Promoting Instructional Change: Using Social Network Analysis to Understand the Hidden Structure of Academic Departments

Kathleen Quardokus
*Mallinson Institute for Science Education, Western Michigan University, Kalamazoo, MI 49008, USA*
e-mail: kathleen.m.quardokus@wmich.edu

Charles Henderson
*Department of Physics and Mallinson Institute for Science Education, Western Michigan University, Kalamazoo, MI 49008, USA*

Acknowledgements

This work was funded by the Howard Hughes Medical Institute through a subcontract from Iowa State University to Western Michigan University. The authors would like to thank Tessa Andrews, Aekam Barot, Andrea Beach, Eric Brewe, Erin Dolan, Xaver Neumeyer, Craig Ogilvie, Emily Walter, and Cody Williams for helpful comments and feedback on earlier versions of this manuscript.

(Submitted for publication -- Please do not cite without permission.)
Promoting Instructional Change: Using Social Network Analysis to Understand the Hidden Structure of Academic Departments

Abstract

Calls for improvement of undergraduate science education have resulted in numerous change initiatives that seek to improve student learning outcomes by promoting changes in faculty teaching practices. Although many change initiatives focus on individual faculty, researchers consider the academic department to be a highly productive focus of change initiatives. In this paper, we argue that it is important for change agents to understand the hidden social structure of the academic department and introduce social network analysis techniques to uncover this hidden social structure. Examples are given from data collected in five academic departments. A short web survey was used to ask instructors in these departments to identify colleagues with whom they discuss teaching and how frequently. Techniques of social network analysis are identified that can be used to determine the current state of the department, target participants for a change initiative, and anticipate the spread of new teaching ideas. Results suggest that these techniques do indeed identify social structures that would otherwise be hidden and that may be important for planning change initiatives.

Keywords Social network analysis, Educational change, Higher education, Faculty

Introduction

Social network analysis (SNA) is a research technique used to identify the roles that individuals play within the social structure of a group, possible subdivisions of a group, and the influence of social ties on individual behavior. A variety of settings have shown SNA to be a powerful tool for explaining the attitudes and behaviors of individuals based on their social ties. These include: the spread of obesity among people (Christakis and Fowler 2007), the structure of gang member allegiance (Malm et al. 2010), and the effectiveness of nursing units in a hospital (Effken et al. 2011). For example, Christakis and Fowler (2009) report that individuals tend to take on the emotions of others with whom they have direct contact. When a college student is assigned a roommate who shows signs of depression, the student tends to also become depressed.

The process of education is influenced by social connections (e.g. Brewe et al. 2012; Moolenaar et al. 2012). Recently, researchers have begun to use SNA techniques in studies of pre-college educators (Coburn and Russell 2008; Penuel et al. 2009). In a study of change initiatives in elementary schools, Penuel et al. (2009) found that an elementary school that experienced successful change had social connections between less experienced teachers and more experienced teachers. On the other hand, an elementary school where the same change initiative was unsuccessful did not have these social connections. The number of experienced and inexperienced teachers in each school was roughly the same. The authors conclude that the connections in the first school provided support to the inexperienced teachers and improved the success of the change initiative.
Although SNA has been shown to be useful in many settings, it has not yet been applied to understanding instructional change in higher education. In a review of the literature of SNA in higher education, Biancani and McFarland (2013) identified 117 articles in which faculty were the focus of a network study. Of these articles, most involved identifying faculty networks based on publication data, such as co-authorship or citations. None of the articles focused on a faculty teaching discussion network. The purpose of this paper is to describe how SNA measurement techniques and metrics can be used to characterize teaching discussion networks. We first discuss the rationale for why and in what ways we expect SNA to be useful for understanding change. We then describe how we collected social network data of five academic departments that will be used to provide examples of applying SNA. We present SNA applications based on the type of change strategy employed and the tasks of the change agent.

**Background: Change Strategies and Social Networks**

Various groups have called for change in undergraduate science, technology, engineering and mathematics (STEM) education (e.g. Association of American Universities 2011; National Research Council 2012; The White House 2009). In 2011, the Association of American Universities embarked on a five year initiative to encourage faculty members to adopt proven teaching practices (Association of American Universities 2011). As this goal suggests, education researchers have developed research-validated teaching methods for a variety of STEM disciplines (e.g. Froyd 2008; Prince and Felder 2006; National Research Council 2012). However, a gap currently exists between the knowledge about effective teaching strategies held by STEM education researchers and the teaching practices used by many STEM faculty (Brainard 2007; Henderson and Dancy 2009; Pollock and Finkelstein 2008).

Change initiatives (organized efforts to encourage change) in STEM disciplines often treat individual faculty as the unit of change (Henderson et al. 2011). However, it has been suggested that the academic department is likely the most productive unit of change (e.g. Edwards 1999; Gibbs et al. 2008; Wieman et al. 2010). There are several reasons for this. First, a department has control over the design of the courses that it offers. Change that is adopted by the department does not need to be accepted by the university at large. Second, a culture that values research-based teaching practices can reward faculty who implement change (e.g. with more desirable teaching assignments or through extending recommendations for promotion). Third, information about teaching practices, the sharing of ideas, and behavior expectations are located in faculty daily discussions (Kezar 2011; Senge 2000).

The design of change initiatives must be sensitive to the social structure and culture of the targeted unit of change (Wieman et al. 2010). The change agent (formal leader of the change initiative) faces three challenges related to departmental-level change: (1) understanding the current state of the department with respect to teaching practices (opinions, practices, and expectations), (2) targeting individuals for participation and (3) anticipating how change may spread throughout the department. SNA of academic departments can be used to help the change agent perform these tasks.
A social network is a compilation of the relational connections between individuals. A tie is formed between two individuals if a relationship (such as friendship) exists between them (Prell 2012). To identify connections through surveys, individuals in the network are asked to identify others with whom he or she has a given relationship (Marsden 2011). In the social network in Fig. 1, the individuals (or nodes) are represented by squares (with letter identifiers) and the lines represent the ties between individuals. For example, because node E has a relationship with node Q, a line exists between them.

Fig. 1 Nodes (squares) are connected by a relationship (lines) in a network (a compilation of all nodes and relations). All images in this paper are created with NetDraw (Borgatti 2002)

A change agent may choose to select leaders in a change initiative based on seniority, experience, or formal responsibilities. However, recent advances in leadership (e.g. Uhl-Bien et al. 2007) and organizational dynamics (e.g. Nonaka and Takeuchi 1995; Senge 1990) have found that much of the knowledge and decision-making within organizations happens outside of this formal structure. Therefore, relying on known (formal) characteristics may not result in the detection of individuals who are influential in the department’s educational tasks. Instead, SNA allows researchers to reveal the structure of connections and to detect network features that can be used to target participants who play particular roles in the educational goals of the department.

Assumptions about change processes shape the design of change strategies and how SNA can inform this design. In a meta-analysis of change efforts in higher education, Henderson et al. (2011) developed four categories of change strategies. For the purposes of this article, we focus on two types of change strategies: those with prescribed outcomes in which the desired final state is known in advance; and those with emergent outcomes in which the desired final state is developed through the change process. In each type of change strategy, the change agent must understand the current state of teaching practices in the department, identify individuals to participate in the change initiative, and anticipate how new teaching practices will spread within
the network. Table 1 is an overview of the relationship between these tasks and the type of change initiative. Note that the change strategies differ in how they target participants.

**Table 1** Change agent considerations according to type of change initiative (rows) and change agent task (columns)

<table>
<thead>
<tr>
<th>Understand Current State</th>
<th>Target Participants</th>
<th>Anticipate Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prescribed Strategies</td>
<td></td>
<td></td>
</tr>
<tr>
<td>How many subgroups are there?</td>
<td>Who are most connected individuals in each subgroup?</td>
<td>How densely connected is the department?</td>
</tr>
<tr>
<td>Who are knowledgeable informants?</td>
<td>Who connects subgroups?</td>
<td>How centralized is the department?</td>
</tr>
<tr>
<td>Emergent Strategies</td>
<td></td>
<td></td>
</tr>
<tr>
<td>How many subgroups are there?</td>
<td>What connections should be built or strengthened (homogeneous, within a subgroup or heterogeneous, across subgroups) to improve productivity?</td>
<td>How many subgroups are there?</td>
</tr>
</tbody>
</table>

For prescribed change strategies, the change agent publicizes a known innovation to individuals and motivates them to adopt it, or changes the policy of the department and requires compliance (Henderson et al. 2011). SNA helps change agents focus their efforts effectively. The current state of a department will inform the creation of the innovation or policy, monitor the adoption of change across the network, and provide insight into why compliance with the policy change is or is not occurring. If no subgroups exist in a department, the change agent can understand the current state of the network with consultation of a few people with many social connections. However, if subgroups exist, then members of a subgroup are more likely to have shared ideas which may be different than members of other subgroups (Christakis and Fowler 2009). To monitor this type of network, the change agent will need to communicate with well-connected individuals from each subgroup. These same individuals (either individuals who are well-connected overall or individuals who are well-connected in particular subgroups) may also be targeted for formal participation in the change initiative. For dissemination of an innovation, these people are most likely to motivate others to adopt the innovation. For policy changes, compliance by these individuals will likely influence the compliance of their social connections. Finally, how quickly the new teaching ideas are likely to spread through the network via social connections is informed by the overall characteristics of the network (its frequency of conversations and subgroups). A less dense network with many subgroups will make it less likely and slower for information and ideas to spread.
For emergent change strategies, the desired outcomes are developed as part of the process of the change initiative (Henderson et al. 2011). The individuals involved in the initiative determine what change is required. The techniques of SNA used for understanding the current state of the network and anticipating spread of new ideas (once developed) are the same for emergent and prescribed change strategies (columns 2 and 4 in Table 1). However, for targeting participants in the change initiative (column 3, Table 1 Error! Reference source not found.), the change agent will be interested in creating groups that will work together either to support individual change or to develop a new shared vision. The groupings may be homogeneous, based on natural subgroups that have been identified by SNA. These groupings are stable and provide support for the process of change. On the other hand, the change agent may wish to create heterogeneous groups from diverse locations in the hidden structure. Heterogeneous groups introduce variety into the environment to facilitate the development of novel ideas for change (Plowman et al. 2007).

**Analysis of Hidden Structures of Social Networks**

The purpose of this paper is to demonstrate how SNA can identify aspects of the hidden structure of academic departments. In this section, we describe six SNA measures (Table 2). Examples from five academic departments demonstrate how these measures can be used to promote the flow of information for prescribed strategies or to identify people to engage in the creation of new knowledge for emergent change strategies. All analyses were completed using UCINET 6 software package (Borgatti et al. 2002).
Table 2 Summary of SNA measures discussed in this paper

<table>
<thead>
<tr>
<th>Calculation</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network-Level Characteristics (Prell 2012)</strong></td>
<td></td>
</tr>
<tr>
<td>Density</td>
<td>Total ties divided by maximum of possible ties.</td>
</tr>
<tr>
<td>Centralization</td>
<td>Sum of the differences between the degree (number of ties) of each node from the maximum node degree divided by the theoretical maximum of this number.</td>
</tr>
<tr>
<td>Transitivity</td>
<td>Count of nodes that form a triangle divided by the counts of nodes that have two legs but fail to make a triangle.</td>
</tr>
<tr>
<td><strong>Individual Roles (Stephenson 2005)</strong></td>
<td></td>
</tr>
<tr>
<td>Hubs of Knowledge</td>
<td>Degree Centrality: Total ties of a node divided by number of possible ties (Prell 2012).</td>
</tr>
<tr>
<td>Gatekeepers</td>
<td>Betweenness: The node that is part of the highest number of shortest paths between otherwise disconnected nodes (Prell 2012).</td>
</tr>
<tr>
<td><strong>Subgroups (Newman and Girvan 2004)</strong></td>
<td></td>
</tr>
<tr>
<td>Newman Communities</td>
<td>Algorithm for creating subgroups by removing the connection with the highest betweenness and choosing the best-fit from the possible divisions.</td>
</tr>
</tbody>
</table>

**Context**

Data presented in this paper were collected from five science departments at a research/doctoral university. A university-wide change initiative invited members from these departments to participate in activities aimed at improving introductory science courses. Some faculty participated in faculty learning communities (regular small groups meetings to discuss aspects of teaching) or in an assortment of one-time presentations about teaching. Other faculty
did not participate directly in the change initiative. Two post-doctoral researchers helped with change implementation. The change agent (the principal investigator of the grant that funded the change initiative) is a faculty member in one of the departments. The social networks of the departments were collected to evaluate the change process and to inform future decisions regarding the change initiative.

Data Collection

Data were collected by surveying instructors about their relationships with other instructors in their department based on how frequently they discuss teaching with one-another. If an individual was nominated by a colleague then the return tie was also included in the network because discussions were assumed to be reciprocal. Individuals are connected to each other if they reported having discussions about teaching at least once a month over the previous academic year. Self-reports of general patterns, such as measured here, have been shown to be more accurate than self-reports of specific interactions (Marsden 2011).

Instructors in each department (professors, lecturers, laboratory coordinators and the change initiative’s post-doctoral researchers) were invited to take the survey (Fig. 2). Each respondent used drop-down menus to identify others within the department with whom he or she discussed teaching. The respondent indicated the frequency with which these discussions occurred (monthly, weekly, or nearly every day). The survey also allowed for individuals outside of the department to be named. When an individual outside of the department was identified by more than one respondent, he or she was added to the network.

Fig. 2 Example of an online survey for collecting network information
For the majority of analyses, we will not be concerned with the strength of ties. If a discussion was identified with a frequency of at least once per month then a link exists. If not, no link exists. If a member of the network chose not to respond to the survey and was not identified by a respondent, he or she was removed from the analysis because the presence or absence of ties to this person is unknown. The response rates of the survey results are in Table 3. The column labeled “individual added to the network” refers to individuals who were not surveyed but were mentioned by at least two respondents. Notice that this was relatively uncommon. The “percent of department included” indicates the percentage of department members (plus any added individuals) who responded to the survey or members who were connected to the network by a respondent.

Table 3 Response rates for network survey

<table>
<thead>
<tr>
<th>Department</th>
<th>Individuals Surveyed</th>
<th>Response Rate</th>
<th>Individuals added to the network</th>
<th>Individuals included in the analysis</th>
<th>Percent of department included</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>57</td>
<td>49%</td>
<td>0</td>
<td>44</td>
<td>77%</td>
</tr>
<tr>
<td>B</td>
<td>21</td>
<td>38%</td>
<td>0</td>
<td>14</td>
<td>67%</td>
</tr>
<tr>
<td>C</td>
<td>38</td>
<td>37%</td>
<td>0</td>
<td>20</td>
<td>53%</td>
</tr>
<tr>
<td>D</td>
<td>43</td>
<td>53%</td>
<td>2</td>
<td>32</td>
<td>71%</td>
</tr>
<tr>
<td>E</td>
<td>40</td>
<td>48%</td>
<td>1</td>
<td>34</td>
<td>83%</td>
</tr>
</tbody>
</table>

Network-Level Characteristics

Metrics calculated on the entire network are used by researchers to summarize group characteristics. Three network metrics will be discussed in this section: density, centralization, and transitivity (Table 2). The density of the network is used to describe how many relationships are present, as compared to how many relations are theoretically possible. The density is calculated by the number of existing ties divided by the number of possible ties in a completed network with the same number of nodes (i.e., where every node is connected to every other node) (Prell 2012). If a network has a very low density, then the information will move slowly or not at all. On the other hand, if a network is very dense, information can flow easily. However, a very dense network is also likely to have a high degree of homogeneity of ideas and, thus, it is less likely that innovative ideas will emerge.

The measure of density does not describe the distribution of ties. Ties are rarely distributed randomly in a network; instead, a few nodes are more popular and have many ties, while other nodes have few or no ties. The degree of a node is the number of ties that it has (Prell 2012). Centralization (sometimes referred to as “degree centralization”) describes how ties are distributed. Centralization is calculated by summing the difference between the degree of each node and the node that has the highest degree, and then dividing by the theoretical maximization of this sum (if all ties in the network were concentrated in the fewest possible nodes) (Prell 2012). The higher the percent centralization, the more the network ties are concentrated in a few nodes. A highly centralized network may have a core of individuals that dominate the flow of
information. Table 4 provides an example of calculated density and centralization on simplified networks.

**Table 4** Density and centralization of simplified networks

<table>
<thead>
<tr>
<th>Network</th>
<th>Density</th>
<th>Centralization</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Network Diagram 1" /></td>
<td>0.4</td>
<td>100%</td>
</tr>
<tr>
<td><img src="image2.png" alt="Network Diagram 2" /></td>
<td>0.4</td>
<td>58%</td>
</tr>
<tr>
<td><img src="image3.png" alt="Network Diagram 3" /></td>
<td>0.4</td>
<td>17%</td>
</tr>
<tr>
<td><img src="image4.png" alt="Network Diagram 4" /></td>
<td>0.5</td>
<td>0%</td>
</tr>
<tr>
<td><img src="image5.png" alt="Network Diagram 5" /></td>
<td>1.0</td>
<td>0%</td>
</tr>
</tbody>
</table>

Transitivity measures the cohesion of a group based on the presence of triad configurations. A closed triad is a group of three people who are all linked to one-another (Table 5). A related configuration of common neighbors (sometimes referred to as a 2-legged triad or broken triad), occurs when one node is connected to two others, e.g. node 1 is connected to node 2 and node 1 is connected to node 3, but node 2 is not connected to node 3. To measure the *transitivity* of a network, the number of closed triads in a network is divided by the number of broken triads (Newman 2003).
Table 5 How common neighbors may form a triad

<table>
<thead>
<tr>
<th>Broken Triad</th>
<th>Closed Triad</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Diagram of Broken Triad" /></td>
<td><img src="image" alt="Diagram of Closed Triad" /></td>
</tr>
</tbody>
</table>

Node 2 and node 3 have a common neighbor (node 1). Node 2 and node 3 become neighbors completing the triad.

High transitivity tends to reinforce groups norms and low transitivity tends to allow differing views and behaviors (Christakis and Fowler 2009). For example, in a network of known drug users, Trotter et al. (1995) found that as transitivity increased, individuals within the network were more likely to participate in risky behavior (such as drug use). The authors hypothesized that this increase in risky behavior was due to the added peer pressure present in a highly transitive network. Transitivity of a network or subgroup can be used to anticipate the likelihood that group norms are strongly enforced and if these norms will be a factor in the adoption of activities proposed by the change initiative.

This section has described three network-level measures that can provide information about how a network will function (summarized in Table 2). Density and centralization indicate how easily information will flow through the network (prescribed change) or if diversity of ideas is available in the network (emergent change). A high density indicates the availability of ties through which information can flow, and the higher the percent centralization, the more likely it will be that information is concentrated in the core of the network. Transitivity indicates how strongly the information, ideas, or behaviors within the network are likely to be influenced by peer pressure.

These summary characteristics were calculated for the five academic departments (Table 6). These metrics can be difficult to compare directly if the departments have different sizes (number of nodes) or density (Anderson et al. 1999). The centralizations of departments D and E may be compared because their size and density are nearly the same. Department D has a higher centralization because more disparity exists between the individuals with many ties and those with few ties. To encourage the spread of information in this department, a change agent may only need a few meetings with key individuals to reach the entire network. However, this department may also be very sensitive to the removal of central individuals. Department E has almost half the centralization with a similar density. Hence, the distribution of ties is spread more evenly throughout the network. Department E is likely to remain intact even if individuals chose to leave.

Department C has the highest density; conversations about teaching are occurring between many faculty. This department also has the highest centralization, indicating that there are a few key individuals, who could be either useful or detrimental to the change initiative. For transitivity, departments C and E are lower than the other departments, suggesting that the
influence of group norms (with respect to teaching) may be weak. A change agent in department C or E may wish to encourage transitive ties to strengthen social support for implementation of change.

Table 6 Summary characteristics of the five academic departments

<table>
<thead>
<tr>
<th>Department</th>
<th>Network</th>
<th>Density</th>
<th>Centralization</th>
<th>Transitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (n=44)</td>
<td></td>
<td>0.060</td>
<td>13.18%</td>
<td>11.36%</td>
</tr>
<tr>
<td>B (n=14)</td>
<td></td>
<td>0.176</td>
<td>24.36%</td>
<td>16.67%</td>
</tr>
<tr>
<td>C (n=20)</td>
<td></td>
<td>0.216</td>
<td>28.65%</td>
<td>8.39%</td>
</tr>
<tr>
<td>D (n=32)</td>
<td></td>
<td>0.117</td>
<td>25.38%</td>
<td>15.94%</td>
</tr>
<tr>
<td>E (n=34)</td>
<td></td>
<td>0.107</td>
<td>14.39%</td>
<td>8.16%</td>
</tr>
</tbody>
</table>
Individual Roles

Social network researchers have studied how individuals participate in different social roles based on the position of the individual with respect to their direct neighbors and to the structure of the network. Stephenson (2005) discusses two of these roles: hubs of knowledge and gatekeepers. Hubs are individuals who have the most ties to other nodes. (Although Stephenson does not define her roles mathematically, we will use her description to define hubs as nodes with high degree centrality). Having many direct neighbors allows hubs to learn information in the network and to spread information. Hubs are typically important and well-respected people. Degree centrality is calculated by dividing the degree of the node by the number of possible ties a node would have if it was connected to every other node in the network (Prell 2012). Fig. 3 uses size of a node to show the degree centrality (or the ranking of the nodes as hubs) of members of department B. The larger the size of the nodes, the more ties it has. Recall that department B had a high centralization, meaning that the distribution of ties is concentrated in a few nodes (A and E) rather than spread across the network.

Fig. 3 Measure of hubs (total degree centrality) is represented by the size of the node in department B. Node E and node A are hubs.

The second role identified by Stephenson (2005) is gatekeepers. Gatekeepers are the individuals that act as links between disconnected clusters of the network. We identified gatekeepers by betweenness, calculating the sum of the number of shortest paths between two disconnected nodes that includes the gatekeeper node divided by all shortest paths between the two nodes (Prell 2012). For example, two nodes in Fig. 4 that are not directly connected are node A and node N. However, the two nodes are connected through a path that includes node E. This is a path of length two (number of lines in the path). It is the shortest path that exists between node A and node N. In order to be considered a gatekeeper node, a node must have many of these shortest paths which connect otherwise disconnected nodes. In Fig. 4, the size of the node symbol in department B is based on betweenness. Node E is the largest size because all the nodes
on the left of the network must have paths through node E to reach the right side of the network. Gatekeepers have access to the information available in otherwise disconnected sections of the network. The gatekeeper can choose to share information across these groups, or may become a “bottleneck” if he or she chooses not to share information (Stephenson 2005).

![Diagram of network](image)

**Fig. 4** Measure of gatekeepers (betweenness) is represented by the size of the node in department B. Node E and node N are gatekeepers.

**Subgroups**

Networks are often subdivided into groups with many connections among members of a group and few connections to members of other groups. Subgroups tend to have higher transitivity and thus, have similar values and behaviors (e.g. attitudes and practices about teaching) (Christakis and Fowler 2009). SNA has identified strategies for distinguishing subgroups within a larger network. These include cliques, K-cores, and lambda sets (Prell 2012). These techniques identify a structure of nodes that have more ties with each other than with the rest of the network.

For subgroup identification, we used the algorithm developed by Newman and Girvan (2004) that is based on removing connections between nodes. In this strategy, the connection that has the highest betweenness (provides the highest number of shortest paths between otherwise disconnected nodes) is removed. If this removal creates disconnected components, then these candidate subgroups are assigned a value of modularity based on the actual number of in group ties (ties between members of a subgroup) versus out of group ties (ties between members of different subgroups) as compared to this relationship in a randomly-developed network with the same subgroups. If the removal does not create disconnected components, then no modularity is assigned. Next, the betweenness is recalculated and the connection with the highest betweenness is removed. These two steps are repeated until all possible numbers of subgroups are found. Finally, the modularity values that were calculated for each set of subdivisions are compared. The subdivision that has the highest calculated modularity is assigned as the subgroups of the
network, called Newman Communities (Table 2). Subgroups may have any number of nodes (including n=1) because the identification process is only based on removing connections.

This strategy is useful because it does not allow for nodes to be members of more than one subgroup and the number of subgroups is not chosen by the user (the algorithm uses modularity value based on in-group ties versus out-of-group ties to pick the most likely number of subdivisions). Fig. 5 shows the five subgroups (different node symbols) in department C identified by the Newman-Girvan algorithm. The network is dominated by two subgroups (filled triangles and open squares). A change agent can use this information to investigate if the subgroups have different teaching-related norms and, if so, how these norms will affect the change initiative.

![Fig. 5 Newman Communities in department C identified by the shape of the node](image)

**Using the Hidden Structure to Inform Change Initiatives**

The tasks of the change agent determine which SNA tools should be used. In this section, we outline three main tasks that can be facilitated through knowledge of the network. These tasks include sampling the current state of the network, identifying which individuals to target for participation, and anticipating the spread of change. This section identifies the SNA related to each task and demonstrates the use of these techniques with the five academic departments. In addition, we will highlight where these tasks may differ between emergent or prescribed change initiatives.

**Current Network State**

The current state of the network can be used to identify the ideas and opinions that are shared among individuals in the network. For both emergent and prescribed change, knowledgeable informants must be located. Time and resources rarely allow for interviews with each faculty member. By using SNA, a few individuals (hubs) can be identified who are likely to have opinions that are representative of the network (either the full network or a particular
subgroup). This information can guide the creation of innovations that meet the needs of most members of the network.

In very dense networks without strong subgroups, it is likely that each individual has similar ideas and practices related to teaching. However, when a network has subgroups, it becomes more likely that ideas and practices will vary across the network. Identifying these subgroups will help the change agent decide the number and variety of hubs needed to represent the network.

The networks of department D and department A had different centralization and subgroup structure (Fig. 6). Department D had a higher centralization and few subgroups. Department D would only require a few interviews with three hubs (identified by visible labels and node size in Fig. 6) because it is likely that this network operates in a unified manner. However, in department A, the centralization was lower and subgroups were prominent. The change agent would need to contact more hubs (visible labels) across subgroups to provide insight into the norms of the subgroups. In department A, it would be important to develop a relationship with the gatekeepers between the subgroups to provide knowledge about how ideas may be transmitted between subgroups and how different the norms of the subgroups were from each other.

**Fig. 6** Department D and department A with different subgroups represented by different symbols. The size of each symbol is proportional to the degree centrality of that person

### Participation

Once the current state of ideas has been uncovered, a change agent will need to recruit participants. The individuals that are asked to participate may partially depend on the role they play in the network structure: hubs, gatekeepers or subgroup membership.

For change initiatives that rely on the diffusion of ideas (i.e. prescribed change), the participants should be hubs who might spread the innovation to their neighbors. This analysis of network structure was used in department D and department A to identify potential participants in the reform (Fig. 6). Two out of four facilitators for the faculty learning communities were
recruited using this approach. The individuals who held roles of hubs and gatekeepers were invited to meet individually with the change agent. At these meetings, they were given information about the change initiative’s goals and were invited to participate in change initiative activities. Even for those individuals who chose not to participate, it is likely that their connections to others allowed for information to circulate throughout the network. This idea is supported by the many studies on SNA that have shown how influence flows throughout the network (e.g. Christakis and Fowler 2009). The other two faculty learning community facilitators were recruited because of their expertise and self-identification as being enthusiastic about the change initiative even though they were not necessarily hubs or gatekeepers.

Change initiative participants may be placed in groups based on the goals of the change agent. To develop relatively stable groups, potential members could be individuals who already report having regular discussions about teaching with one another. Stable relationships among a group are likely to persist throughout the challenges of implementing and sustaining change. Frequency of discussions can be used to identify robust relationships. Fig. 7 identifies the core members of department C based on frequency. In this department, many of the individuals who discussed teaching on a weekly basis were invited to participate in a faculty learning community, although not all of them accepted. Many of the individuals who did participate have sustained dedication to the change initiative (~3 years).

![Graphs](Fig. 7 Department C discussions about teaching analyzed by frequency)

Instead of steady-state interactions, a change agent may encourage the development of new ideas (emergent change) by connecting faculty members that do not usually interact and, thus, may have diverse perspectives (Plowman et al. 2007). Analysis of subgroups can identify these individuals. The current state of department E is shown in Fig. 8. A change agent may wish to connect individuals from different subgroups who are likely to have diverse ideas (i.e. nodes CC, AA, Z, GG, and KK). This novel grouping with members from unique subgroups may include too much diversity (individuals that have such differing opinions that they are not able to make progress as a group). By analyzing the current state of opinions before creating novel groupings, the change agent can decide how much diversity is needed. This is an area of future research that may result in more specific advice in creating diverse groupings with productive qualities.
Fig. 8 Department E with subgroups (by shape). A possible novel grouping with members from different subgroups is identified. The department chair is node S

Anticipating Spread

After new practices have been adopted by particular individuals or developed through novel groupings, the change agent will be interested in expanding use of these practices. The expansion of change across the network may be based on two ideas. First, expansion may be through spread of ideas from one individual to another (Rogers 2003). For this process, new adopters of the innovation spread the idea to their contacts and eventually the innovation reaches all members of the network. The second possibility is change flows from the faculty development groups to the formal leadership of the department. Change is adopted by the department as a whole when formal leadership structurally supports the emergent ideas (Plowman et al. 2007).

The density of the network can indicate how soon individuals on the periphery of the network will be connected to someone involved in the innovation. The spread of innovations will be dictated by the gatekeeper nodes. For example, in department A (Fig. 6) the periphery nodes are several social connections away from the hubs (potential early adopters). The small square nodes located near the bottom of the image are only connected through a single gatekeeper. Because of these periphery nodes, this department may require prolonged support before the entire network is reached. Change agents should also be aware of the isolated individuals. It is likely that new ideas will need to reach these individuals through means other than social connections (possibly by formal meetings or indirectly through department culture).

To anticipate the spread of emergent ideas through policy changes, the change agent will need ensure the ideas developed by novel groupings are reaching the formal leadership. Studies have found that the department chair plays a crucial role in connecting the innovations created by the individual faculty with the administration of the university; much like a middle manager may function in a company (e.g. Edwards 1999; Senge 2000). In Fig. 8, the department chair is node
S. By ensuring that she is connected to the novel groupings, the change agent can encourage the spread of change to the formal administration of the department. With the novel grouping example, node S is only connected to node KK. The change agent may desire to encourage more of these connections to the department chair to increase the knowledge flow to the administration.

**Is the Hidden Structure Really Hidden?**

We have argued that SNA is needed to understand the structure of academic departments. In this section, we provide evidence that the network of teaching-related discussions cannot be identified by the formal structure of the department (i.e. office location, research collaborations) or by the personal attributes of individuals. We first test the hypothesis that the teaching discussion network may have developed because of personal characteristics, such as years of experience. SNA has revealed that an individual is likely to form relational ties with other individuals that have similar personal characteristics. This process is called homophily (Prell 2012). Furthermore, once ties are formed between groups of individuals, these groups tend to share norms that are reinforced by social ties (Christakis and Fowler 2009). The interaction between personal characteristics and social ties may suggest personal attributes could be used as a proxy for the social network.

We chose to test for these correlations on two departments (A and C). Personal attributes were correlated with social ties to test if any of these attributes might be the defining factor of a social network (summarized in Table 7). The tested attributes were: gender, ethnicity, job title (lecturer, assistant professor, associate professor, professor), office location and hire decade (groups of individuals hired in the 70s, 80s, 90s, etc.). The statistical test partitions the network according to the categories of the attributes. In other words, the network is put into subgroups according to category membership. Next, it performs a test similar to a chi-squared test, except with randomized networks (with the same number of nodes and ties as the original network) as comparison instead of the chi-square distribution (Relational Contingency- Borgatti et al. 2002). If the test is statistically significant, it means that tie formation is related to the categorical attribute (the categorical membership of a node influences how ties are formed, such as males tend to form ties with other males). Statistical significance was not found with any of the tested characteristics in departments A or C. This means that discussions about teaching among individuals within the same category were no greater than discussions that occurred across categorical lines. The lack of significance led to the conclusion that the relation between the discussion network and attributes cannot be known in advance of analysis. One of the limitations of this evaluation is that not all potentially predictive attributes were tested. However, it seems unlikely that any easily-obtainable attributes could be used as a proxy for the social network.
Table 7 Summary of p-values for the statistical tests of homophily

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Department A P-values</th>
<th>Department C P-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>0.33</td>
<td>0.25</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>0.18</td>
<td>0.38</td>
</tr>
<tr>
<td>Job Title</td>
<td>0.10</td>
<td>0.25</td>
</tr>
<tr>
<td>Office Location</td>
<td>0.65</td>
<td>0.40</td>
</tr>
<tr>
<td>Hire Decade</td>
<td>0.50</td>
<td>0.29</td>
</tr>
</tbody>
</table>

It was also hypothesized that the faculty teaching discussion network may be related to research collaborations. If this was the case, it would be possible to use a research collaboration network to inform the change agent tasks. This would be desirable since research collaboration data already exists and can be compiled without relying on faculty surveys. To test this idea, the publications of individuals within each department were identified using the citation indexing website Web of Science® (Thomson Reuters 2013) for the years of 2009, 2010, and 2011 (teaching discussion network data were collected in early 2012). If two members of the network co-authored a publication, then a link was created between them. Fig. 9 shows the networks of department C and department A with respect to teaching discussion and co-authorship of publications.

For department C, only three relations between faculty members are replicated in both networks. Although three of the five links in the co-authorship network are also present in the teaching discussion network, if the co-authorship network was used as a proxy for the teaching discussion network, much of the detail would be lost. For example, node II is central in both networks. However, the co-author publication network reduces the number of individuals with whom node II is connected. In contrast, the department A co-authorship network is much denser. However, there are only three overlapping links between the co-publication and teaching discussion networks (A and QQ; II and QQ; OO and QQ). Thus, in neither case would knowledge of the co-authorship network allow the researcher to predict the teaching discussion network. Therefore, we argue that survey measurement is a reasonable way to access this otherwise hidden structure of teaching-related discussions.
SNA has been used by many disciplines to explain individual and group behavior. In education, teaching-related change initiatives at the pre-college level have been informed by SNA. But, SNA has not yet been applied to teaching-related change initiatives in higher education. Change agents in higher education are attempting to move away from approaches to change that focus on individual faculty to departmental-level approaches. The power of the academic department over course structure and the expectations of behavior from faculty make it a productive unit of change. Because of the power of social connections on group behavior, the purpose of this paper has been to demonstrate how SNA might be applied by change agents to inform departmental change initiatives in higher education. Techniques were demonstrated to identify the social structure of academic departments through a survey of self-reported discussions about teaching and six measures were introduced to describe important characteristics. We have shown that this structure cannot be identified through known characteristics or research collaborations.

In this introduction to the use of SNA in change in higher education, we have demonstrated how networks can inform emergent and prescribed change strategies by identifying key individuals, subgroups and network level features. These features inform change agent tasks of monitoring the flow of ideas, targeting participants, creating groupings, and encouraging
spread of an innovation. A change agent can use hubs of knowledge and gatekeepers to monitor the current state of the department and to recruit individuals. Choosing these informants depends on the presence of subgroups. When subgroups exist, the change agent must be aware that opinions and norms may vary across subgroups. Targeting individuals across subgroups can increase the likelihood of involving every subgroup in change. The potential variety of opinions in different subgroups is also important for creating diverse ties to encourage the development of emergent change.

The exploratory nature of this paper has allowed us to introduce SNA measures that have the potential to inform change agent tasks. However, these measures are only a sampling of the tools that SNA researchers are developing to understand how networks influence people (for an introduction see Prell 2012). Furthermore, with only five academic departments, future work is needed to investigate typical ranges and ideal measures for the teaching discussion networks of academic departments. Investigations are needed to test and refine the suggestions for use of SNA to inform change initiatives. Important questions for future study include: What level of diversity of ties is needed to promote knowledge creation? How can a change agent use preliminary network analysis to make decisions about initiative activities? How will social networks of academic departments evolve throughout the process of a change initiative? A change agent can begin to explore the measures and recommendations provided in this paper while also being aware that there is much room for additional study and expansion of the use of social networks in higher education.

References


