# Department-Level Change: Using Social Network Analysis to Map the Hidden Structure of Academic Departments

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**Abstract.** Efforts to improve teaching in higher education have often focused on individual faculty. However, there is a growing consensus that the academic department is a more productive focus of change initiatives. Yet, academic departments are not all the same. Understanding the structure of relationships within a department is important for identifying who should be involved in the change effort and in what roles. It is also likely that a successful change effort will modify the structure of relationships within a department. This paper presents the preliminary results from a study of two academic departments at a research university. A social network for each department was constructed based on a web survey that asked faculty to identify colleagues with whom they had teaching-related conversations. We identify characteristics of the individuals and departments and describe how learning about this hidden structure can be beneficial to change agents.

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# **INTRODUCTION**

In recent decades, educational researchers have developed significant knowledge about instructional practices that improve student learning in undergraduate physics courses. Similar practices appear to be effective across all science disciplines. In efforts to promote the use of these improved instructional practices, change agents based in the sciences typically treat the problem by focusing on individual faculty [1]. Yet, there is a growing body of evidence that suggests the academic department is the most productive unit of change [2].

Researchers, though, are only just beginning to develop knowledge about how to work with the department as a unit of change. This paper describes a preliminary study of the use of social network analysis as a tool to understand the hidden social structures of academic departments. We first discuss the methods used to model a departmental social network. We then use examples of the social networks of two science departments at a large research university to describe how knowing about the network structure might be useful for change agents.

# **METHODS**

This preliminary study is based on the network structure of teaching discussions in two science departments at a research university. Both departments were involved in a multi-departmental four-year reform effort; however, not every faculty member participated directly in the reform.

Data were collected using an online survey sent to individual faculty members. The survey asked respondents to identify others within the department with whom they had discussions about teaching. Respondent chose people from a dropdown list of names (that included all faculty in the department) and identified the frequency with which the teaching discussions occurred over the last academic year (never, less than once per month, monthly, weekly, and nearly every day). The survey also included a freeresponse question to allow respondents to include individuals outside of the department.

#### RESULTS

Department 1 had a response rate of 44% and Department 2 had a response rate of 52%. Responses were analyzed using standard social network analysis with the ORA software tool [3]. Links between faculty members represent discussions about teaching. The social networks were assumed to be undirected [4] and non-respondents were treated the same as respondents who reported no conversations about teaching [5].

The results will be presented in two parts. First, we will discuss issues related to the community structure of each department. Then, we will discuss the roles that individuals play within the department. In both cases, we will highlight aspects of the analysis that are likely to be most useful for change agents.

#### **Part 1: Community Structure**

The analysis of each department began with an investigation of Newman Communities [6]. Newman developed an algorithm for identifying partitions (communities) within a network in such a way that the number of links between individuals within a community is as large as possible and the number of links between individuals in different communities is as small as possible. Communities within a larger group are subdivisions of individuals who have more conversations amongst themselves than with individuals outside of the subdivision. Newman also developed a measure of modularity to describe the extent to which the network has modular/community structure (on a scale of 0 to 1, with 0 representing no community structure, or the structure that would be expected in a randomly-created network with the same number of individuals and links). According to Newman, modularity values between .3 and .7 are expected for networks that have community structure. Networks with a modularity value greater than .7 are rare and a modularity of less than .3 represents very low community structure.

Department 1 (N=57): The resulting network consisted of 19 isolated faculty members (no recorded discussions about teaching) two pairs of dyads (individuals that only discussed teaching with each other) and the remaining 34 in a single component. The Newman community algorithm identified four subdivisions of the main component (Figure 1). The modularity for Department 1 was .56, indicating a significant level of community structure in the department. The division of the network into community structure has implications for identifying key actors within the entire network and within communities (discussed in the following section).



**FIGURE 1.** Department 1's main component and community structure. Circles, pentagons, triangles and squares represent the community membership.

Department 2 (N=46): Although the survey was only distributed to the 44 members of Department 2, two non-department members were mentioned by more than one respondent. These were added to the network. The resulting network consisted of one main component and 18 isolated faculty members. The community algorithm Newman found four communities in the main component (Figure 2). In contrast to Department 1, Department 2 had a modularity value of 0.35 which is close to the threshold of values expected for networks that have community structure. Therefore, the community divisions in Department 2 were less prominent than in Department 1. This lack of relatively isolated subgroups (with respect to discussions about teaching) means that there are unlikely to be different 'camps' of faculty within the department with disjointed views about teaching and learning.



**FIGURE 2.** Department 2's main component and community structure. Circles, diamonds, triangles and squares represent the community membership.

### **Part 2: Important Individuals**

Our main interest in understanding the structure of discussions about teaching within these departments is to inform educational change efforts. Understanding this structure can allow change agents to identify individuals who will be useful to spread information throughout the network and to monitor the flow of information across the network. Researchers have identified three important roles that individuals can play in a network (see Ref. [7] and Table 1): hubs, pulse takers, and connectors. Individuals that play these roles were identified using the ORA software tool.

*Hubs* of information are individuals that have many discussions about teaching. These members are central

in the network. Hubs are important allies for reform leaders because these individuals can quickly spread information across the network. They can spread information about procedures of the reform, as well as reform successes (that may be important for recruiting new science faculty into the reform).

*Pulse takers* have quick access to information in the network. They have many links within a cluster, but are not important for the flow of information because they do not connect otherwise unconnected individuals. Pulse takers do not spread information, but are important for change agents since they can provide the status of information and attitudes within the network.

*Connectors* are individuals who act as gate keepers between clusters (or hubs). These individuals can choose to share information across the network, or may restrict information flow by withholding information. A change agent needs to have a relationship with these individuals to ensure the flow of information about the change effort is reaching across the network. The change agent will also want this information to represent the change effort in a positive way.

Figures 3 and 4 show the top five hubs, pulse takers, and connectors in each department. The community structure must be taken into account when identifying important individuals. For example, in Department 1 the community structure was more prominent. When identifying connectors, there were no individuals recognized in the square community (pictured in Figure 1). Because the community structure is present in the network, it may be important for the reform leader to include Faculty Member 'CC' (a connector in the square community and across communities) in discussions about the flow of information in the network. In departments that show community structure, this extra analysis is necessary to make sure all communities are represented in the knowledge gained from and shared with the network.



**FIGURE 3.** Top 5 hubs, pulse takers, and connectors in Department 1.



**FIGURE 4.** Top 5 hubs, pulse takers, and connectors in Department 2.

THE I. The important Roles of Individuals in Boeni (Retworks (adapted Holin Refs. [7,6]).		
Role	Why Important?	How to Calculate [8]
Hubs	Have many discussions about teaching with many other individuals.	High total degree centrality (number of links divided by total number of possible links).
Pulse Takers	Have many discussions with well-connected individuals, but are not themselves important links in the flow of information.	High closeness centrality (the average of the shortest path to all other network members) and low betweenness centrality (how many shortest paths between pairs of network members pass through the individual).
Connectors	Promote flow of information via discussions with individuals in separated parts of the network.	High betweenness centrality (how many shortest paths between pairs of network members pass through the individual).

TABLE 1. Three Important Roles of Individuals in Social Networks (adapted from Refs. [7,8]).

### **DISCUSSION AND FUTURE WORK**

In this paper we have presented the preliminary results of a study of the social network structure of academic departments with respect to discussions about teaching. Although we have discussed how to measure community structure and individual roles, we have not yet demonstrated how this knowledge is useful for change agents. Here we present three anecdotes to illustrate the potential utility of the type of social network analysis presented here.

We have argued that information about the hidden departmental structure can be important for change agents. For this study, the information about these two departments was given to the leader of the multidepartmental change effort. The leader indicated that this information was very helpful in being able to identify particular faculty members to include in the change effort and for identifying the individuals that were important to information flow.

In addition to being able to identify communities within departments, a natural question is to ask why such communities arise. Since these are departments at a research university, one might think the communities we identified for teaching-related discussions resulted from the research subfields of these faculty. If this were correct, then it would not be necessary to create a separate network for teaching-related discussions. Yet, there was only one community (out of the eight communities we identified) that was strongly associated with a research subfield. Through other information we have about these departments, we know that this research subfield has a weekly meeting for the discussion of research issues, but at which teaching discussions often occur before or after.

Finally, we suggest that this type of social network analysis can be used to document the impact of change efforts. For example, in Department 2, faculty members were asked to recall the individuals with whom they discussed teaching before the reform effort began. The resulting network had a Newman modularity value of .54, indicating that the department previously had a much higher community structure than it does currently (current modularity is .35). One activity of the reform effort was the development of a group of faculty who met biweekly throughout the school year to discuss instructional concerns. The impact of this meeting may have caused the decrease in community structure of Department 2, into a more centralized group. This reduction in community structure is a positive sign for a change effort that takes the department as the unit of change.

## CONCLUSIONS

Understanding the structure of the department's social network appears to be promising for informing change efforts that focus on the department level as the unit of change. We have shown how to identify community structure and individuals within a network (or community) that represent hubs, pulse takers and connectors. These individuals can be targeted by reform leaders to advance information throughout the network and to be key actors in change efforts. We have also presented preliminary evidence to suggest that social network analysis may be a useful tool in measuring alterations in departmental structure due to change activities. This type of measurement is useful for both documenting the impact of change initiatives as well as improving theory related to creating change.

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- 3. http://www.casos.cs.cmu.edu/projects/ora/
- 4. This means that if one person reported having discussions about teaching, then the return connection was also created. If the strengths were not equal, the highest frequency was assumed.
- Both types of individuals could still have links to the network, if they were identified by other respondents. However, non-respondents add a limitation to the study by increasing the possibility of unreported teaching conversations between faculty members.
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