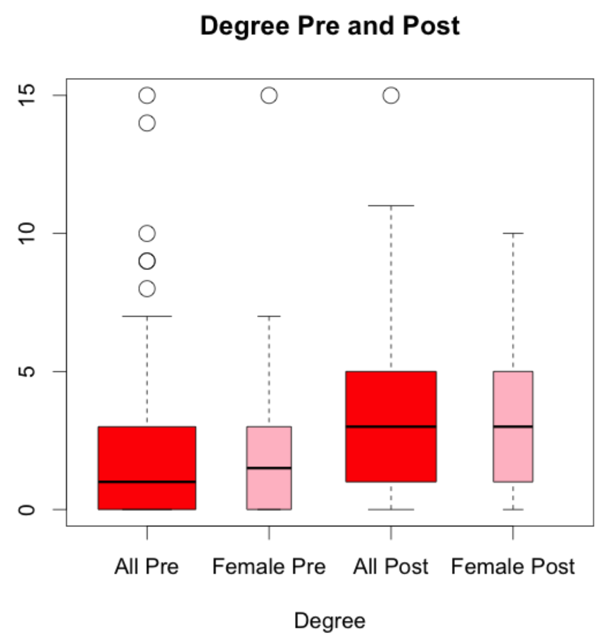
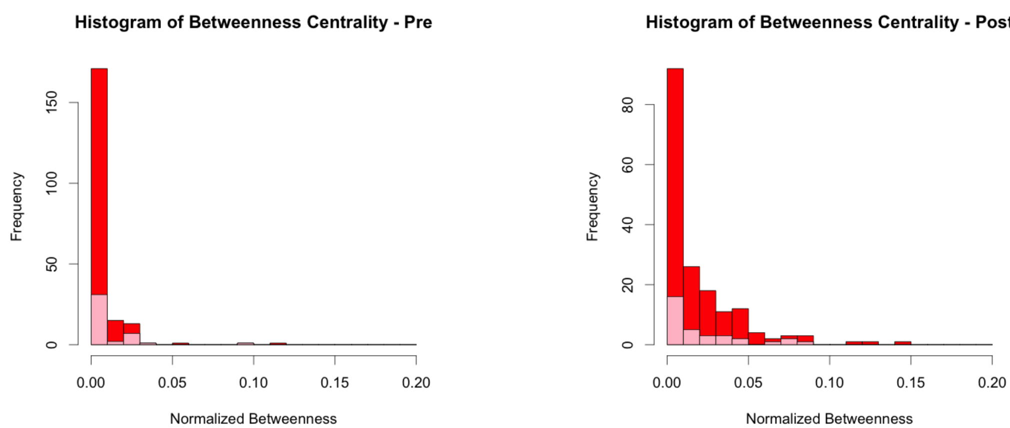


Figure 4.9: Boxplot of Degree Centrality Pre and Post

Figure 4.10 shows the histogram plots of the normalized betweenness centrality for the pre and post course networks. Betweenness centrality is a measure of the position of a node relative to other nodes in the network. Normalized betweenness allows for a maximum centrality value of 1 and in both the pre and post course networks, no node has betweenness centrality above 0.15. In both networks, the majority of students have betweenness centrality values between 0 and 0.01. The post network does indicate that the betweenness centrality increased for students over the course of the semester and Figure 4.11 shows this as well. There is a broader range of values for normalized betweenness centrality in the post course network, indicating that a higher number of students were situated between others in the post course network, when compared to the pre course network.



(a) Pre Network (b) Post Network

Figure 4.10: Section A Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.11 shows that 75% of the pre course has betweenness centrality values between 0 and 0.005, with a maximum value of 0.112. In the post course, 75% of students have betweenness centrality values between 0 and 0.017, with a maximum value of 0.142.

Figure 4.12 shows the histogram plots for eigenvector centrality for the pre and post course networks of Section A. The pre course histogram shows that approximately 150 students had eigenvector centrality of less than 0.1 but this number decreased slightly in the post course network. Eigenvector centrality is a measure of the connectedness of a

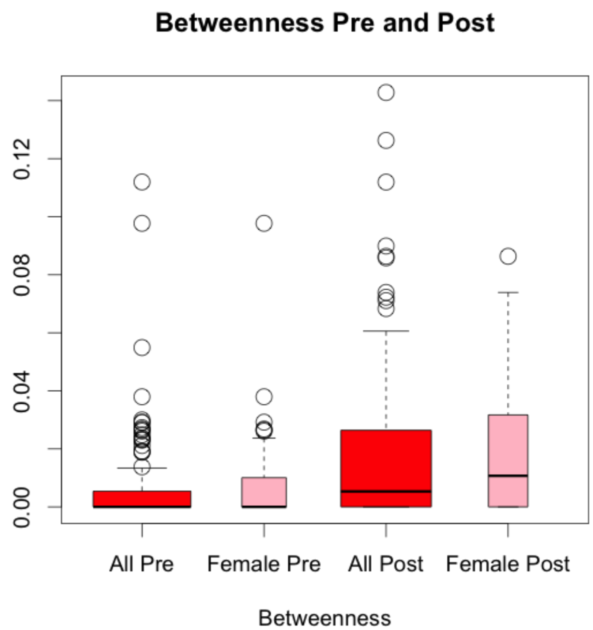
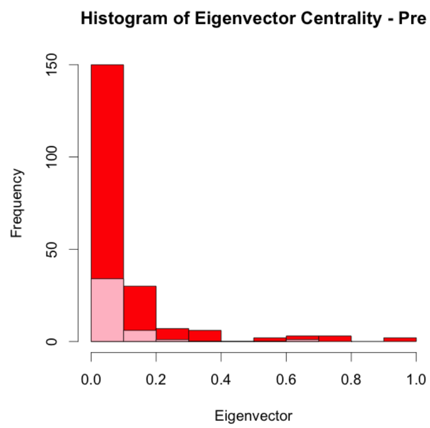
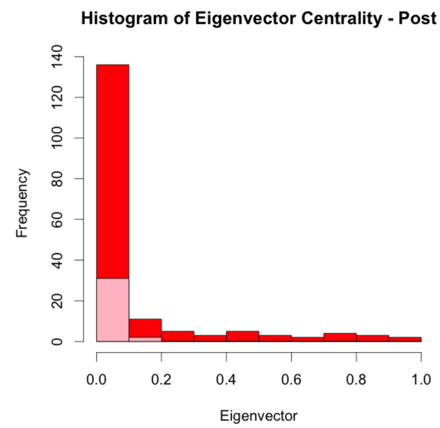


Figure 4.11: Boxplot of Normalized Betweenness Centrality Pre and Post

nodes' connections, and Figure 4.13 shows that while the pre course network had roughly half the course with between 0 and 0.1 eigenvector centralities, the post course network has nodes connected to more connected nodes, as the median eigenvector centrality measure is higher in the post course network than the pre course. It can also be seen that outliers exist in both the pre and post course networks, as the range of eigenvector centrality for both networks goes from 0 to 1, despite a high number of nodes having low eigenvector centrality.



(a) Pre Network



(b) Post Network

Figure 4.12: Section A Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

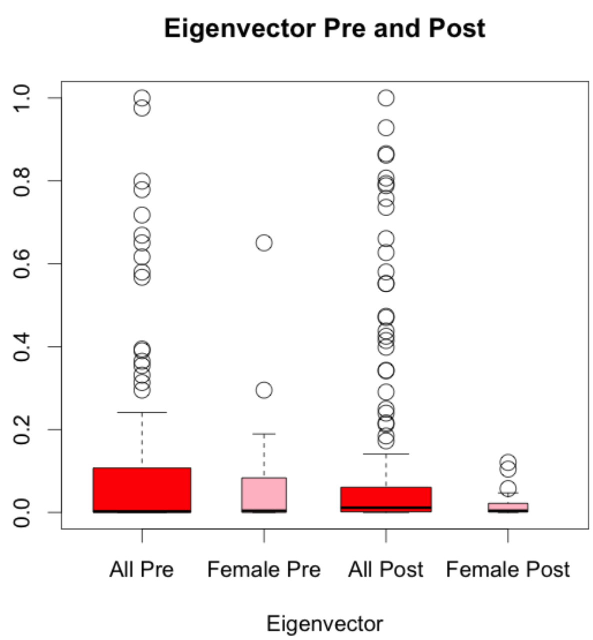
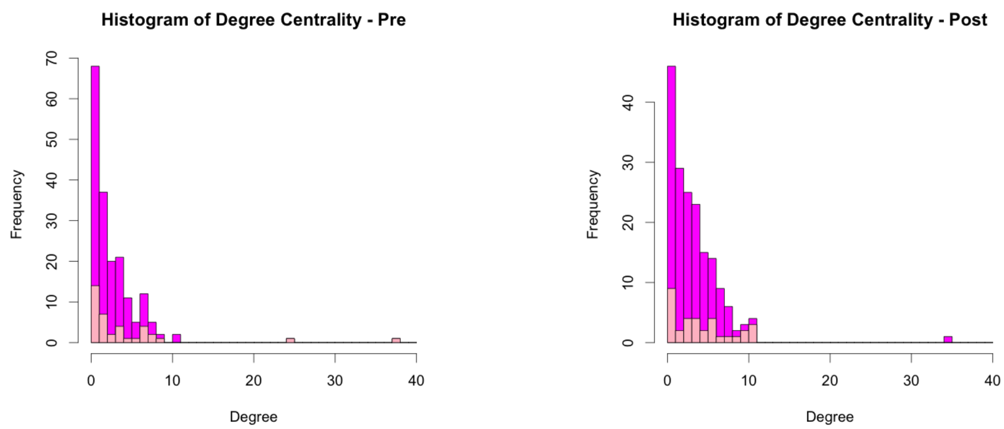


Figure 4.13: Boxplot of Eigenvector Centrality Pre and Post

4.2.2 Section B

Figure 4.14 shows the histograms of degree centrality for the pre and post course networks of Section B. The range of degree centrality in the pre network is 0 to 38, while the post course network has a range of 0 to 35. In the overall course, nearly 70 students had degree centrality of 0 or 1, while this number was closer to 50 in the post course network. For female students specifically, about 15 students had degree centrality of 0 or 1 in the pre network, while less than 10 did in the post course network.



(a) Pre Network (b) Post Network

Figure 4.14: Section B Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

The median degree centrality increased for both the overall and female networks. Figure 4.15 shows a boxplot of the degree centrality for Section B, where the median degree centrality increased for both the overall and female networks. In the overall pre network 50% of students have degree centrality between 1 and 4.00, while in the post course network, 50% have degree centrality between 1 and 5. In the female pre network, 50% have degree between 1 and 5.75 and between 1 and 6 in the post network.

Figure 4.16 shows the betweenness centrality for the pre and post course networks for Section B. The range of betweenness centralities for the pre course network is 0 to 0.37, and is 0 to 0.51 for the post course network. In the pre course network, 75% of students have betweenness centrality less than 0.09, and in the post course network, this number is 0.14.

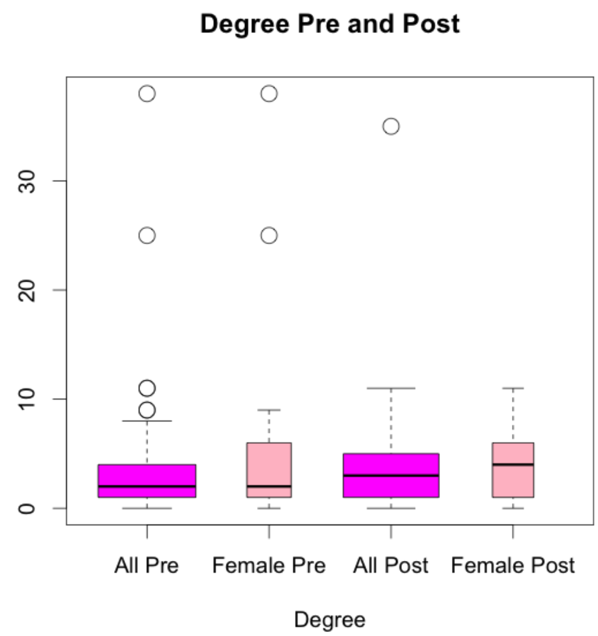
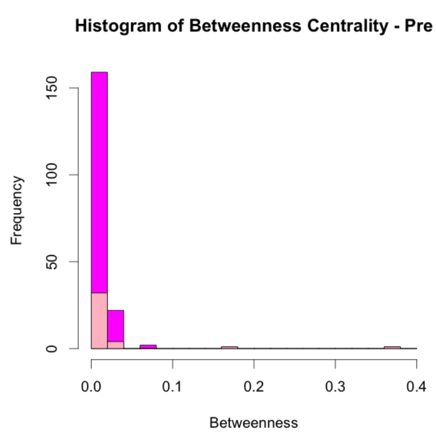
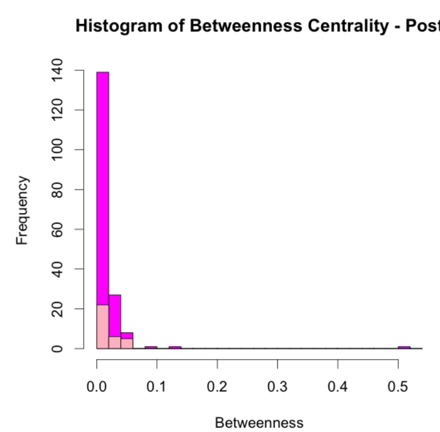


Figure 4.15: Boxplot of Degree Centrality Pre and Post. The median degree centrality for the overall network increased from 2 in the pre network to 3 in the post, while the median in the female network increased from 2 to 4.



(a) Pre Network



(b) Post Network

Figure 4.16: Section B Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.17 shows that the median betweenness centrality increased from pre to post, starting at a value of 0.0007 in the pre, and increasing to 0.003 in the post. The mean value increased as well, from 0.009 to 0.0138 and outliers exist in both cases.

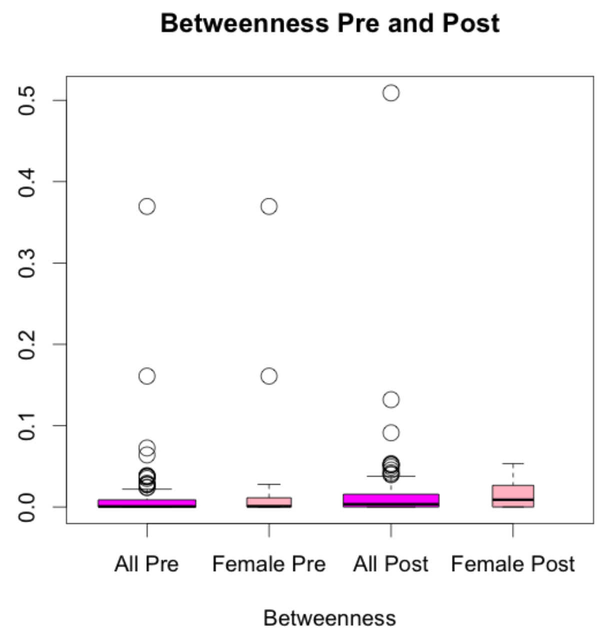
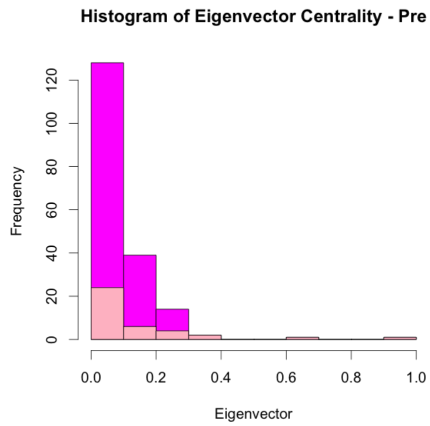
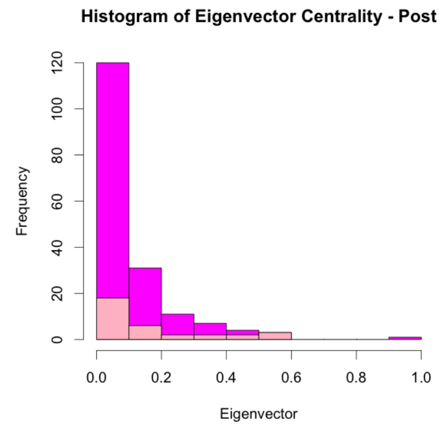


Figure 4.17: Boxplot of Normalized Betweenness Centrality Pre and Post

Figure 4.18 shows that the ranges of eigenvector centralities for the pre and post course networks go from 0 to 1. The mean eigenvector centrality increased from pre to post (from 0.08 to 0.098) while the median decreased (from 0.049 to 0.045), indicating that overall the larger centralities increased and the smaller values remained the same or decreased. This can also be seen in Figure 4.19.



(a) Pre Network



(b) Post Network

Figure 4.18: Section B Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

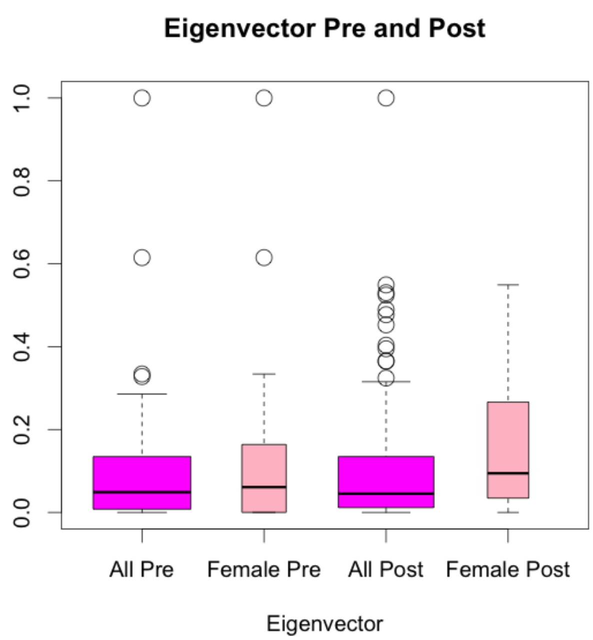
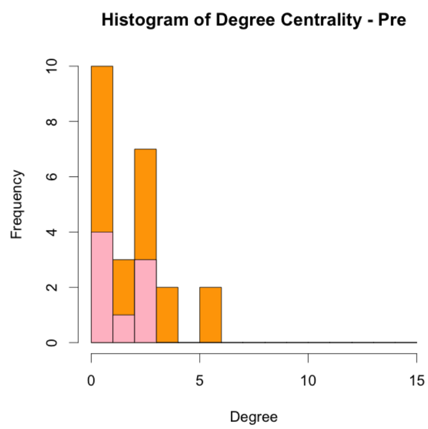


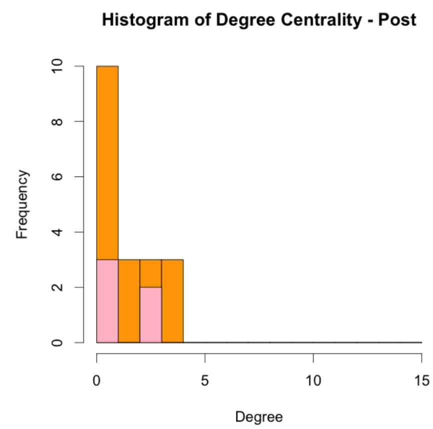
Figure 4.19: Boxplot of Eigenvector Centrality Pre and Post

4.2.3 Section C

Figure 4.20b shows the pre and post course degree distributions for Section C. In this section, the overall pre course degree centralities range from 0 to 6, and in the post course, they range from 0 to 4. In the female pre course network, degree centralities range from 1 to 3, and from 0 to 3 in the post course. In this section, the median and mean degree centralities decreased for both the overall and female networks from pre to post, which can be seen in Figure 4.21 and may be due to the small size of the class (25 students).



(a) Pre Network



(b) Post Network

Figure 4.20: Section C Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.22 shows the betweenness centralities of the pre and post course networks of Section C. In the pre course network, betweenness ranges from 0 to 0.63, and in the post from 0 to 0.25. At both the beginning and end of the course, 50% of students had betweenness values of 0. The mean betweenness centrality decreased from 0.107 in the pre network to 0.041 in the post network, indicating that the students in the course were less situated between others in the post network than in the pre network. This can also be seen in Figure 4.23.

Figure 4.24 shows the eigenvector centrality distributions for Section C. These values range from 0 to 1 in both the pre and post course networks. Both the mean and median values of eigenvector centrality decreased from pre to post, as can be seen in Figure 4.25.

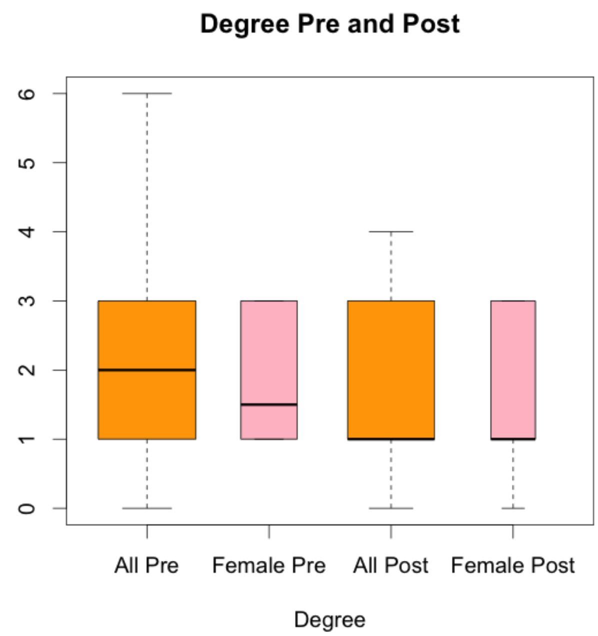
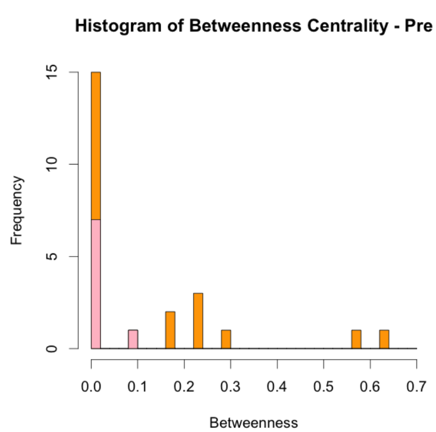
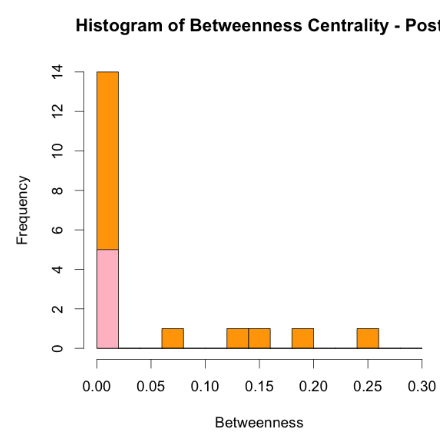


Figure 4.21: Boxplot of Degree Centrality Pre and Post. Overall median degree is 2 for the pre course and 1 for the post course. Female median degree is 1.5 for the pre course, and 1 for the post course.



(a) Pre Network



(b) Post Network

Figure 4.22: Section C Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

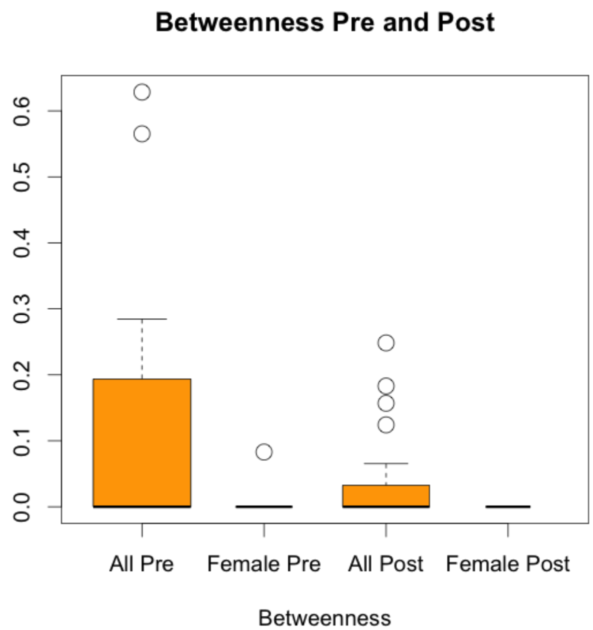
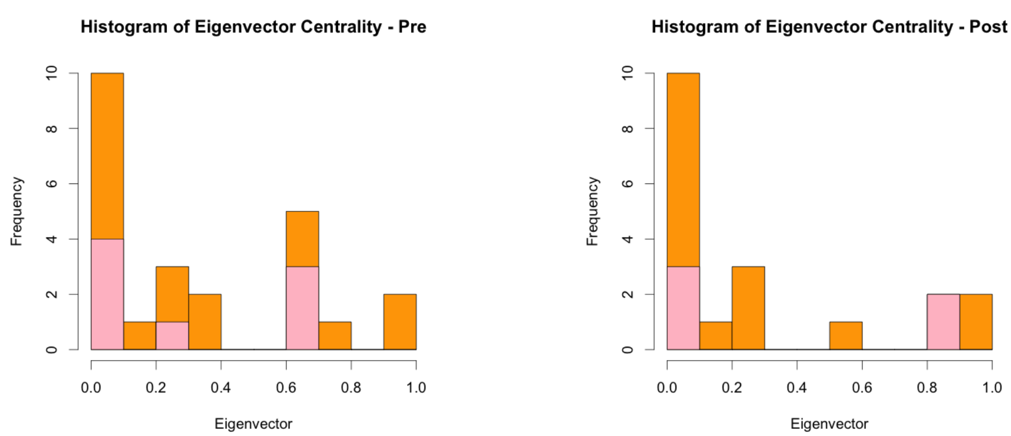


Figure 4.23: Boxplot of Normalized Betweenness Centrality Pre and Post



(a) Pre Network

(b) Post Network

Figure 4.24: Section C Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

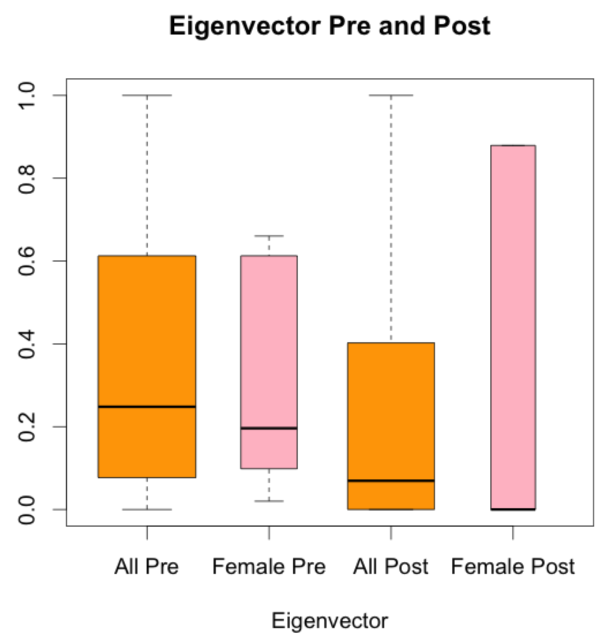
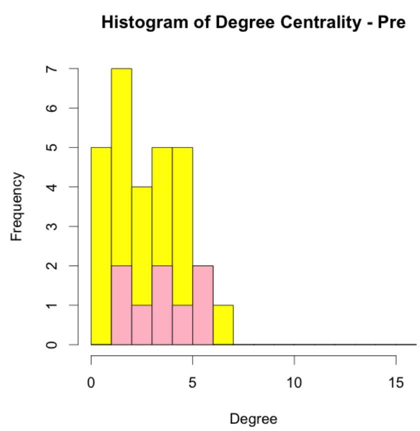


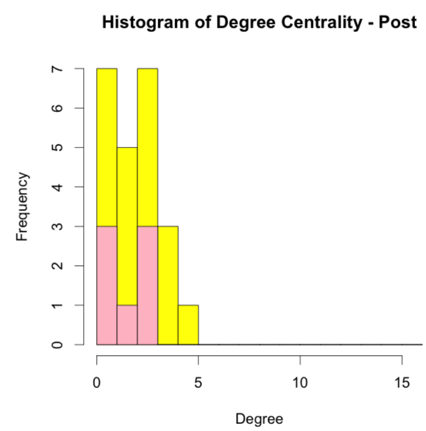
Figure 4.25: Boxplot of Eigenvector Centrality Pre and Post

4.2.4 Section D

Figure 4.26 shows the degree distributions for the pre and post course overall and female networks of Section D. In the pre course network, degree centralities range from 0 to 7 and in the post course network they range from 0 to 5. Both the median and mean values of degree centrality of the overall and female networks decreased from pre to post for this section. Figure 4.27 shows a boxplot of the degree centrality data where the overall median value decreased from 3 to 2, and the female median decreased from 4 to 2. The mean values also decreased, with the overall network decreasing from 3.24 to 2.35 and the female network decreasing from 4 to 1.86. This unusual decrease could be due to the small class size of Section D, which contained approximately 25 students.



(a) Pre Network



(b) Post Network

Figure 4.26: Section D Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.28 shows the betweenness centrality distributions for the pre and post networks. The pre course betweenness ranges from 0 to 0.236 and the post course betweenness ranges from 0 to 0.244. The median and mean betweenness values decreased from pre to post. The median decreased from 0.012 to 0.002 and the mean decreased from 0.067 to 0.055. This can also be seen in Figure 4.29.

Figure 4.30 shows the eigenvector centrality distributions for the pre and post course networks. The range of eigenvector centralities are 0 to 1 for both pre and post course. The median and mean eigenvector centralities decreased from pre to post. The median

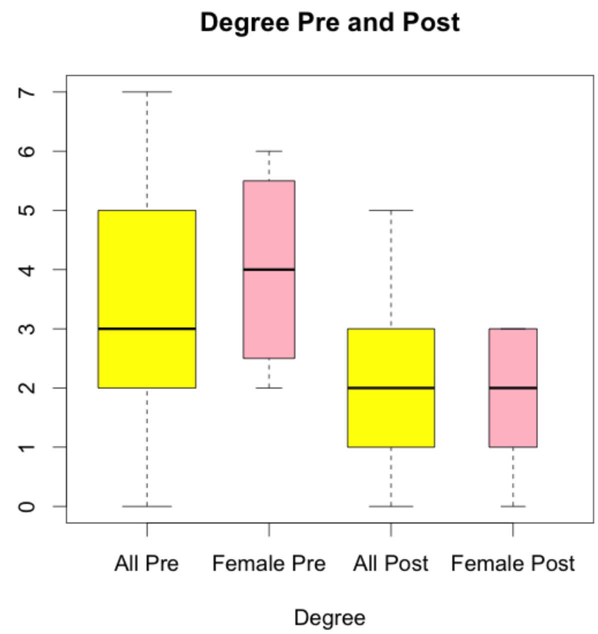
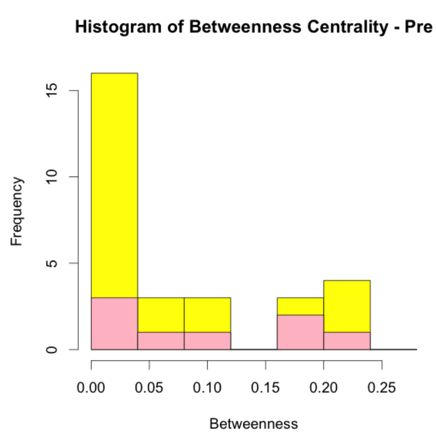
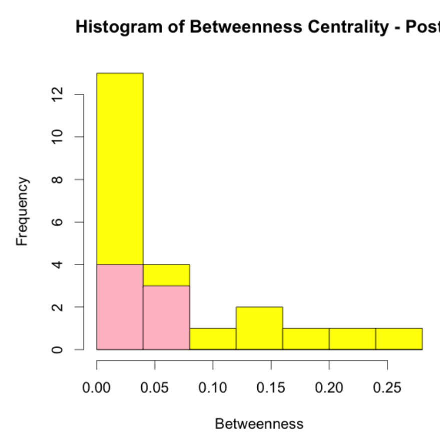


Figure 4.27: Boxplot of Degree Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.28: Section D Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

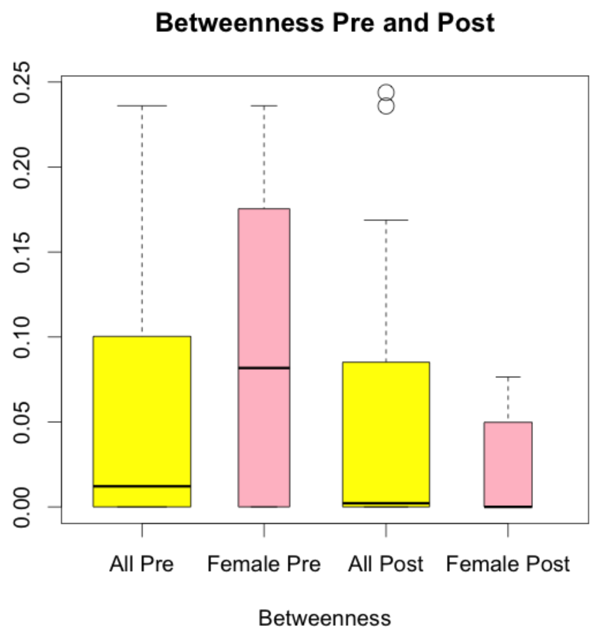
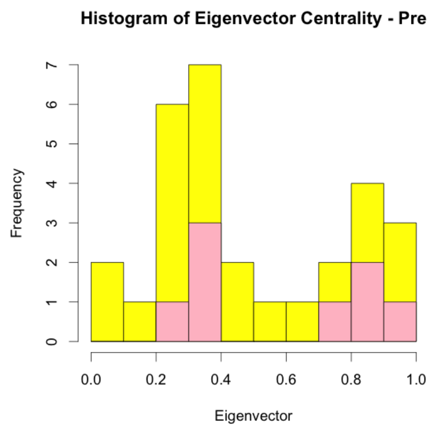
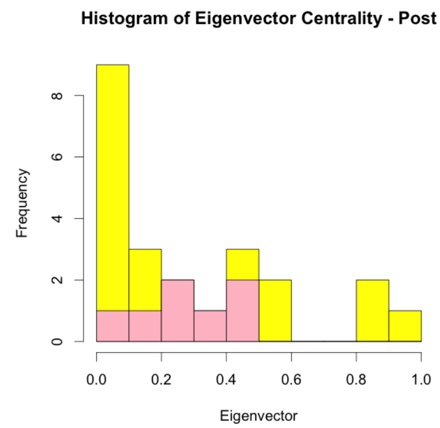


Figure 4.29: Boxplot of Normalized Betweenness Centrality Pre and Post

decreased from 0.387 to 0.167 and the mean decreased from 0.482 to 0.287. This information can also be seen in Figure 4.31.



(a) Pre Network



(b) Post Network

Figure 4.30: Section D Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

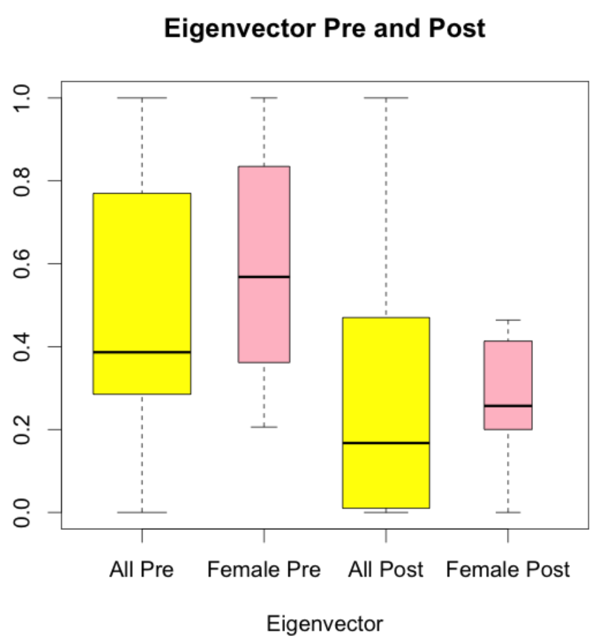
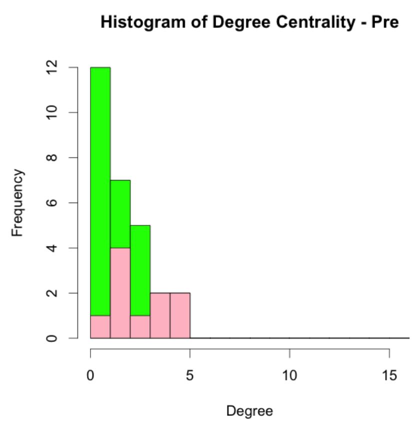


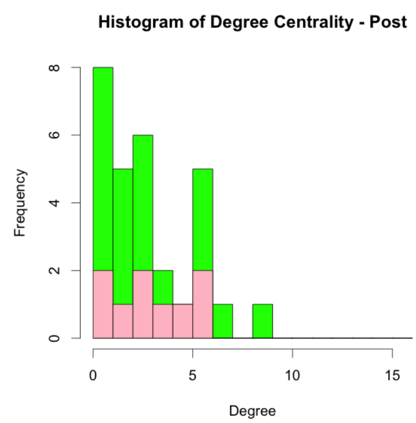
Figure 4.31: Boxplot of Eigenvector Centrality Pre and Post

4.2.5 Section E

Figure 4.32 shows the degree centrality distributions for the pre and post course overall and female networks of Section E. The degree centrality values range from 0 to 5 in the pre network and 0 to 9 in the post network. Both the median and mean degree centrality values increased for the overall and female networks from pre to post. Figure 4.33 shows that the overall median increased from 2 to 3, and the female median increased from 2.5 to 3. The overall mean increased from 2 to 3.24, and the female mean increased from 3 to 3.44.



(a) Pre Network



(b) Post Network

Figure 4.32: Section E Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.34 shows the betweenness distributions of the pre and post networks. The pre network betweenness ranges from 0 to 0.208 and the post network ranges from 0 to 0.28. The median value of betweenness centrality increased from pre to post, starting at a value of 0.0057 and ending at 0.0097 while the mean value decreased from 0.055 to 0.046. This can be seen in Figure 4.35.

Figure 4.36 shows the eigenvector centrality distributions for the pre and post course networks. In both the pre and post course networks, the values range from 0 to 1, and both the mean and median eigenvector centrality values increased. This can also be seen in Figure 4.37.

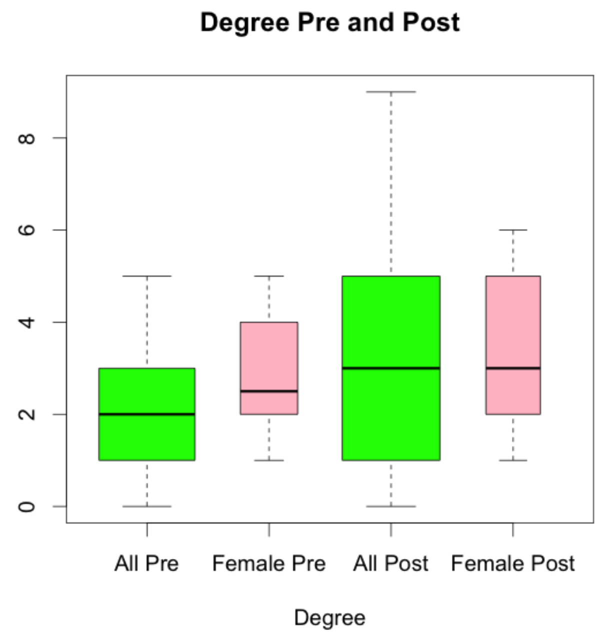
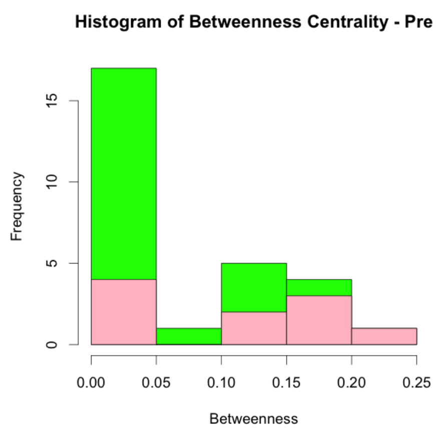
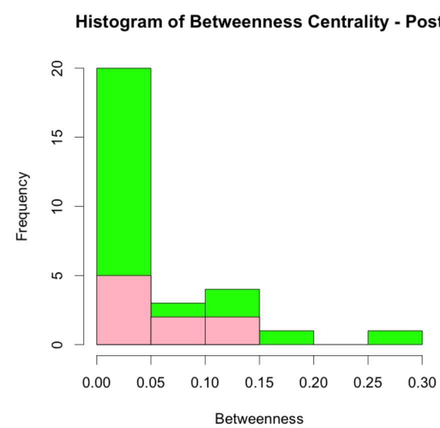


Figure 4.33: Boxplot of Degree Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.34: Section E Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

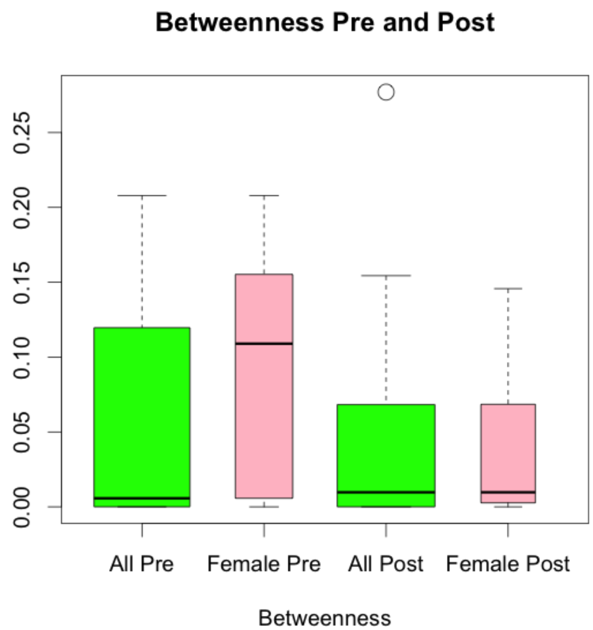
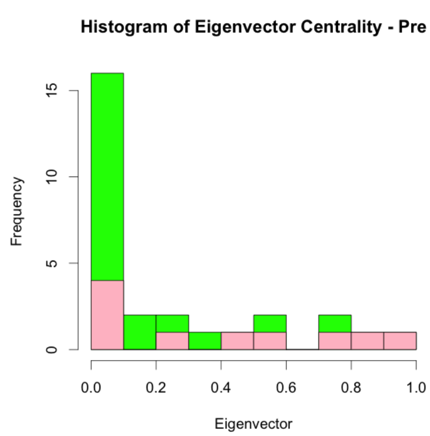
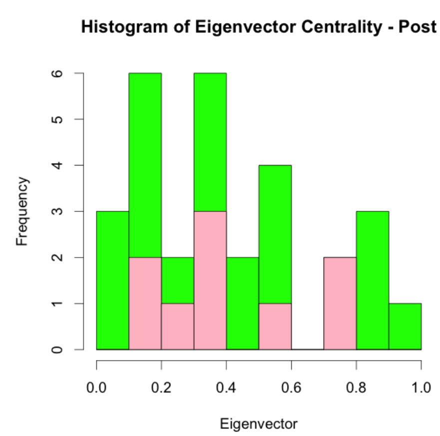


Figure 4.35: Boxplot of Normalized Betweenness Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.36: Section E Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

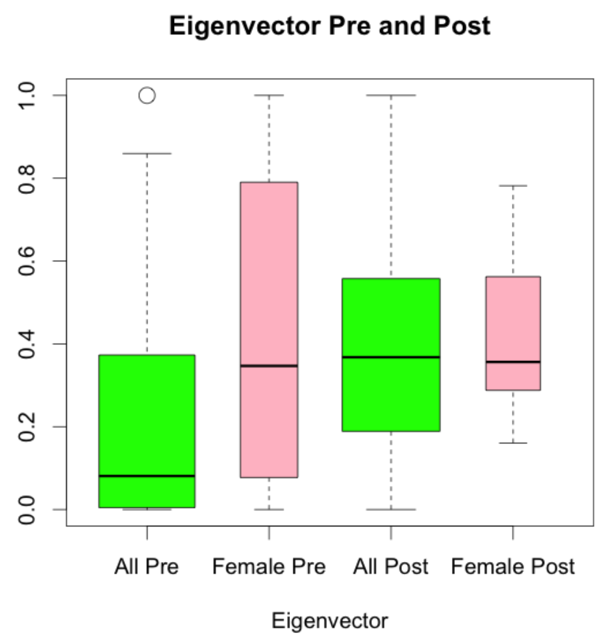
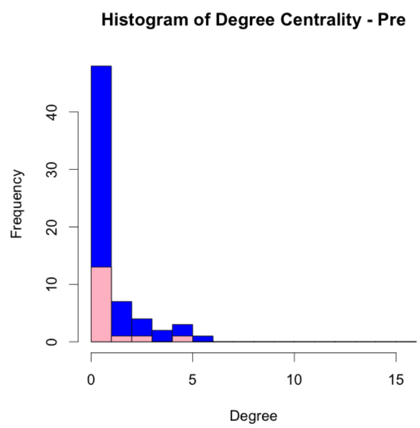


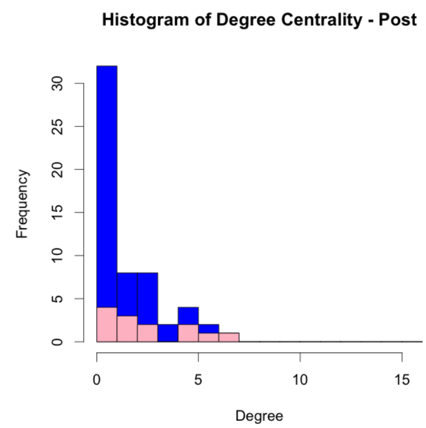
Figure 4.37: Boxplot of Eigenvector Centrality Pre and Post

4.2.6 Section F

Figure 4.38 shows the degree centrality distributions of the pre and post course overall and female networks for Section F. The range of degree centrality values for the pre network is 0 to 6, and is 0 to 7 in the post course network. Figure 4.39 shows that the overall median value of degree centrality remained constant at 1, while the female median increased from 0.5 to 2. The mean degree centrality increased for both the overall (from 1.26 to 1.97) and for the female network (from 0.94 to 2.850).



(a) Pre Network



(b) Post Network

Figure 4.38: Section F Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.40b show the betweenness centrality distributions for the pre and post course networks. Betweenness ranges from 0 to 0.052 in the pre network, and 0 to 0.35 in the post network. The median betweenness value remained constant at 0 from pre to post while the mean decreased from 0.0048 to 0.0047. The pre course network has 75% of students with betweenness centrality of 0. This can also be seen in Figure 4.41.

Figure 4.42 shows the eigenvector centrality distributions for the pre and post course networks. In both the pre and post course, the range of centralities is 0 to 1 and the median and mean eigenvector centrality values increased from beginning to end. The median increased from 0 to 0.027 and the mean increased from 0.094 to 0.142.

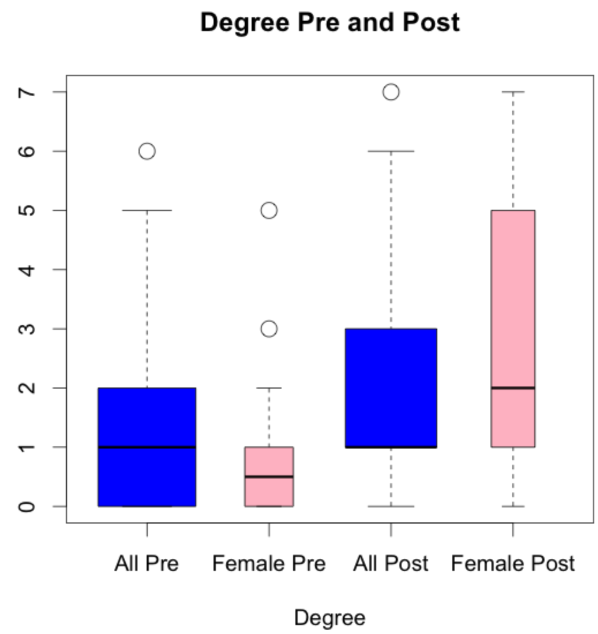
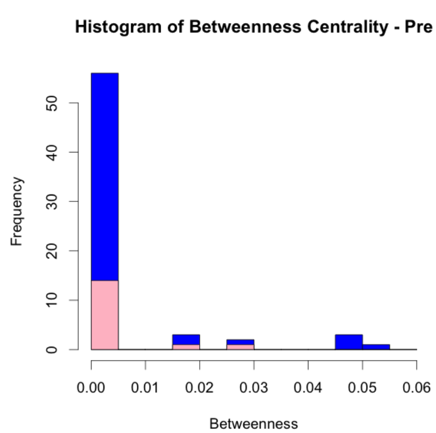
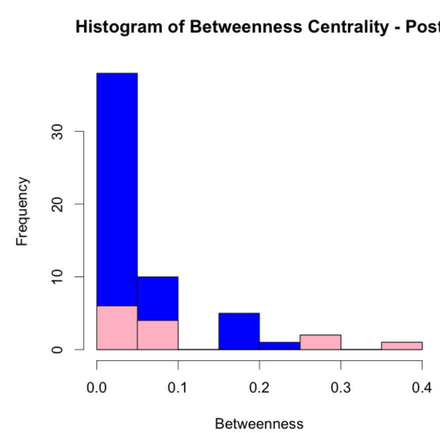


Figure 4.39: Boxplot of Degree Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.40: Section F Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

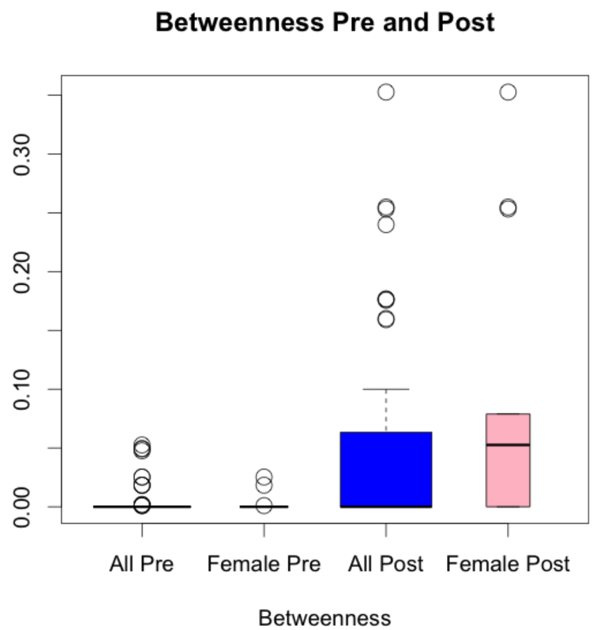
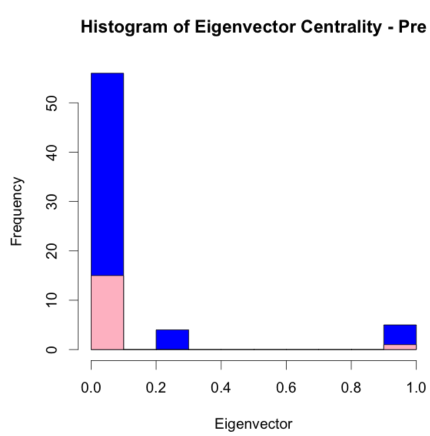
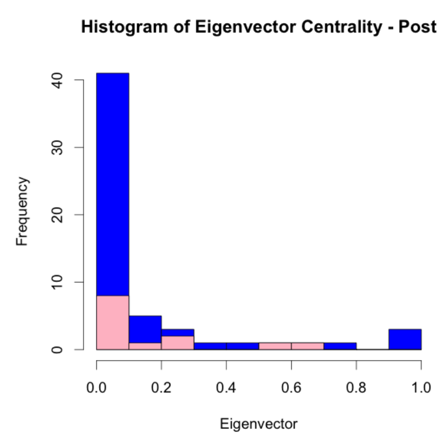


Figure 4.41: Boxplot of Normalized Betweenness Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.42: Section F Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

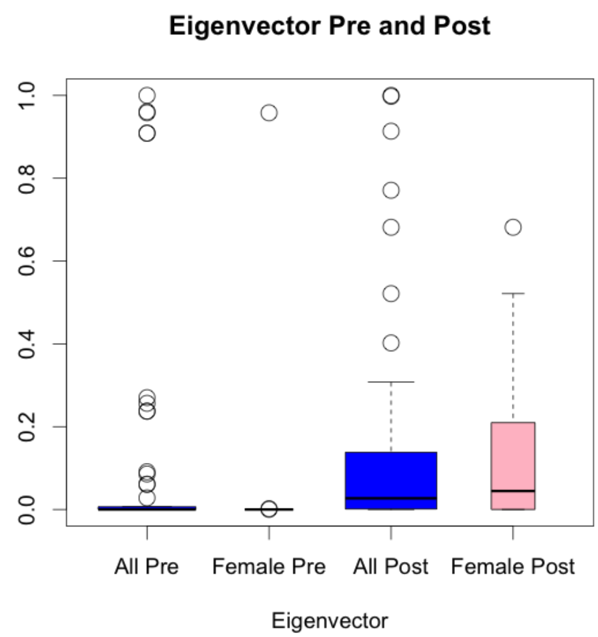
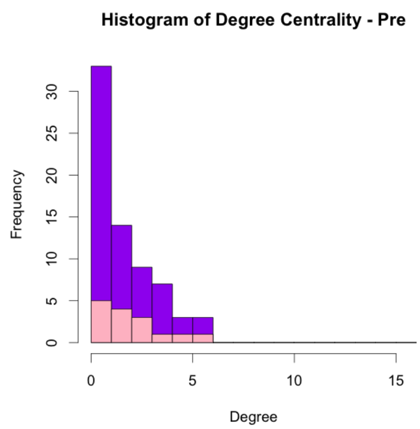


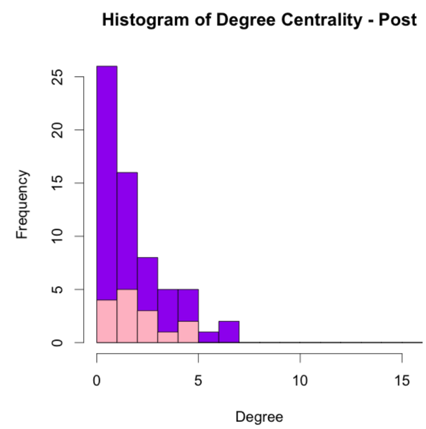
Figure 4.43: Boxplot of Eigenvector Centrality Pre and Post

4.2.7 Section G

Figure 4.44 shows the degree centrality distributions for the pre and post course overall and female networks of Section G. In the pre network, degree values range from 0 to 6 and in the post they range from 0 to 7. Figure 4.45 shows that the median value of degree centrality remained constant at 2 for the overall and female network. The mean degree values both increased, with the overall starting at 2 and increasing to 2.22, and the female network starting at 2.26 and ending at 2.33.



(a) Pre Network



(b) Post Network

Figure 4.44: Section G Degree Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

Figure 4.46 shows the betweenness centrality distributions for the pre and post course networks. The pre network betweenness values range from 0 to 0.25 and the post network values range from 0 to 0.428. The median betweenness centrality value remained constant at 0 from pre to post while the mean value increased from 0.027 to 0.059. This can also be seen in Figure 4.47.

Figure 4.48b shows the eigenvector centrality distribution for the pre and post course networks. The eigenvector centrality values range from 0 to 1 in both pre and post, and the mean and median values increased from beginning to end. The mean increased from 0.095 to 0.16 and the median increased from 0.0125 to 0.0141. This can also be seen in Figure 4.49

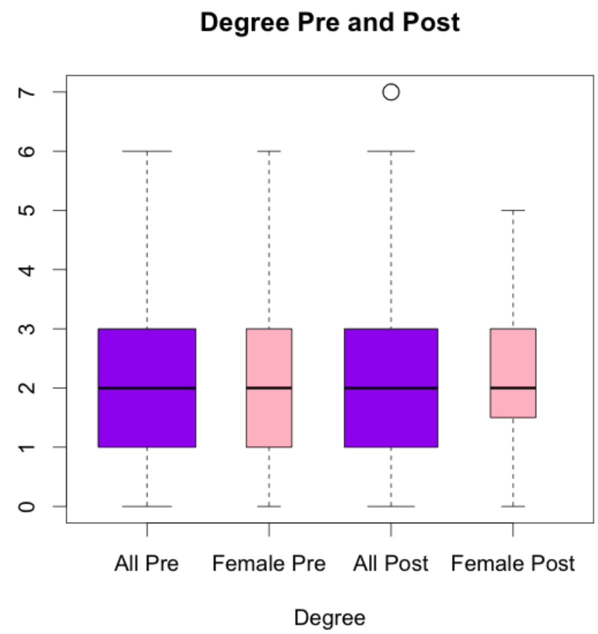
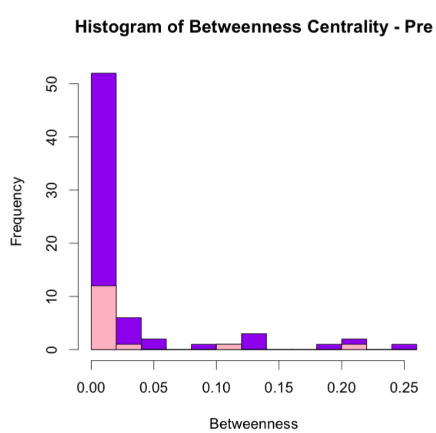
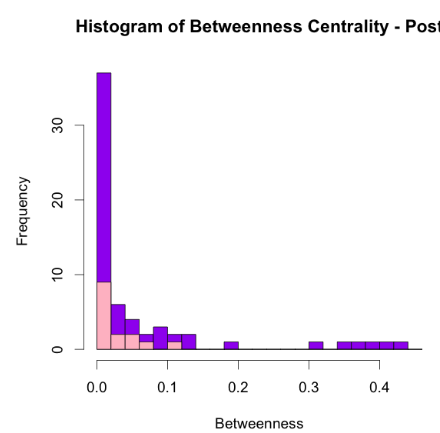


Figure 4.45: Boxplot of Degree Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.46: Section G Betweenness Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

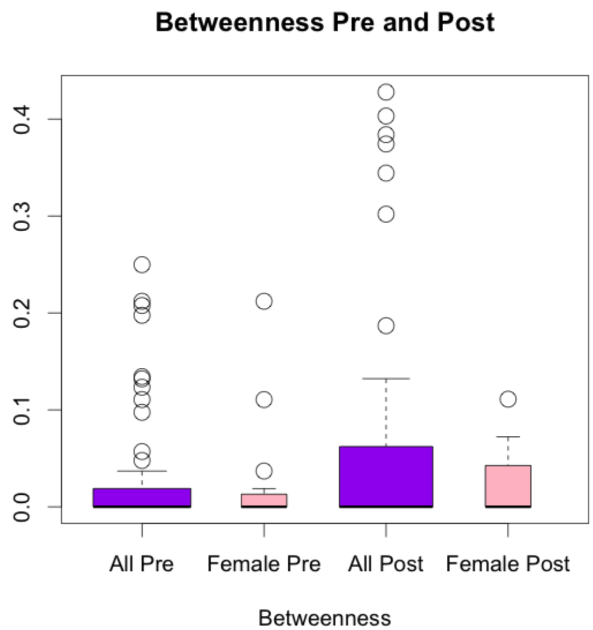
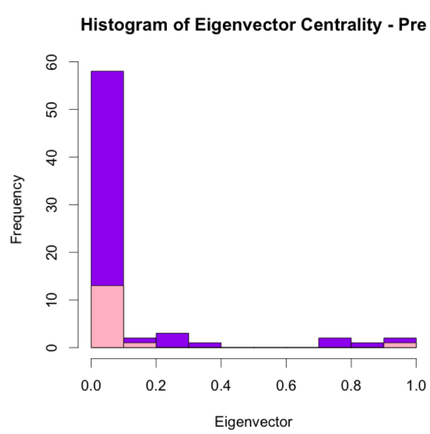
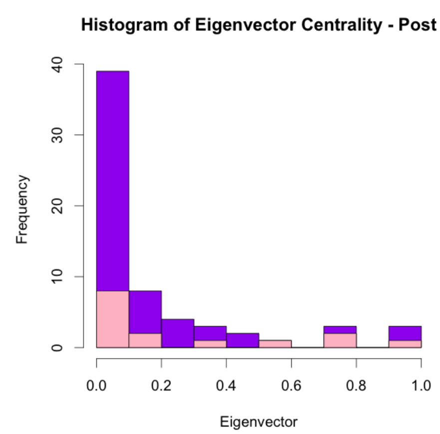


Figure 4.47: Boxplot of Normalized Betweenness Centrality Pre and Post



(a) Pre Network



(b) Post Network

Figure 4.48: Section G Eigenvector Centrality Histograms. It is important to note that the scale of the vertical axes of the plot are not equivalent.

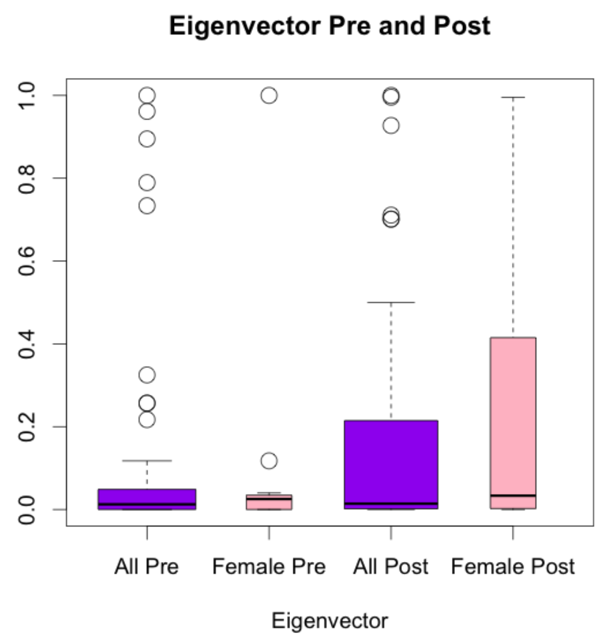


Figure 4.49: Boxplot of Eigenvector Centrality Pre and Post

4.2.8 Summary

Figures 4.50 and 4.51 show the summary boxplots for sections A through G, including pre and post degree centrality spreads for both the overall networks and the female networks. The width of these plots is dependent on the number of students represented in each (so smaller sections like C, D, and E are narrower than larger sections like A and B). For sections A, B, E, and F, the median degree centrality increased for both the overall network and for the female network, while in sections C, D, G, the median degree centrality for both the overall and female network either decreased (C,D) or remained nearly the same (G). These results are also summarized in Table 4.3 which shows how the mean ($\bar{x}$) and median (Med.) changed for each centrality measure from the pre network to the post of each section. An up arrow indicates that the centrality measure increased, a down arrow indicates a decrease, and a – indicates no change from the beginning to end of the semester.

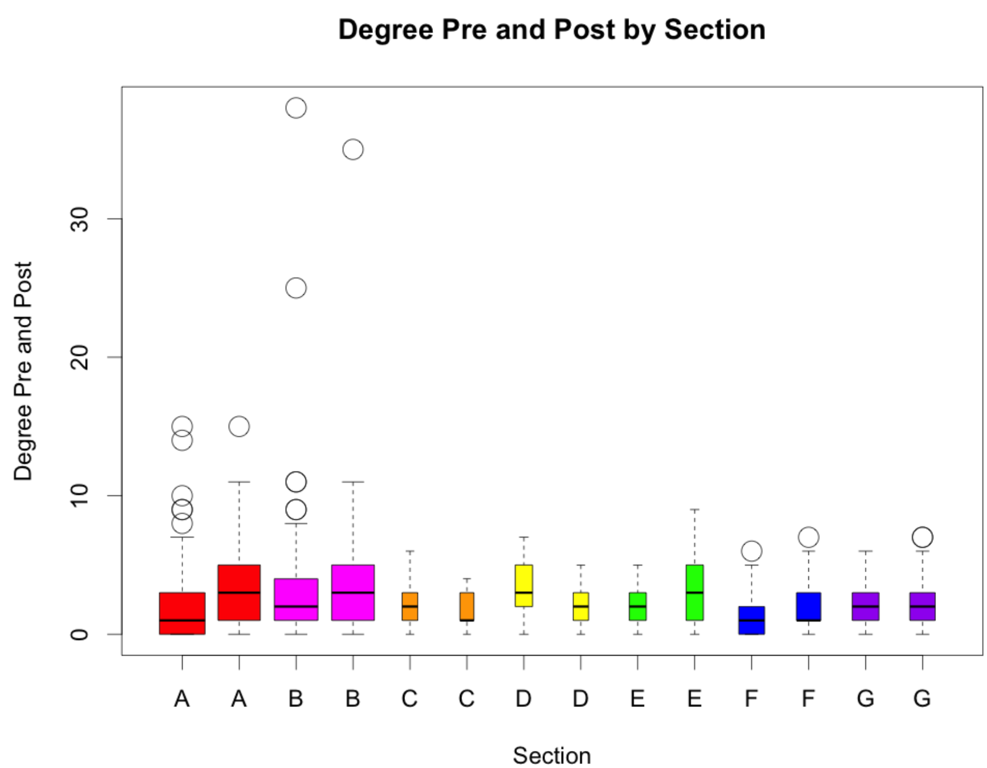


Figure 4.50: Boxplot of Degree Centrality Pre and Post by Section

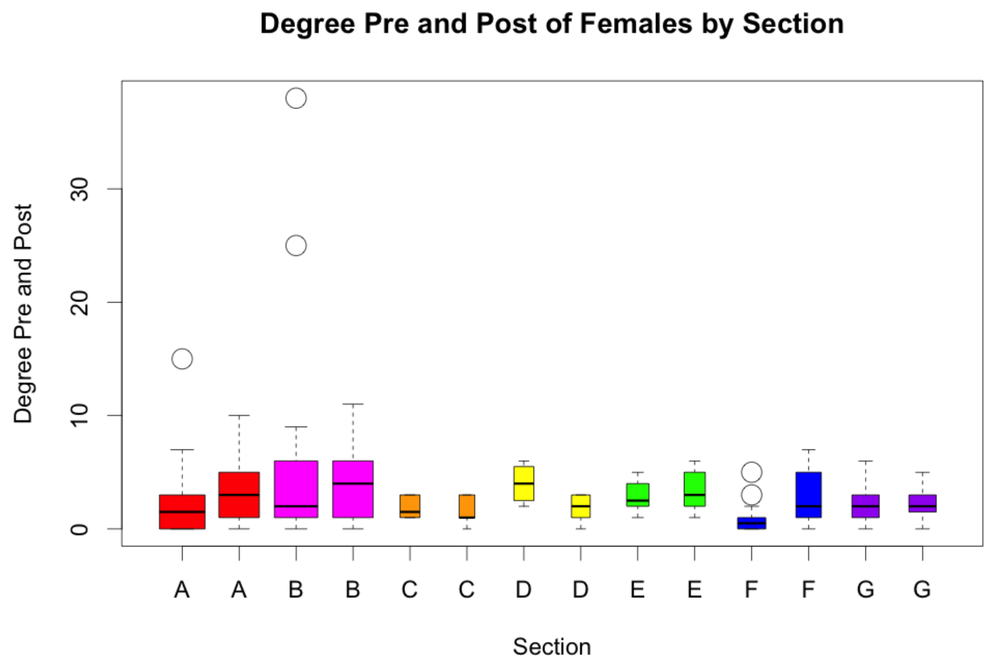


Figure 4.51: Boxplot of Degree Centrality Pre and Post of Females by Section

Table 4.3: Overall Pre-Post Centrality Changes by Section

	Centrality											
	Degree				**Betweenness**				**Eigenvector**			
	Overall		Female		Overall		Female		Overall		Female	
Section	$\bar{x}$	Med.	$\bar{x}$	Med.	$\bar{x}$	Med.	$\bar{x}$	Med.	$\bar{x}$	Med.	$\bar{x}$	Med.
A	↑	↑	↑	↑	↑	↑	↑	↑	↑	↑	↓	↑
B	↑	↑	↑	↑	↑	↑	↓	↑	↑	↓	↑	↑
C	↓	↓	↓	↓	-	↓	-	↓	↓	↓	↑	↓
D	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓
E	↑	↑	↑	↑	↓	↑	↓	↓	↑	↑	↑	↑
F	↑	-	↑	↑	↑	-	↑	↑	↑	↑	↑	↑
G	↑	-	↑	-	↑	-	↓	-	↑	↑	↑	↑

4.3 Degree Plots

These plots demonstrate the fraction of the class that had a given degree centrality and are differentiated for the male and female pre and post course networks of each section. The proportion of students with a given degree is shown on the y-axis, using a logarithmic scale and degree centrality, shown linearly, is on the x-axis.

4.3.1 Section A

Figure 4.52 shows the cumulative degree distribution for the female and male pre and post networks of Section A. This plots shows that a smaller and smaller fraction of the male and female networks had higher degree centralities. This would indicate that higher degree centralities made up a smaller portion of the course and that a larger portion of students had lower degree centralities.

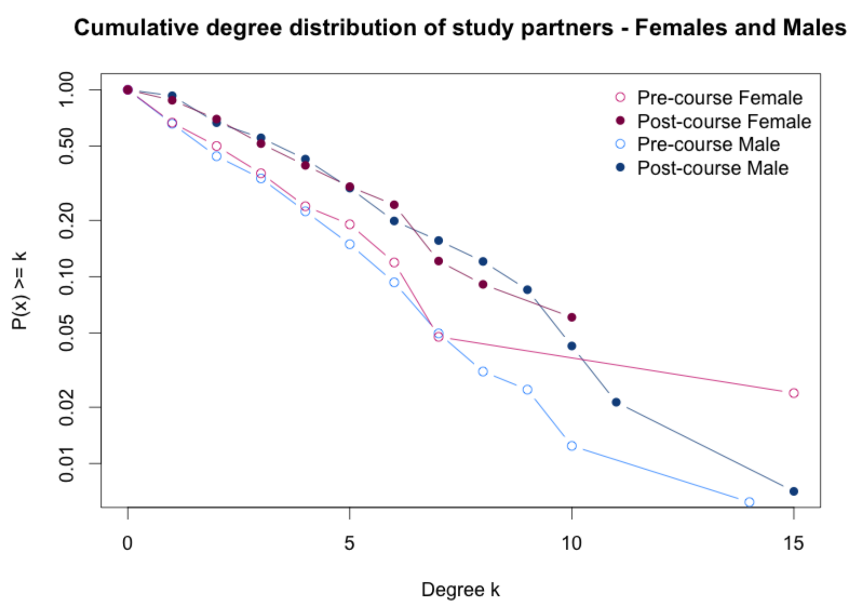


Figure 4.52: Cumulative Degree Plot - Male and Female

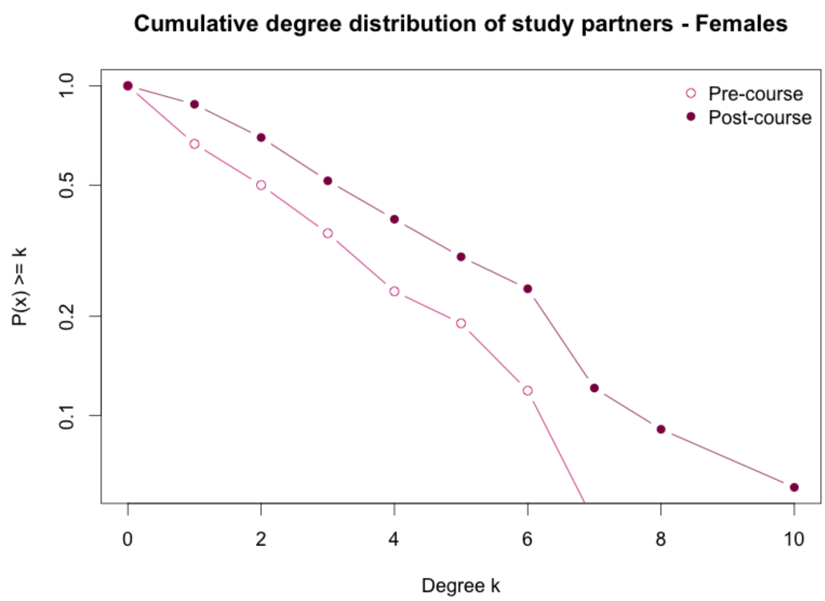


Figure 4.53: Cumulative Degree Plot - Female

4.3.2 Section B

Figure 4.54 shows the cumulative degree distribution for the female and male pre and post networks of Section B. In this plot, the outliers who had very high degree centrality make up a very low portion of the class. This plot also shows that female students at higher degrees are represented with larger proportions than the male students. A similar trend is seen in the plots for Section E and G, which are not shown.

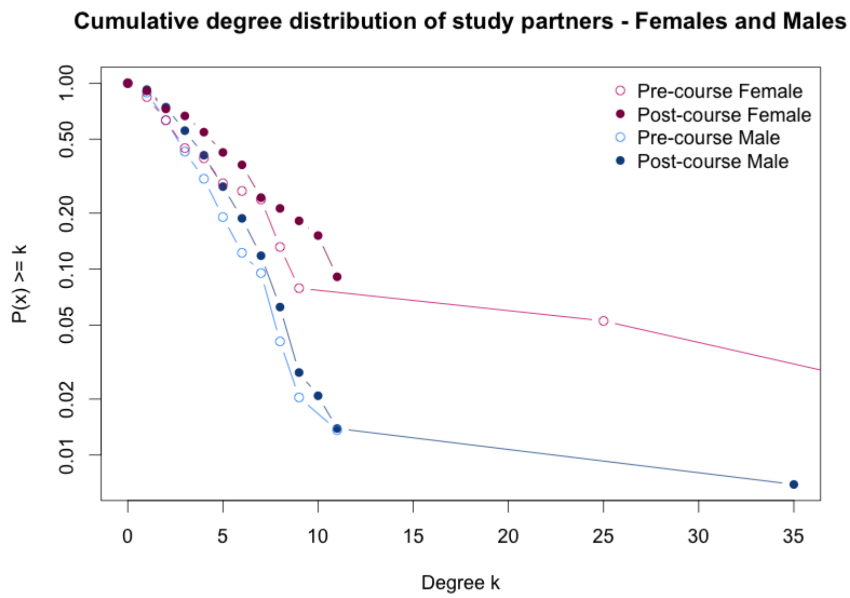


Figure 4.54: Cumulative Degree Plot - Male and Female. The y-axis is log-scale proportion of the network and the x-axis is linear-scale degree centrality

4.3.3 Section C

Figure 4.55 shows the cumulative degree distribution for the female and male pre and post networks of Section C. This figure shows that the proportion of male students with higher pre degree centralities are larger than female students at the higher degree centralities but the proportions are closer at the lower degree centralities. Section D reveals a similar trend and is not shown.

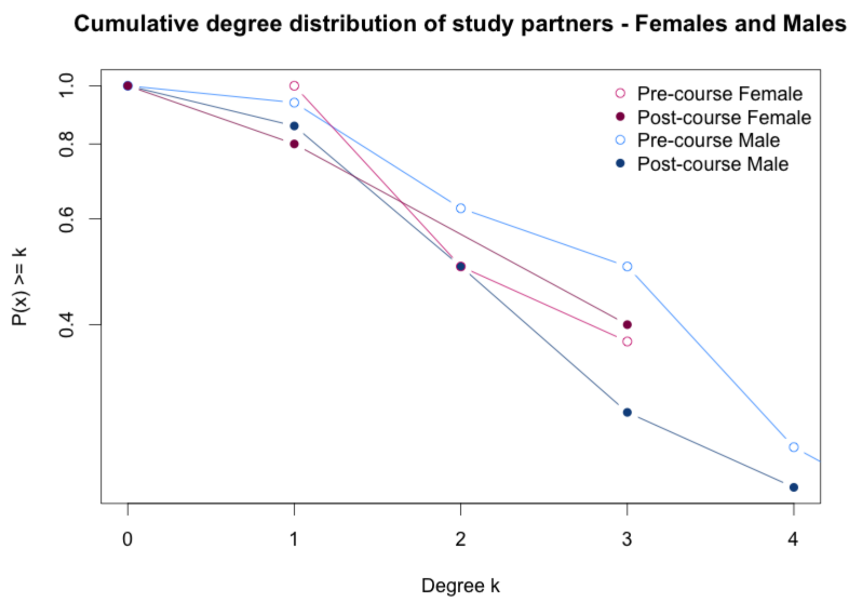


Figure 4.55: Cumulative Degree Plot - Male and Female. The y-axis is log-scale proportion of the network and the x-axis is linear-scale degree centrality

4.3.4 Section F

Figure 4.56 shows the cumulative degree distribution for the female and male pre and post networks of Section F. In this plot we can see that as the degree centrality increases, higher proportions of female students are present than male students. This course was a traditional lecture with a separate recitation which may have allowed female students to work with more students than in some of the others sections.

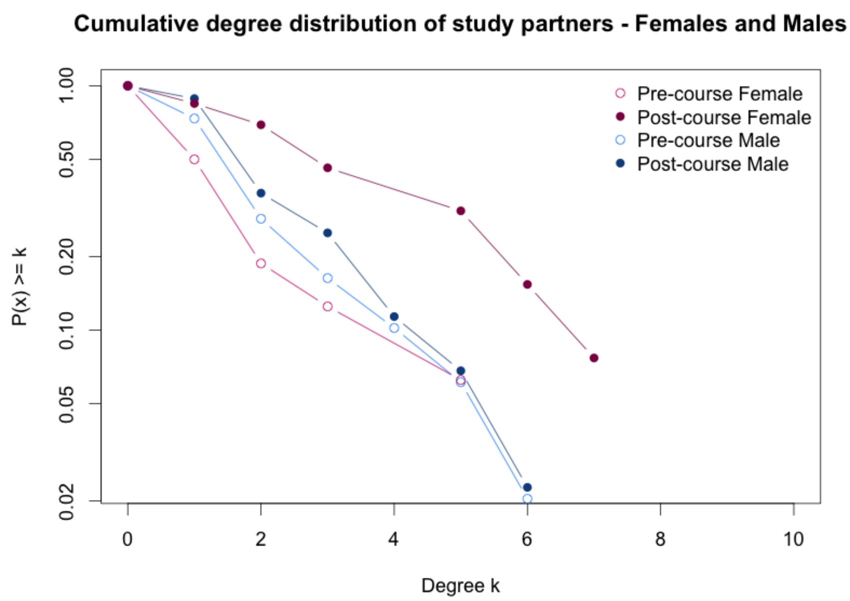


Figure 4.56: Cumulative Degree Plot - Male and Female. The y-axis is log-scale proportion of the network and the x-axis is linear-scale degree centrality

4.4 Force Concept Inventory Statistics

4.4.1 Section A

Tables 4.4 and 4.5 show the FCI pre, post, and gain statistics for the overall course and for female students specifically for Section A. Table 4.4 includes the five number summary (which includes the minimum value, first quartile, median, third quartile, and maximum values of the data set) statistics of the FCI for the pre and post network, along with the FCI gains, while Table 4.5 lists the mean and standard error of these statistics. In this large section, the median and mean FCI scores for both the overall course and female portion increased from pre to post. Female students had a slightly smaller range of FCI gain values, however the maximum post score earned by females was lower than that of the overall network. Female students also started and ended with lower median and mean FCI scores, when compared with the overall network, as shown in Figure 4.57. The median improvement of females in this course is the same as the overall network, at 4 points.

Table 4.4: FCI Statistics - Five Number Summary

		Min	1st Qu.	Med	3rd Qu.	Max
Overall	FCI pre	2.00	7.00	10.00	14.00	28.00
	FCI post	1.00	8.00	12.00	21.00	30.00
	FCI gain	-6.00	1.00	4.00	7.50	18.00
Female	FCI pre	2.00	7.00	9.00	12.00	22.00
	FCI post	5.00	8.25	11.50	18.00	28.00
	FCI gain	-5.00	1.00	4.00	7.00	18.00

Table 4.5: FCI Statistics - Mean and Standard Error

		Mean	S.E.
Overall	FCI pre	10.92	0.37
	FCI post	14.28	0.66
	FCI gain	4.29	0.45
Female	FCI pre	9.225	0.66
	FCI post	13.27	1.13
	FCI gain	4.00	0.97

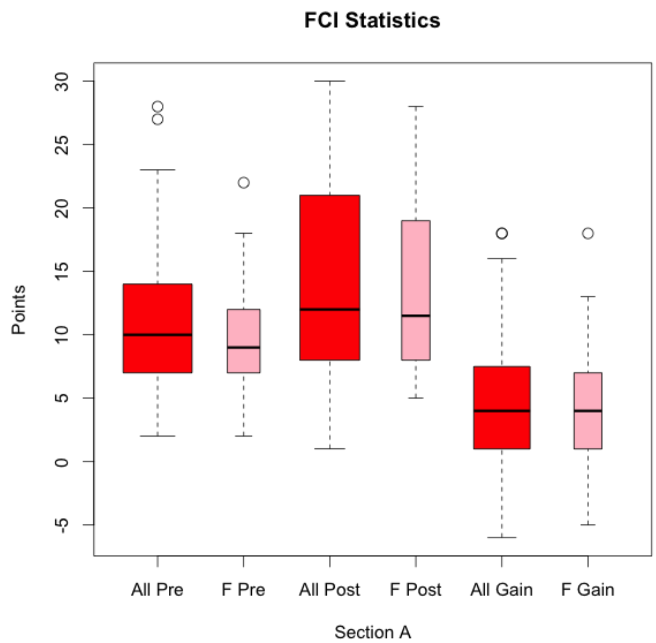


Figure 4.57: Boxplots of FCI Statistics - Overall and Female

4.4.2 Section B

FCI data is not available for this section of PHY 2400.

4.4.3 Section C

Tables 4.6 and 4.7 show the FCI statistics for Section C. In this section, female students begin and end the course with lower median and mean FCI scores when compared to the overall course. Additionally, their maximum pre scores, post scores, and gains are also lower than the overall network, however their minimum scores are equivalent to the overall network. This can be seen in Figure 4.58.

Table 4.6: FCI Statistics

		Min	1st Qu.	Med	3rd Qu.	Max
Overall	FCI pre	1.00	7.00	11.00	17.00	25.00
	FCI post	15.00	19.50	22.50	26.00	27.00
	FCI gain	4.00	5.50	7.00	12.00	24.00
Female	FCI pre	1.00	6.50	8.00	10.25	18.00
	FCI post	15.00	15.75	18.00	20.50	22.00
	FCI gain	4.00	4.50	5.00	6.00	7.00

Table 4.7: FCI Statistics - Mean and Standard Error

		Mean	S.E.
Overall	FCI pre	12.00	1.41
	FCI post	22.08	1.21
	FCI gain	9.64	1.84
Female	FCI pre	8.67	2.31
	FCI post	18.25	1.65
	FCI gain	5.33	0.88

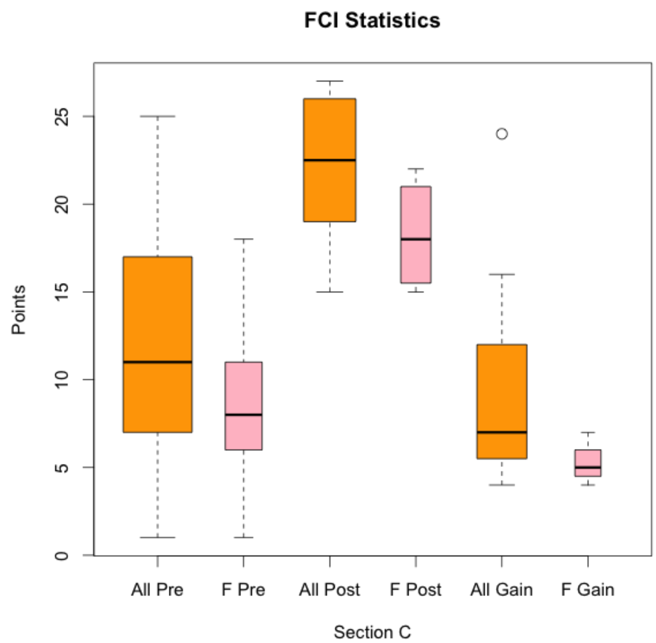


Figure 4.58: Boxplots of FCI Statistics - Overall and Female

4.4.4 Section D

Tables 4.8 and 4.9 show the FCI statistics for Section D. In this section, the lowest pre and post score of females is higher than the overall course. The mean pre scores, post scores, and gains of females is lower than that of the overall network. The span of scores for the female portion is smaller for the pre and post scores, but is equivalent with the overall network for gains, as can be seen in Figure 4.59.

Table 4.8: FCI Statistics

		Min	1st Qu.	Med	3rd Qu.	Max
Overall	FCI pre	2.00	8.00	10.00	14.00	19.00
	FCI post	10.00	14.50	18.00	21.00	29.00
	FCI gain	1.00	4.75	8.50	10.00	15.00
Female	FCI pre	5.00	6.75	9.00	11.00	14.00
	FCI post	11.00	12.25	16.50	20.00	24.00
	FCI gain	1.00	2.50	6.50	9.75	15.00

Table 4.9: FCI Statistics - Mean and Standard Error

		Mean	S.E.
Overall	FCI pre	10.55	0.84
	FCI post	18.60	1.29
	FCI gain	8.00	0.90
Female	FCI pre	9.00	1.05
	FCI post	16.67	2.19
	FCI gain	6.83	2.21

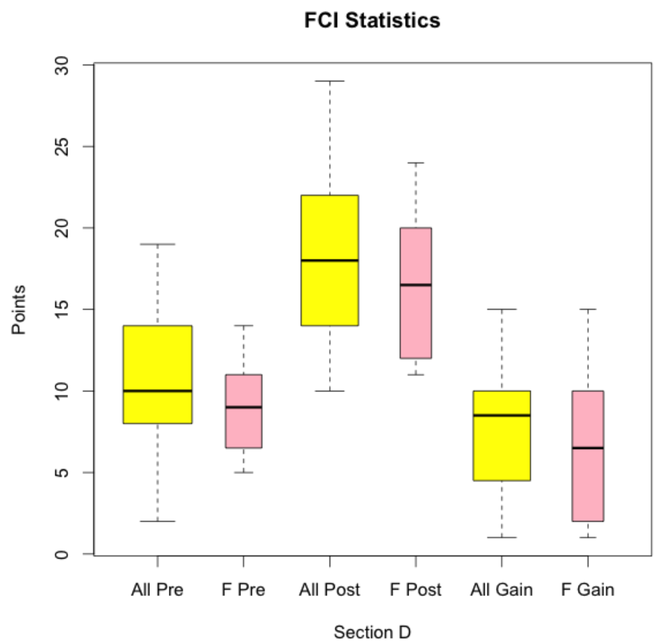


Figure 4.59: Boxplots of FCI Statistics - Overall and Female

4.4.5 Section E

Tables 4.10 and 4.11 show the FCI statistics for Section E. The mean and median gains of female students in this course are higher than the overall network, while the mean and median pre and post scores of female students are lower than the overall network. The overall network has wider spans of pre scores, post scores, and gains than female students. This can be seen in Figure 4.60.

Table 4.10: FCI Statistics

		Min	1st Qu.	Med	3rd Qu.	Max
Overall	FCI pre	3.00	6.00	8.00	11.25	15.00
	FCI post	5.00	7.00	11.00	17.00	22.00
	FCI gain	-5.00	-1.00	3.00	6.00	13.00
Female	FCI pre	3.00	4.50	6.00	6.00	12.00
	FCI post	7.00	7.00	7.50	8.75	15.00
	FCI gain	-5.00	3.00	3.50	5.50	7.00

Table 4.11: FCI Statistics - Mean and Standard Error

		Mean	S.E.
Overall	FCI pre	8.21	0.69
	FCI post	11.94	1.35
	FCI gain	2.85	1.39
Female	FCI pre	6.10	0.80
	FCI post	8.83	1.28
	FCI gain	3.00	1.73

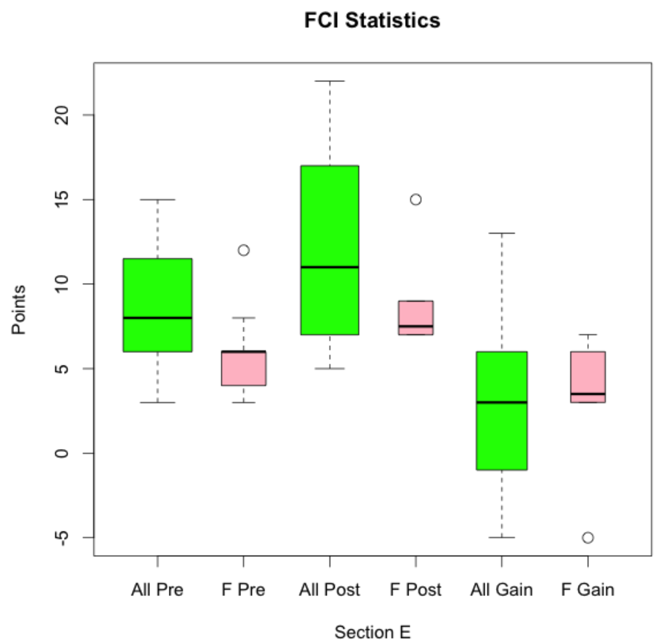


Figure 4.60: Boxplots of FCI Statistics - Overall and Female

4.4.6 Section F

Tables 4.12 and 4.13 show the FCI statistics for Section F. Female students have higher median and mean gains than the overall network. The overall network does have wider spans of data for pre scores, post scores, and gains than the female network. The median and mean pre scores for the overall network are higher than the female network, while the post scores are closer together. These trends are well illustrated in Figure 4.61.

Table 4.12: FCI Statistics

		Min	1st Qu.	Med	3rd Qu.	Max
Overall	FCI pre	4.00	7.75	11.00	14.00	26.00
	FCI post	4.00	11.25	14.50	21.00	26.00
	FCI gain	-1.00	2.00	5.00	6.75	17.00
Female	FCI pre	4.00	6.00	9.00	12.00	18.00
	FCI post	10.00	12.50	14.00	19.25	23.00
	FCI gain	0.00	2.75	5.50	6.25	10.00

Table 4.13: FCI Statistics - Mean and Standard Error

		Mean	S.E.
Overall	FCI pre	11.41	0.71
	FCI post	15.96	0.87
	FCI gain	5.03	0.62
Female	FCI pre	9.33	1.13
	FCI post	15.58	1.32
	FCI gain	5.08	0.85

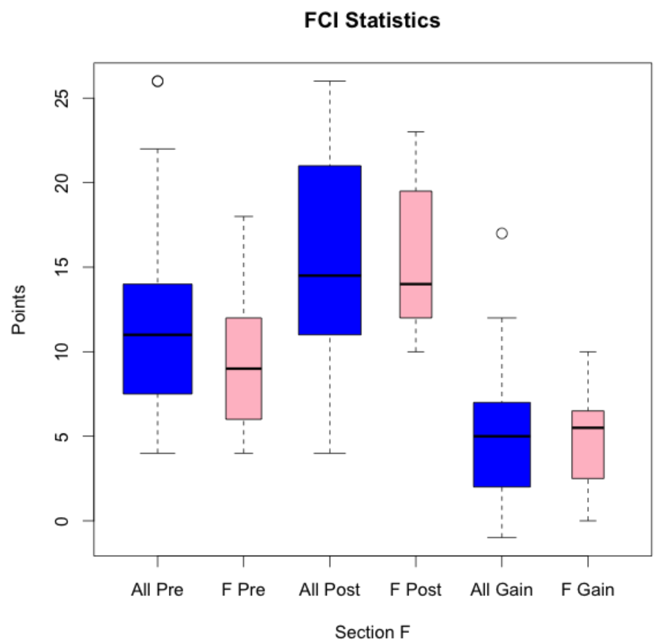


Figure 4.61: Boxplots of FCI Statistics - Overall and Female

4.4.7 Section G

Tables 4.14 and 4.15 display the FCI statistics for Section G. The minimum pre scores are the same for the overall and female network, however female students have much larger median and mean gains than the overall network. The ranges of pre scores, post scores, and gains for the overall network are much larger than the female network. Female students also began with lower pre scores than the overall network, as seen in Figure 4.62

Table 4.14: FCI Statistics

		Min	1st Qu.	Med	3rd Qu.	Max
Overall	FCI pre	2.00	6.00	11.00	15.00	30.00
	FCI post	3.00	10.00	15.00	25.00	30.00
	FCI gain	-5.00	0.00	3.50	7.00	14.00
Female	FCI pre	2.00	5.00	6.00	7.75	10.00
	FCI post	6.00	9.50	14.50	15.00	16.00
	FCI gain	7.00	7.50	8.00	8.50	9.00

Table 4.15: FCI Statistics - Mean and Standard Error

		Mean	S.E.
Overall	FCI pre	12.41	1.06
	FCI post	16.41	1.31
	FCI gain	3.75	0.81
Female	FCI pre	6.20	0.70
	FCI post	12.33	1.73
	FCI gain	8.00	1.00

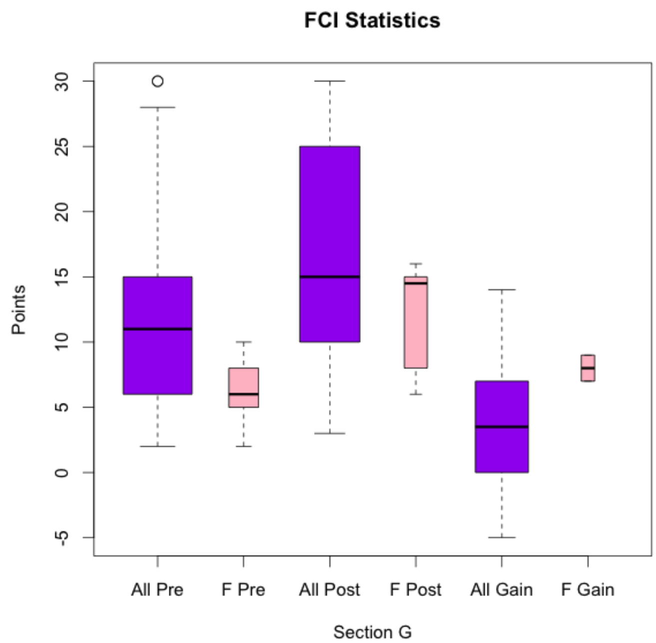


Figure 4.62: Boxplots of FCI Statistics - Overall and Female

4.4.8 Summary

Figures 4.63 and 4.64 show the boxplot distributions of FCI pre and post scores for the overall and female network. In each one of the overall networks the median FCI score increased from pre to post, as it also did in the female network. In the overall network, some sections underwent larger changes, like sections C and D, while others underwent nearly the same changes, as seen for sections A, E, F, and G. In the female network, sections C, D, F, and G underwent large changes, while sections A and E saw smaller changes in the median FCI scores from pre to post. Figures 4.65 and Figure 4.66 show the FCI gains for the overall and female networks for each section. These figures that the FCI gains have relatively large spans for the middle 50% of the data (located between the first and third quartiles) for the overall and female networks, and that the gains for each appear to fall roughly around 5 points of gain.

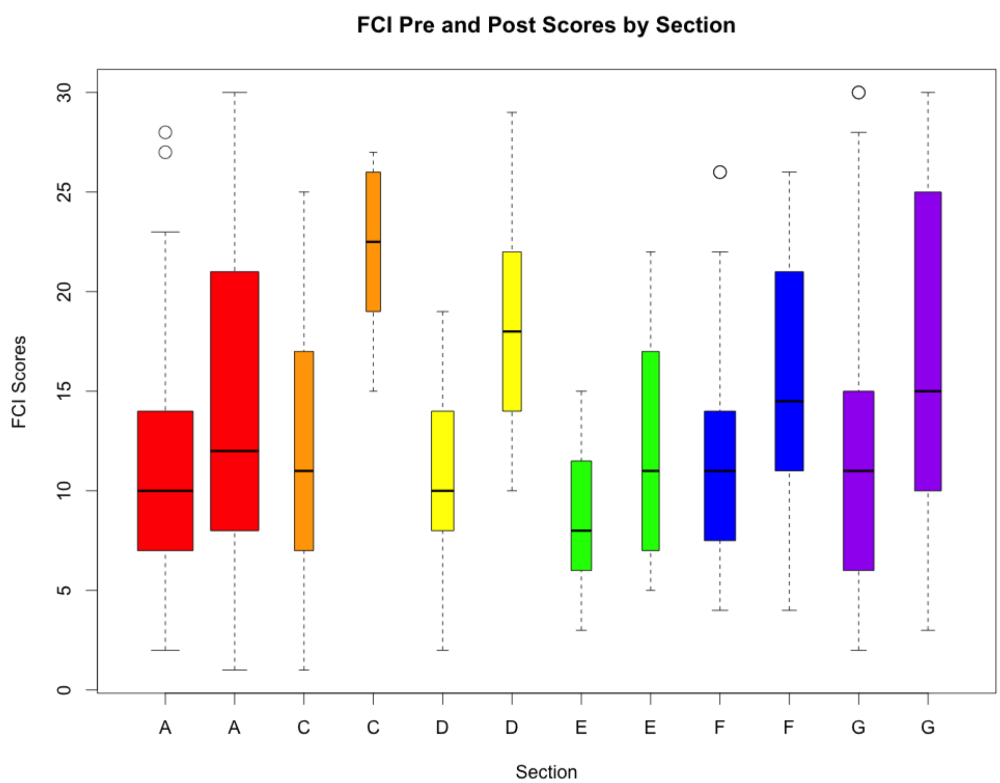


Figure 4.63: FCI Pre and Post scores by section

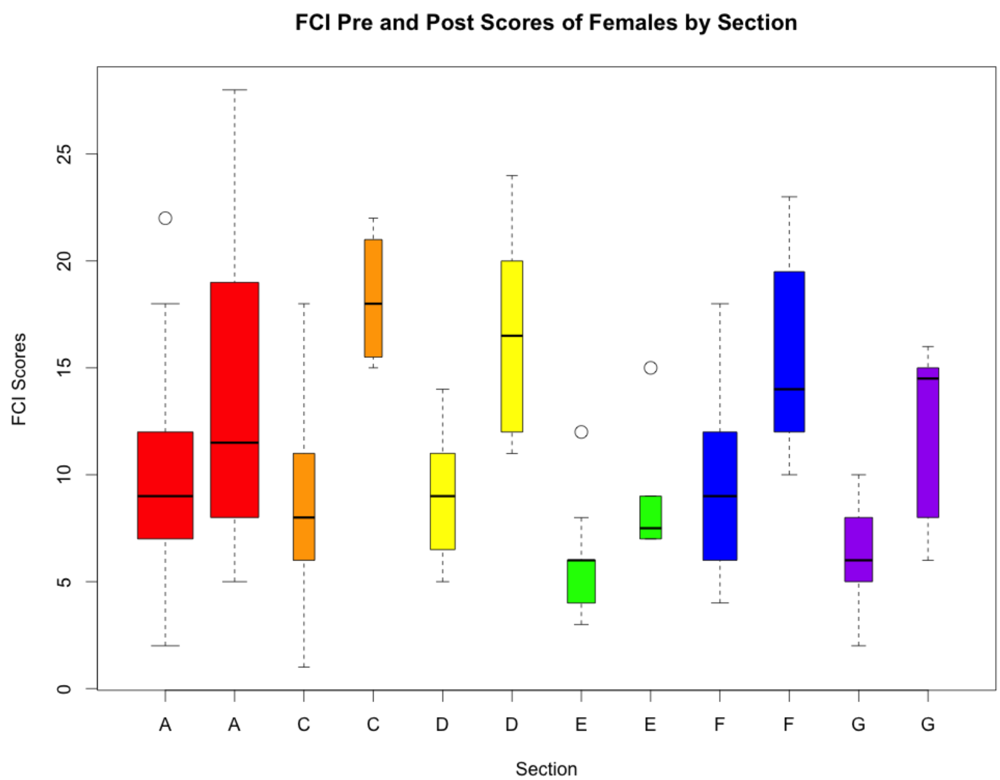


Figure 4.64: FCI Pre and Post scores of Females by section

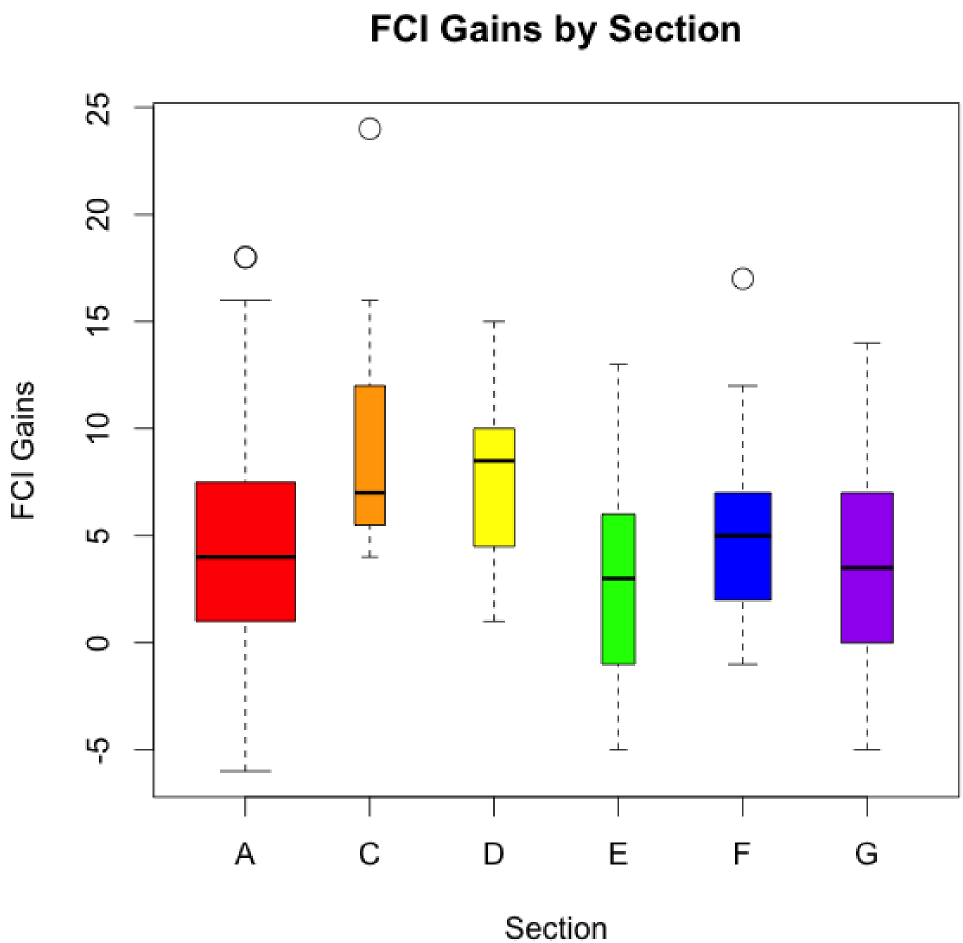


Figure 4.65: FCI Gains by Section

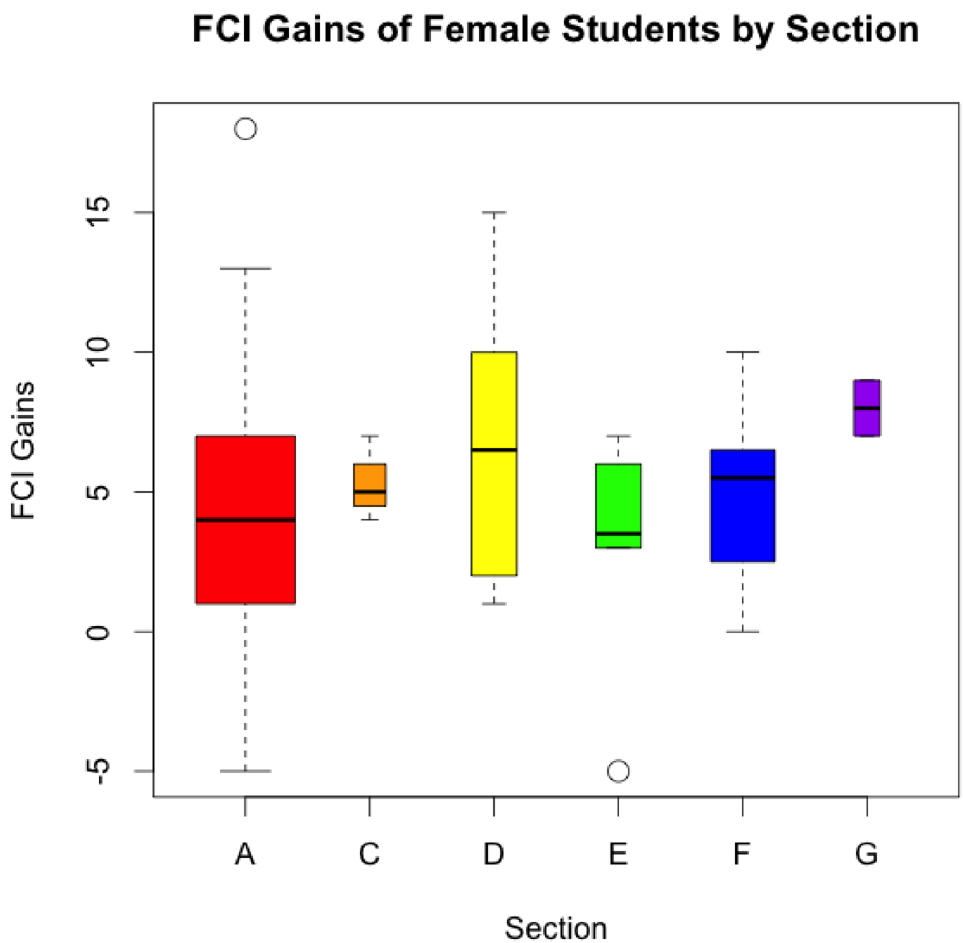


Figure 4.66: Female FCI Gains by Section

4.5 Correlations

4.5.1 Centrality and FCI correlations

Permutation correlation statistics were conducted on each semesters data set in order to compare the FCI post scores and score gains with the pre and post degree, betweenness, and eigenvector centralities for the entire network and the female network separately. The correlations were run and p values were compared to an alpha of 0.05. Significant correlations were those with a p-value of less than 0.05, indicating a relationship may be present between the variables. Using the correlation coefficient as the effect size, we can determine if our samples are large enough to comment on the size of the effect between the variables. The number of students, and female students specifically, are presented by section in Table 4.16.

Table 4.16: Student Counts

		Overall	Female
Section A	Pre	203	42
	Post	174	33
Section B	Pre	185	38
	Post	177	33
Section C	Pre	24	8
	Post	19	5
Section D	Pre	29	8
	Post	23	7
Section E	Pre	28	10
	Post	29	9
Section F	Pre	65	16
	Post	57	13
Section G	Pre	69	15
	Post	63	15

Below are the correlation values for each of the combinations. Table 4.17 shows that Sections E, F, and G have significant correlations at the 0.05 level. Sections not presented did not have statistically significant correlations, however the correlation coefficients and corresponding p-values for these sections can be found in the Appendix. For Section E, both FCI post and FCI gain, when correlated with post degree, have correlation coefficients of 0.5872 and 0.7293 respectively. This would indicate that students who ended the course with a higher number of connections to other students also had higher FCI post scores and gains. Section F has a significant correlation for FCI post scores and post degree with a correlation coefficient of -0.2996. This would indicate that students who ended the course with a higher number of connections to other students had lower FCI post scores and gains. Section G has a significant correlation between FCI post and post degree with a correlation coefficient of -0.3517. This would indicate that students who ended the course with a higher number of connections had lower FCI post scores.

Table 4.17: Correlation Results - Overall Network - Degree and FCI

Semester	Exam Stat	Pre Degree	Pr ($\rho \geq$ obs)	Post Degree	Pr ($\rho \geq$ obs)
Section E	FCI Post	-0.2413	0.3880	**0.5872**	**0.0120**
	FCI Gain	-0.1028	0.7306	**0.7293**	**0.0037**
Section F	FCI Post	-0.0816	0.5650	**-0.2996**	**0.0409**
	FCI Gain	0.0211	0.8968	-0.2425	0.1452
Section G	FCI Post	-0.0739	0.6328	**-0.3517**	**0.0237**
	FCI Gain	-0.0006	0.998	-0.0915	0.6200

Table 4.18 shows correlation results for the subset of female students. The correlation of 0.3693 for FCI post scores with pre degree in Section A was significant at the 0.05 level. This would indicate that female students who entered the course with a high number of connections to other students had higher FCI post scores. All other correlations from Section A are not significant, and neither are correlations conducted for Sections C, D, E, F, and G.

Table 4.18: Correlation Results - Female Network - Degree and FCI

Semester	Exam Stat	Pre Degree	Pr ($\rho \geq$ obs)	Post Degree	Pr ($\rho \geq$ obs)
Section A	FCI post	**0.3693**	**0.0308**	-0.134	0.4836
	FCI gain	0.05769	0.7472	-0.01898	0.9235

Table 4.19 shows that Section E had a significant correlation at the 0.05 level of 0.5025 for FCI post scores with post betweenness. This would indicate that students who had higher betweenness centrality at the end of the course also had higher FCI post scores. Sections C, D, E, F, and G did not have any significant correlations for FCI post or gain with pre or post betweenness at the 0.05 level. Table 4.20 shows correlation results for the subset of female students. A positive correlation of 0.5227 was present between pre

betweenness centrality and FCI post scores of female students for Section A. This would indicate that female students who entered the course with a higher betweenness centrality had higher FCI post scores.

Table 4.19: Correlation Results - Overall Network - Betweenness and FCI

Semester	Exam Stat	Pre Betweenness	Pr ($\rho \geq$ obs)	Post Betweenness	Pr ($\rho \geq$ obs)
Section E	FCI Post	-0.2415	0.3761	**0.5025**	**0.0325**
	FCI Gain	-0.2490	0.4074	0.4994	0.0849

Table 4.20: Correlation Results - Female Network - Betweenness and FCI

Semester	Exam Stat	Pre Betweenness	Pr ($\rho \geq$ obs)	Post Betweenness	Pr ($\rho \geq$ obs)
Section A	FCI post	**0.5227**	**0.0018**	-0.1529	0.411
	FCI gain	0.1215	0.492	NA	NA

Table 4.21 shows that the overall networks of Sections A, E, and G had significant correlations at the 0.05 level for betweenness centrality and FCI post scores and gains. Section A had correlation coefficients of -0.2023 and -0.3439 for FCI post with pre eigenvector, and FCI post with post eigenvector respectively. This would indicate that students in this course who entered or ended the course with high eigenvector centrality had lower FCI post scores. Section A also had a correlation of -0.2086 for FCI gain with post eigenvector. This would indicate that students who ended the course with higher eigenvector centrality had lower FCI gains. Section E had correlation coefficients 0.5765 and 0.6509 for FCI post with post eigenvector and FCI gain with post eigenvector respectively. This would indicate that students who ended the course with higher eigenvector centrality had higher FCI post scores and gains. Section G had a correlation of -0.3748 for FCI post with post eigenvector. This would indicate that students who ended the course with higher eigenvector centrality had lower FCI post scores. Sections C, D, and F did not have any significant correlations for FCI post or gain with pre or post eigenvector at the 0.05 level.

There were no significant correlations of FCI post scores or gains with pre or post eigenvector centrality values for the female student network of any section at the 0.05 level.

Table 4.21: Correlation Results - Overall Network - Eigenvector and FCI

Semester	Exam Stat	Pre Eigenvector	Pr ($\rho \geq$ obs)	Post Eigenvector	Pr ($\rho \geq$ obs)
Section A	FCI Post	**-0.2023**	**0.0156**	**-0.3439**	**0.0002**
	FCI Gain	-0.1183	0.1834	**-0.2086**	**0.0235**
Section E	FCI Post	-0.2862	0.3058	**0.5765**	**0.0151**
	FCI Gain	-0.1696	0.5807	**0.6509**	**0.0161**
Section G	FCI Post	0.2849	0.0545	**-0.3748**	**0.0122**
	FCI Gain	0.1413	0.4180	-0.1044	0.5717

4.5.2 Centrality Ranking Correlations

Tables 4.22 and 4.23 present the pre and post centrality ranking correlation coefficients between degree, betweenness and eigenvector centrality . All of the following correlation coefficients were significant at the 0.05 level, indicating that the ranking of students based on different centrality measures appear in similar order. While both Kendall and Spearman correlations give slightly different values, they reinforce the relationships of these centrality values because all of the correlations gave significant results. The larger the correlation coefficient between two centrality measures, the more likely that that ranking of students based on a given centrality measure will appear in similar order. In other words, if each student in the course is characterized by a degree and betweenness centrality value, these correlation coefficients indicate that most of the time the students would appear in a similar ranking order when ranked by either centrality measure. Table 4.22 shows that degree centrality and betweenness centrality tend to be the most correlated, while eigenvector centrality and betweenness centrality tend to correlate the least. In most cases, the Spearman coefficient is higher than the Kendall coefficient in both the pre and post correlations. Additionally, the correlations do not seem to follow a trend when comparing pre and post coefficients for the same course. In some instances the post correlation ranking coefficients are higher than the pre, in some they are lower than the pre, and in some they are roughly the same.

Table 4.22: Correlation Results - Centrality Ranks - Pre Data

Section	Method		Degree	Eigenvector	Betweenness
Section A	Kendall	Degree	-	0.6833	0.7289
		Eigenvector	-	-	0.5804
	Spearman	Degree	-	0.8327	0.8403
		Eigenvector	-	-	0.7263
Section B	Kendall	Degree	-	0.5349	0.7121
		Eigenvector	-	-	0.4787
	Spearman	Degree	-	0.6772	0.8597
		Eigenvector	-	-	0.6157
Section C	Kendall	Degree	-	0.7337	0.6152
		Eigenvector	-	-	0.4128
	Spearman	Degree	-	0.8470	0.6817
		Eigenvector	-	-	0.4793
Section D	Kendall	Degree	-	0.7089	0.7255
		Eigenvector	-	-	0.6172
	Spearman	Degree	-	0.8468	0.8594
		Eigenvector	-	-	0.8008
Section E	Kendall	Degree	-	0.5662	0.8047
		Eigenvector	-	-	0.3805
	Spearman	Degree	-	0.6912	0.9065
		Eigenvector	-	-	0.5100
Section F	Kendall	Degree	-	0.2036	0.6512
		Eigenvector	-	-	0.2301
	Spearman	Degree	-	0.2628	0.7098
		Eigenvector	-	-	0.2909
Section G	Kendall	Degree	-	0.6422	0.6909
		Eigenvector	-	-	0.4667
	Spearman	Degree	-	0.7622	0.8149
		Eigenvector	-	-	0.5919

Table 4.23: Correlation Results - Centrality Ranks - Post Data

Section	Method		Degree	Eigenvector	Betweenness
Section A	Kendall	Degree	-	0.5811	0.6995
		Eigenvector	-	-	0.4137
	Spearman	Degree		0.7291	0.8496
		Eigenvector	-	-	0.5639
Section B	Kendall	Degree	-	0.6326	0.6584
		Eigenvector	-	-	0.5128
	Spearman	Degree	-	0.7785	0.8155
		Eigenvector	-	-	0.6865
Section C	Kendall	Degree	-	0.7507	0.5996
		Eigenvector	-	-	0.4382
	Spearman	Degree	-	0.8662	0.6956
		Eigenvector	-	-	0.5141
Section D	Kendall	Degree	-	0.5018	0.6385
		Eigenvector	-	-	0.4882
	Spearman	Degree	-	0.5952	0.7880
		Eigenvector	-	-	0.6025
Section E	Kendall	Degree	-	0.8409	0.8351
		Eigenvector	-	-	0.7255
	Spearman	Degree	-	0.9441	0.9356
		Eigenvector	-	-	0.8836
Section F	Kendall	Degree	-	0.5456	0.7390
		Eigenvector	-	-	0.4464
	Spearman	Degree	-	0.6636	0.8431
		Eigenvector	-	-	0.5577
Section G	Kendall	Degree	-	0.5531	0.6937
		Eigenvector	-	-	0.3256
	Spearman	Degree	-	0.6882	0.8071
		Eigenvector	-	-	0.4363

Chapter 5

Discussion

5.1 Centrality and Network Representation

Social Network Analysis allows us to mathematically characterize and analyze students within a network. Using SNA in PER to apply descriptive results is still a relatively new technique and extracting information from different centrality measures when applied to many different class sizes and structures is difficult. The expected results of degree, betweenness, and eigenvector centralities would typically show increases over the course of a semester as students meet and have more opportunities to work together but this wasn't the case in every section.

The larger sections of data (A, B, F and G) do show that the mean degree centrality values increased for both the overall and female networks, while the median values either remained constant or increased. For the smaller sections of data (C, D, and E), these values were less consistent. Sections C and D both saw decreases in the mean and median values for the overall and female network degree centralities, while Section E saw increases in these values. This may be due to different instructional methods, as sections C and D were based on peer-instruction models taught by instructor 3, and section E was a newly adapted SCALE-UP model taught by instructor 1. In sections C and D students may have entered the course with more connections but by the end, they may have only identified the students they worked closely with at their tables, causing the number of connections to decrease. In section E students were encouraged to work within their assigned groups, which were shuffled over the course of the semester, and may have allowed students to increase the number of individuals they worked with. Additionally, because of the small class sizes, omitting even one high degree student from the correlation calculation could have a more meaningful effect in comparison to removing a high degree student from a class with more students.

Betweenness centrality saw mixed results throughout this study. One section saw increases in both the median and mean (Section A) for both the overall and female networks, one section saw decreases in both the median and mean (Section D) for the both the overall and female networks, and another section saw the mean decrease for the overall network while the median increased for the overall network and decreased for the female network (Section E). The remaining sections (B, C, F, and G) saw varying results for the mean and median for both the overall and female student networks.

Eigenvector centrality experienced the same inconsistent results, with the mean and median increasing in sections A, E, F, G, both decreasing in sections C and D, and a mean increase with a median decrease in Section B. These results indicate that more information may be necessary to further understand the effects. By asking students to characterize the relationships they form with others, we may be able to study the different groups within a network of students. This could provide addition insight into how students form connections and how they change depending on instructional methods.

However, this apparent decrease in centrality values may also be an artifact of the small class sizes. It is inevitable that some students will be represented in pre or post data but not in both, which would cause some differences in centrality distributions even if nothing else about the network changed. In larger sections these effects are small against the overall averages, but in small sections the removal of one high-degree node could noticeably change the shape (and the corresponding calculations) of the network.

5.2 Success and Gender

Extrapolating the effects of gender on success using social network analysis and conceptual gains on the FCI revealed inconclusive results. Previous research using SNA in PER has characterized students by gender, in addition to other factors, but results of correlations between centrality and conceptual gains on the FCI have not been reported for networks that were subset by gender. While the overall networks of sections E, F, and G showed significant relationships between post network degree centrality and FCI scores and/or gains, significant results were not obtained for the female subset of the network in these sections. This could be due to the smaller proportion of female students within these networks, which is then further complicated when response rates are not as high as possible (in other words, if all female students do not complete the network survey or the FCI at the beginning and end of the course, an already small part of the class is even less represented in the network). When trying to detect significant correlations in a small subset of a network, having an incomplete response from the population makes it difficult to conduct correlation calculations. Conversely, the female network of Section A showed a significant correlation between FCI post scores and initial degree centrality, indicating that female students who began the class with more connections may fare better when taking the FCI at the end of the course. This section also saw a strong, positive correlation between female pre course betweenness centrality and FCI post scores. This could indicate that female students who entered the course being located between higher numbers of other students may have had better success when taking the FCI at the end of the semester.

Section E showed a strong, positive correlation between overall post course degree, betweenness, and eigenvector centralities and FCI post scores, but this relationship was not significant for the female student subset of the network. Unfortunately eigenvector centrality when correlated with FCI post scores and gains did not reveal any significant relationships in the female network, and more data collection is necessary to further study this centrality measure. Perhaps with higher response rates and more points of data collection, we may be able to discern correlations between each of the centrality measures and FCI post scores or gains for both the overall network and the female student subset of the network in each of the sections, or in future ones.

Chapter 6

Conclusions and Future Work

Physics Education Research is actively working to improve the learning experience and conceptual understanding of students in physics courses. By utilizing a powerful tool like Social Network Analysis (SNA), we can gain insight to the relationships that students build throughout these courses. For example, we anticipated seeing centrality measures increase throughout the semester as students work together with others, however this was not the case in all sections of data, and was not always true for the overall networks or the female student subset. Specifically, eigenvector centrality was inconsistent across the sections presented in this study, which was unexpected. In fact, in some of the smaller sections of data, centrality measures decreased from the pre to post networks, where we would have expected to see an increase with students having more of an opportunity to work together. It's difficult to say with certainty what may have caused this effect, but by asking more detailed questions about the relationships students form with others, we can further characterize students in order to study their centralities. Additional points of data collection throughout the semester could provide insight on how frequently student connections are formed or lost and could also differentiate social aspects student connections from those that are purely academic.

In correlating centrality measures, which quantify these connections, with success measures like the Force Concept Inventory, we can draw conclusions about whether increasing student connections also increases their conceptual gains in a physics course. While the data in this study was sporadic and hard to discern trends from, it still shows that SNA can be used in a meaningful way to describe students relationships and graphically represent them. Additional measures could also be used in these correlation calculations, such as exam scores, final grades and even drop-fail-withdrawal (DFW) rates. Students could be further characterized by their lab sections, pre-requisite grades, and even grade levels to determine what impact these factors may have on their centrality and conceptual gains.

In order to look closer at the female student subset of these networks, community detection could be used to investigate group formation within these networks. This could then be used further to determine how female students are represented within these groups relative to the overall networks. For example, do female students appear to congregate together, or do they make up an equivalent proportion of groups relative to their proportion in the overall network? Future work could use SNA and the FCI to correlate conceptual gains with different forms of centrality, or to study other under-represented minority groups. These tools could also be used to compare different instructional methods, or be used to study different class sizes and setups like SCALE-UP and traditional lectures.

Chapter 7

Appendices

7.1 Additional Figures

7.1.1 Correlations

Table 7.1 includes the correlation results for the overall network between pre and post degree centralities and FCI post scores and gains. The information presented in this table contains the tests that revealed nonsignificant relationships between the variables in question. Data with significant correlations can be found in Table 4.17.

Table 7.1: Correlation Results - Overall Network - Degree and FCI

Semester	Exam Stat	Pre Degree	Pr ($\rho \geq$ obs)	Post Degree	Pr ($\rho \geq$ obs)
Section A	FCI Post	-0.1536	0.686	-0.1641	0.0619
	FCI Gain	-0.0793	0.3691	-0.0374	0.6823
Section C	FCI Post	0.2772	0.406	0.0114	0.9714
	FCI Gain	0.0436	0.8990	-0.0862	0.8081
Section D	FCI Post	0.1074	0.6436	0.2616	0.2636
	FCI Gain	0.0759	0.7452	0.3089	0.1861

Table 7.2 includes the correlation results for the female network between pre and post degree centralities and FCI post scores and gains. The information presented in this table contains the tests that revealed nonsignificant relationships between the variables in question. Data with significant correlations can be found in Table 4.18.

Table 7.2: Correlation Results - Female Network - Degree and FCI

Semester	Exam Stat	Pre Degree	Pr ($\rho \geq$ obs)	Post Degree	Pr ($\rho \geq$ obs)
Section C	FCI Post	0.6099	NA	0.2621	0.696
	FCI Gain	-0.9449	NA	-0.9449	0.2661
Section D	FCI Post	0.6175	0.1885	0.6497	0.1607
	FCI Gain	0.7878	0.0707	0.7294	0.1055
Section E	FCI Post	-0.5241	0.3023	0.3814	0.5199
	FCI Gain	-0.5000	0.3305	0.5081	0.3255
Section F	FCI Post	-0.3599	0.3026	-0.1909	0.5512
	FCI Gain	-0.4831	0.1974	-0.4582	0.1345
Section G	FCI Post	-0.1265	0.8157	0.5985	0.2181
	FCI Gain	-1	NA	NA	NA

Table 7.3 includes the correlation results for the overall network between pre and post betweenness centralities and FCI post scores and gains. The information presented in this table contains the tests that revealed nonsignificant relationships between the variables in question. Data with significant correlations can be found in Table 4.19.

Table 7.3: Correlation Results - Overall Network - Betweenness and FCI

Semester	Exam Stat	Pre Betweenness	Pr ($\rho \geq$ obs)	Post Betweenness	Pr ($\rho \geq$ obs)
Section A	FCI Post	0.0271	0.7659	-0.0549	0.5358
	FCI Gain	0.0383	0.6745	0.0169	0.8608
Section C	FCI Post	0.4337	NA	0.3715	NA
	FCI Gain	0.2049	NA	0.2763	NA
Section D	FCI Post	0.2062	0.3592	0.2477	0.2937
	FCI Gain	0.1318	0.5571	0.2779	0.2401
Section F	FCI Post	-0.0815	0.5973	-0.0955	0.5294
	FCI Gain	0.0229	0.8820	0.0046	0.9787
Section G	FCI Post	-0.0809	0.6111	-0.1098	0.4985
	FCI Gain	-0.0394	0.8218	-0.2236	0.2201

Table 7.4 includes the correlation results for the female network between pre and post betweenness centralities and FCI post scores and gains. The information presented in this table contains the tests that revealed nonsignificant relationships between the variables in question. Data with significant correlations can be found in Table 4.20.

Table 7.5 includes the correlation results for the overall network between pre and post eigenvector centralities and FCI post scores and gains. The information presented in this table contains the tests that revealed nonsignificant relationships between the variables in question. Bold-faced data represent statistically significant correlations that can also be

Table 7.4: Correlation Results - Female Network - Betweenness and FCI

Semester	Exam Stat	Pre Betweenness	Pr ($\rho \geq$ obs)	Post Betweenness	Pr ($\rho \geq$ obs)
Section C	FCI Post	NA	NA	NA	NA
	FCI Gain	NA	NA	NA	NA
Section D	FCI Post	0.3937	0.4144	0.6053	0.1935
	FCI Gain	0.5536	0.2504	NA	NA
Section E	FCI Post	-0.7905	0.0711	0.4265	0.3827
	FCI Gain	-0.6803	0.1168	NA	NA
Section F	FCI Post	-0.4553	NA	0.0476	0.8833
	FCI Gain	-0.3798	NA	NA	NA
Section G	FCI Post	-0.7527	NA	0.4488	NA
	FCI Gain	-1	NA	NA	NA

found in Table 4.21.

Table 7.5: Correlation Results - Overall Network - Eigenvector and FCI

Semester	Exam Stat	Pre Eigenvector	Pr ($\rho \geq$ obs)	Post Eigenvector	Pr ($\rho \geq$ obs)
Section C	FCI Post	0.0644	0.8547	-0.2708	0.4021
	FCI Gain	-0.4441	0.1674	-0.4426	0.1617
Section D	FCI Post	0.0118	0.9586	-0.0297	0.8939
	FCI Gain	0.0964	0.666	-0.1717	0.4698
Section F	FCI Post	-0.0469	0.7689	-0.0909	0.5557
	FCI Gain	-0.0614	0.692	0.0018	0.9924

Table 7.6 includes the correlation results for the female network between pre and post eigenvector centralities and FCI post scores and gains. The information presented in this table contains the tests that revealed nonsignificant relationships between the variables in question.

Table 7.6: Correlation Results - Female Network - Eigenvector and FCI

Semester	Exam Stat	Pre Eigenvector	Pr ($\rho \geq$ obs)	Post Eigenvector	Pr ($\rho \geq$ obs)
Section A	FCI post	0.2791	0.1121	-0.1254	0.5244
	FCI gain	-0.1868	0.2991	-0.3325	0.0763
Section C	FCI Post	0.6099	0.6025	0.2621	0.6374
	FCI Gain	-0.9449	0.2397	-0.9449	0.2727
Section D	FCI Post	0.2596	0.5949	0.5068	0.2961
	FCI Gain	0.5065	0.2887	0.5314	0.284
Section E	FCI Post	-0.1373	0.7780	0.5037	0.3126
	FCI Gain	-0.4386	0.4024	0.4590	0.3739
Section F	FCI Post	-0.3757	0.2382	0.0197	0.9565
	FCI Gain	-0.4717	0.2452	-0.0470	0.8900
Section G	FCI Post	0.2302	0.7588	0.1090	0.8758
	FCI Gain	-1	NA	1	NA

7.2 Informed Consent Materials

Approval for this study was provided by the Institutional Review Board at Wright State University under study number SC 5951. As part of this study, students were provided with the following consent form at the time they took the Force Concept Inventory.

SURVEY COVER SHEET

Students will read this information before taking the surveys, and either agree or disagree to participate in place of a signed informed consent. If they do not agree, their results will not be saved or used for analysis, but they will still receive credit for participation.

Introductory physics courses include a variety of learning strategies in addition to lecture. The use of cooperative learning is designed to give you practice at working in groups, as professional scientists and engineers do, and to help your learning by collaborating on challenging problems. This semester, Dr. Adrienne Traxler will be evaluating this strategy in the course. The evaluation is important in determining how cooperative learning can best be used for this class, and how it can be improved. The evaluation data collected will not be a part of your grade for the course (there are no âĂIJrightâĂİ or âĂIJwrongâĂİ answers on the surveys), but will be used for future planning.

If the evaluation of the learning strategies is useful, Dr. Traxler would like to share it with other educators and researchers to help them in teaching physics. Therefore, she is requesting permission to share the data you provide with other educators as part of a summary report and research work. These reports will be about results from the whole class, so you will not be identifiable as an individual. Your survey results will be kept only in password-protected electronic storage or locked physical storage, and only people who are part of the research project will have access. Survey responses will not be seen by your instructor during the semester, and so specific answers cannot influence your grade. All data will be treated confidentially, and if shared in the scientific literature, will not identify the particular class that provided the information.

This method of protecting your identity and the confidentiality of the data has been approved by the appropriate review board at Wright State University.

As part of taking PHY 2400, you are required to participate in all learning activities and to complete the pre-course, mid-semester, and post-course surveys. If you are unable to participate in the learning activities or surveys due to an excused absence, you will be given a written make-up assignment.

You do have an option to allow or not allow the information you provide as part of this evaluation of learning strategies to be shared with educators beyond this university. It is hoped that you will consent to including your data in the analysis, because there will be no way to identify you as an individual. After having any questions answered (email the instructor or Dr. Traxler, adrienne.traxler@wright.edu, with any questions), please indicate your willingness to have your data included as part of the summary report by checking the appropriate box below.

The consent question will be stored as part of the survey, and all will be kept on a password-protected website until the end of the semester. Dr. Traxler will not review which students have chosen to allow their data to be shared in a group summary until after the end of the semester and final grades have been posted.

- All my questions about the evaluation of the learning strategies and the confidentiality of any information I provide have been answered.
- I understand that all evaluation data I provide will be treated confidentially.
- I also understand that in the event a summary of the evaluation is shared with the wider educational community, no individuals providing data will be able to be identified.
- I further understand that if I have any additional questions about this evaluation or the procedure for maintaining the confidentiality of my data, I may call Dr. Traxler at 937-775-3139 or email her at adrienne.traxler@wright.edu.

I have read the cover letter and voluntarily: (check the appropriate response)

_____ consent

_____ do not consent

to allow my data to be included in a summary report shared with the wider education community.

Name: ____________________

UID: ____________________

7.3 Surveys and FCI

Surveys

Students in each section took an online survey-style questionnaire which consisted of two parts, only one of which was used for the this study. The first portion asked students to answer the question shown below. The second portion was the CLASS (Colorado Learning Attitudes about Science Survey) and can be found at `http://www.colorado.edu/sei/surveys/Faculty/CLASS-PHYS-faculty.html`, the data from which was not used in this study.

NETWORK SURVEY

This survey will be given at the beginning, midpoint, and end of the semester to collect information about learning community structures that form in the class.

The physics department is conducting several surveys to understand how to better accommodate learning in introductory physics courses. In this survey you will be asked to identify other students enrolled in this course that you have studied with or that you discuss physics concepts with. The responses will not be made public, and will not affect your grade.

1. What is your name?
2. What is your UID?
3. Who do you work with to learn physics? Please select as many students as you study with.

   [List of names from course roster]

7.3.1 FCI

The Force Concept Inventory can be found at `http://modeling.asu.edu/R&E/Research.html`.

Bibliography

Alsop, S. and Watts, M. (1998). Interviews-about-scenarios: Exploring the affective dimensions of physics education. *Research in Education*, 63:21–32.

Antonellis, J. C., Brogt, E., Buxner, S. R., Dokter, E. F., and Foster, T. (2012). Regulations and Ethical Considerations for Working with Human Participants in Physics and Astronomy Education Research. In Henderson, C. and Harper, K., editors, *Getting Started in PER*, pages 1–18. American Association of Physics Teachers.

Aronson, J. (2004). The Threat of Stereotype. *Educational Leadership*, 62(3):14–19.

Aronson, J., Lustina, M. J., Good, C., Keough, K., Steele, C. M., and Brown, J. (1999). When White Men Can't Do Math: Necessary and Sufficient Factors in Stereotype Threat. *Journal of Experimental Social Psychology*, 35(1):29–46.

Beichner, R. (2009). An Introduction to Physics Education Research. In *Getting Started in PER*, volume 2, pages 57–71.

Beichner, R. J., Saul, J. M., Abbott, D. S., Morse, J. J., Deardorff, D. L., Allain, R. J., Bonham, S. W., Dancy, M. H., and Risley, J. S. (2007). The Student-Centered Activities for Large Enrollment Undergraduate Programs (SCALE-UP) Project. In *Research-Based Reform of University Physics*, pages 1–42.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology*, 92(5):1170–1182.

Brewe, E., Kramer, L., and Sawtelle, V. (2012). Investigating student communities with network analysis of interactions in a physics learning center. *Physical Review Special Topics - Physics Education Research*, 8(1):1–9.

Brewe, E., Kramer, L. H., and O'Brien, G. E. (2010). Changing Participation Through Formation of Student Learning Communities. *AIP Conference Proceedings*, 1289:85–88.

Bruun, J. and Bearden, I. G. (2014). Time development in the early history of social networks: Link stabilization, group dynamics, and segregation. *PLOS ONE*, 9(11):1–11.

Bruun, J. and Brewe, E. (2013). Talking and learning physics: Predicting future grades from network measures and Force Concept Inventory pretest scores. *Physical Review Special Topics - Physics Education Research*, 9(2):1–13.

Cohen, J. (1992). A Power Primer. *Psychological Bulletin*, 112(1):155–159.

Cook, K. S., Emerson, R. M., Gillmore, M. R., and Yamagishi, T. (1983). The Distribution of Power in Exchange Networks : Theory and Experimental Results. *The American Journal of Sociology*, 89(2):275–305.

Csárdi, G. and Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal Complex Systems*, 1695:1695.

Fan, X. (2001). Statistical significance and effect size in education research: Two sides of a coin. *The Journal of Educational Research*, 94(5):275–282.

Freeman, L. C. (1978). Centrality in Social Networks Conceptual Clarification. *Social Networks*, 1(3):215–239.

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., and Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences of the United States of America*, 111(23):8410–8415.

Goertzen, R. M., Brewe, E., and Kramer, L. (2012). Expanded Markers of Success in Introductory University Physics. *International Journal of Science Education*, 35(2):262–288.

Gonsalves, A. J. (2012). âĂIJPhysics and the girly girlâĂŤthere is a contradiction somewhereâĂİ: doctoral students' positioning around discourses of gender and competence in physics. *Cultural Studies of Science Education*, 9(2):503–521.

Gonzales, P. M., Blanton, H., and Williams, K. J. (2002). The Effects of Stereotype Threat and Double-Minority Status on the Test Performance of Latino Women. *Personality and Social Psychology Bulletin*, 28(5):659–670.

Grunspan, D. Z., Wiggins, B. L., and Goodreau, S. M. (2014). Understanding classrooms through social network analysis: A primer for social network analysis in education research. *CBE Life Sciences Education*, 13(2):167–178.

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics*, 66(1):64–74.

Heller, P. and Hollabaugh, M. (1992). Teaching problem solving through cooperative grouping. Part 2: Designing problems and structuring groups.

Heller, P., Keith, R., and Anderson, S. (1992). Teaching problem solving through cooperative grouping. Part 1: Group versus individuel problem solving. *American Journal of Physics*, 60(7):627–636.

Henderson, C. (2002). Common Concerns About the Force Concept Inventory. *The Physics Teacher*, 40(9):542–547.

Hestenes, D., Wells, M., and Swackhamer, G. (1992). Force concept inventory. *The Physics Teacher*, 30(3):141–158.

Huffman, D. and Heller, P. (1995). What does the force concept inventory actually measure? *The Physics Teacher*, 33(3):138–143.

Jovanovic, J. and King, S. S. (1998). Boys and Girls in the Performance-Based Science Classroom: Who's Doing the Performing? *American Educational Research Journal*, 35(3):477–496.

Kendall, M. (1938). A New Measure of Rank Correlation. *Biometrika*, 30(1/2):81–93.

Marsden, P. V. (2011). Survey Methods for Network Data. In *The Sage Handbook of Social Network Analysis*, pages 370–388. Sage Publications, London.

National Research Council (2004). *How People Learn: Brain, Mind, Experience, and School*. National Academy Press, Washington, D.C.

National Research Council (2012). *Discipline-Based Education Research: Understanding and Improving Learning in Undergraduate Science and Engineering*. National Academy Press, Washington, D.C.

National Research Council (2013). *Adapting to a Changing World–Challenges and Opportunities in Undergraduate Physics Education*. National Academy Press, Washington, D.C.

Page, L., Brin, S., Motwani, R., and Winograd, T. (1998). The PageRank Citation Ranking: Bringing Order to the Web. *World Wide Web Internet And Web Information Systems*, 54(1999-66):1–17.

Rodriguez, I., Brewe, E., Sawtelle, V., and Kramer, L. H. (2012). Impact of equity models and statistical measures on interpretations of educational reform. *Physical Review Special Topics - Physics Education Research*, 8(2):1–7.

Rosvall, M. and Bergstrom, C. T. (2010). Mapping Change in Large Networks. *PLOS ONE*, 5(1):1–7.

Seymour, E. (1995). The Loss of Women from Science, Mathematics, and Engineering Undergraduate Majors: An Explanatory Account. *Science Education*, 79(4):437–473.

Sfard, A. (1998). On Two Metaphors for Learning and the Dangers of Choosing Just One. *Educational Researcher*, 27(2):4–13.