Methods for Triangulation and Revealing Interaction

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Abstract: Quantitative methods in educational research tend to be heavily reductionist and to disregard interaction; most statistical models include an assumption of no interaction. Qualitative methods allow complexity and interaction, but tend not to include representations or otherwise allow the reader to "see" the interaction as the researcher can. By combining traditional qualitative methods with statistical modeling, we are afforded a better opportunity to see aspects of a phenomenon, but not always greater integration; interpretation does not easily emerge from potentially divergent data sets. By including social network analysis, which provides both summary statistics and graphical depiction of interaction we are afforded a better opportunity to examine collaborative work. Furthermore, technology facilitates collection and analysis of change over time in computer supported collaborative work. These methods enable a multifarious view of quantitative data, and allow for interpretation to more naturally emerge from multiple data sets.

Purpose

The purpose of this interactive event is to demonstrate innovative ways to analyze and represent collaborative learning processes and products. Static and "snap-shot" analyses predominate, resting on an implicit assumption that outcomes and products accurately reflect learning processes. Technology offers great potential for analysis of complex interactions and processes, though much of this potential is out of reach to many because of a lack of programming experience. By employing familiar programs (Excel and a graphics program such as Illustrator or a concept mapping program such as Inspiration or CMap) in creative ways, we can move beyond purely reductionist uses of numerical data, and evolve hybrid graphs in conversation with qualitative data, and as a tool for mixed methods integration. An illustrative example, derived from student design teams reporting on the productivity and utility of mentor interactions, is provided.

Objectives

Participants will learn basics about social network analysis (SNA) and about the limitations to current SNA software, such as UCINET (Borgatti, Everett, & Freeman, 2002) and Pajek (Batagelj & Mrvar, 1998), which tend to represent data according to projections which may or may not be appropriate and are rarely deliberately and meaningfully chosen by the researcher. Instead, participants will use either a graphical or concept map program to represent data (This may be data they already have, data collected about learning as a result of CSCL interactions during the conference, or data from the presenters on student design team interactions related to the illustrative example, described later).

SNA is an attempt to formalize and empirically explicate relationship ties and their patterns. Systemic relationship ties are considered as structures, and are measured by structural variables, whereas individuals are considered to be actors. Actors are viewed as interdependent and therefore are seen to influence each other. This view is critical for studying systems in which distributed cognition is ubiquitous. Relations between actors may be evaluative (like, respect, friendship, etc), may be based on movement (either physical, as in migration, or social, as in changes in employment), may represent types of relationships (kinship, other formal, societal roles, may represent transfer or flows (of material resources such as money, or non-material such as communication of knowledge), or may be based on types of interactions. Relations may be directional or non directional and dichotomous or valued (Wasserman & Faust, 1995).

SNA may provide descriptive context for relationships. Alternatively, hypotheses about relationship properties of the model may be tested via several methods (Wasserman & Faust, 1995). The unit of analysis is the whole group, not the individual actor, though differences of actors within groups may be contrasted. Outcomes from a model may be used as variables in other statistical modeling techniques (Wasserman & Faust, 1995). Additionally changes to structures or growth over time may be modeled (Wasserman & Faust, 1995). SNA produces several options for examining relationships and roles based on relationships. These include degree centrality, which reflects the number of direct connections to an actor; betweenness centrality, which reflects the degree to which an actor has influence over flow within a network; and closeness centrality, which reflects closeness between actors.

There is a very productive relationship between qualitative research and SNA, which may demonstrate whether interactions of subsets are different from a larger population, or be used to detect the extent of a network or to identify roles. The two have been effectively paired in diverse domains, from analysis of gang relationships (Fleisher, 2005), to studies of nomadic peoples (White & Johansen, 2006), to studies of computer supported collaborative learning (Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003).

SNA is at once graph theory and matrix algebra. It affords representations that preserve the complexity of interaction, yet also provides variables summarizing characteristics of the group. For instance, group degree centralization (Cd) summarizes the variance in (strength of) ties each individual has to others. This may be used as a measure of cohesion, which can be included in statistical models involving collaborative learning.

When studying groups, it is critical to have group level measures, though these are challenging to procure, especially when it is the interactions between members, and not simply a group product that may be measured as one item. Interactions may not be considered to be unidimensional, adding to the difficulty. By having group members rate each other (bidirectional, valued data) and rate their other mentors (unidirectional, valued data) along multiple facets (likert scaled), we may produce group level summary statistics of these ratings. Such summary statistics may then be used in a statistical model (Figure 1).

Alternatively, SNA may be used to identify the boundaries of a group, and to locate cliques or subgroups and individuals who hold differing roles within a group. In this case, binary data may be most appropriate. In this interactive event, we will consider how participants' reported interactions during the conference may be represented, but will consider other uses of SNA for understanding collaborative learning.

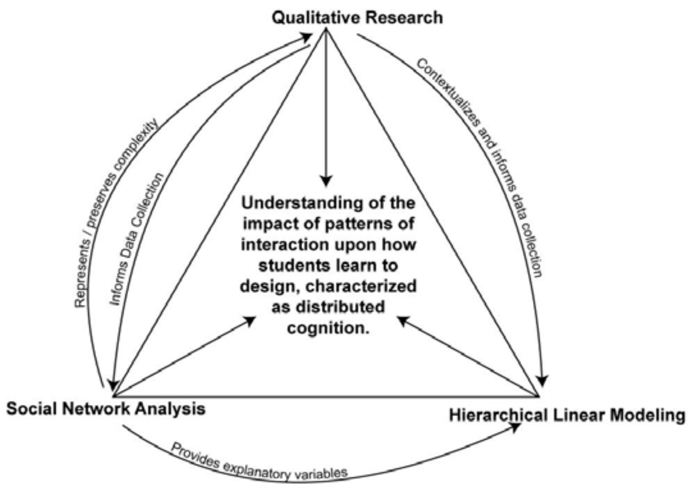

Figure 1. An example of how Social Network Analysis can act as a bridge between methods

Format

This event will begin with a brief discussion of the objectives, and participants will be asked to consider current issues they are having both in representing interaction and in interpretation and triangulation of mixed data. We will briefly discuss an example, then engage in our own analysis.

Participants may opt to complete a survey for each day of the conference (responding to "CSCL is an opportunity for learning. From whom have you learned something today?"), providing data for us to analyze at the interactive event. Alternatively, participants may bring their own data or use data related to the illustrative example. Participants will then contribute to a CMap (http://cmap.ihmc.us/conceptmap.html), a collaborative and free concept mapping program, which we will repurpose to consider both the quantitative analyses possible with these data, as well as the ways in which the graph may better reflect the interactions by also considering qualitative aspects of the interactions. We will also explore ways to produce summary statistics in a spreadsheet program (e.g., Excel) and consider how and when these might explain variance in statistical models of learning.

We will discuss ways to make different aspects of the graphs salient, and ways to use the various affordances of graphs. By deliberately choosing to define location, line thickness, color, and proximity, we may think about powerful ways to represent rather than uncritically allowing automatically-generated representations to coerce us into using ill-conceived models (for instance, using 3-D bar graphs when this may misconstrue the actual differences) (Tufte, 1983).

Illustrative Example

In this example, students within design teams were surveyed at three time points about the quality of their interactions with their mentors. Summary statistics of team cohesion were generated through social network analysis of these data and combined with other explanatory variables to explore whole class trends related to innovative design. Three case study teams were observed throughout their design processes, and these data were combined with the surveys from the case study teams to create graphs representing team interaction (Figure 2).

In this case, location of actors (the black rectangles) is an interpretation based on who reports interactions, who is observed interacting, how individuals interact, and who is referenced as helpful, both in surveys and in conversations.

In this example, we see the utility in representing groups over time. A singular graph would be messy and difficult to interpret. By including graphs from various time points, and by looking at several different groups, various features may become salient. Traditionally, only quantitative aspects are included, and the locations are determined by some sort of projection. Within the context of mixed methods research, we may capture the quantitative aspects by using the summary statistics of group interaction in a statistical model, and therefore use the graph as a base for creating hybrid interpretative graphs of the recorded and observed interaction. In this case, we notice greater change across teams rather than across time, but can still quickly pick out changes over time within teams. By letting these graphs evolve in conversation with qualitative analysis, location, rather than a projection based on an algorithm, becomes meaningful.

The process of generating such graphs allows the researcher to combine qualitative and quantitative data in a hybrid way, and to consider how these sometimes divergent data both reflect aspects of phenomena under study. This can be a powerful exercise towards triangulation of results, which can be an effortful and challenging task (Creswell & Clark, 2007).

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