

# Grounded Neural Networking: Modeling Complex Quantitative Data

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*The latest advances in artificial intelligence software (neural networking) have finally made it possible for qualitative researchers to apply the grounded theory method to the study of complex quantitative databases in a manner consistent with the postpositivistic, neopragmatic assumptions of most symbolic interactionists. The strength of neural networking for the study of quantitative data is twofold: it blurs the boundaries between qualitative and quantitative analysis, and it allows grounded theorists to embrace the complexity of quantitative data. The specific technique most useful to grounded theory is the Self-Organizing Map (SOM). To demonstrate the utility of the SOM we (1) provide a brief review of grounded theory, focusing on how it was originally intended as a comparative method applicable to both quantitative and qualitative data; (2) examine how the SOM is compatible with the traditional techniques of grounded theory; and (3) demonstrate how the SOM assists grounded theory by applying it to an example based on our research.*

A new moment has arrived in the tradition of grounded theory (Charmaz 2000): grounded theory is no longer limited to the methodological formalities of its original users (e.g., Glaser and Strauss 1967) but is instead open to new ideas. Examples are Charmaz's (2000) constructivist—contra objectivist—approach to grounded theory; Soulliere, Britt, and Maines's (2001) grounded conceptual modeling; Strübing's (1998) simulated grounded theory; and computer-assisted grounded theory (Richards and Richards 1994). Even Strauss and Corbin (1990, 1998) offer a new post-positivistic version of grounded theory.

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The reasons for this new moment in grounded theory are several and include the criticisms of postmodernists (e.g., Richardson 1993), advances in computer technology (Richards and Richards 1994), and the explosion of new forms of qualitative inquiry (Denzin and Lincoln 1994, 2000). As Charmaz (2000:511) explains, “[R]esearchers starting from other vantage points—feminist, Marxist, phenomenologist—can [now] use grounded theory strategies for their empirical studies. These strategies allow for varied fundamental assumptions, data gathering approaches, analytic emphases, and theoretical levels.”

The strategy we offer in this essay is *grounded neural networking* (GNN) (Garson 1998; Strübing 1998). The specific technique we focus on is the Self-Organizing Map (SOM) (Kohonen 2001). The SOM represents the latest advance in qualitative computing (Richards and Richards 1994; Strübing 1998; Weitzman 2000) and joins the list of software programs being used by grounded theorists, including *QSR N6*, *QSR NVivo*, *The Ethnograph*, and *Atlas.ti* (see [www.scolari.co.uk](http://www.scolari.co.uk)). These programs aim to assist in collecting, organizing, coding, and analyzing data. The main difference between the SOM and these other techniques, however, is that the SOM can analyze complex quantitative data. The SOM, as we explain below, is a postpositivistic, nonlinear clustering technique that can comb through large, complex numerical databases to find nonobvious patterns and relationships between conceptual indicators derived from various forms of data: quantitative, graphic, narrative, and audio. Familiar examples of the SOM are facial pattern recognition, analysis of disease trends, tumor detection, and primitive learning in robots and smart machines (Kohonen 2001; Kosko 1993).

In terms of grounded theory, the most important feature of the SOM is that, while it analyzes quantitative-numerical data, it is a qualitative technique. Unlike statistics, the SOM is not driven by hypotheses; it is not governed by the linear model; it searches for patterns of difference rather than aggregate norms and trends; it focuses on the relationships between conceptual indicators rather than the most powerful single variables; and, most important, while “intelligent,” it is actually dumb: the SOM does not tell you why it arrived at the results it gives you. There are no t-tests of significance or weighted regression coefficients to interpret. The output is open-ended, visual, and intuitive. To make sense of the nonobvious patterns and trends found, the researcher must apply traditional grounded theory techniques, including coding, memo writing, and theoretical sampling. In short, the SOM allows researchers to use grounded theory as originally intended by Glaser and Strauss—as a comparative method that blurs the boundaries between quantitative and qualitative data for the purposes of generating theory. In these ways, the SOM is part of the new paradigm shift in social science inquiry.

To demonstrate the utility of the SOM, we begin with a brief review of grounded theory as originally conceptualized by Glaser and Strauss, focusing on how it was intended as a comparative method applicable to both quantitative and qualitative data. Second, we briefly review how the SOM, as a qualitative conceptual modeling technique, is compatible with the techniques of grounded theory. Finally, we

demonstrate how the SOM assists grounded theory by applying it to an example based on our research.

## GROUNDING THEORY AND THE ANALYSIS OF QUANTITATIVE DATA

As numerous qualitative researchers have made clear over the past thirty-six years (e.g., Charmaz 2000), grounded theory is an exploratory approach to theory construction based on the comparative method that researchers use to find nonobvious patterns and relationships in a systematically collected set of data. Such inquiry aims to make theory and data inseparable from one another so that no theory can be stated apart from the data on which it is grounded and no data can be talked about without being grounded in the theoretical framework organizing it. As Glaser and Strauss (1967:2) state: “The basic theme in our book is the discovery of theory from data systematically obtained from social research.”

Most qualitative researchers do not realize, however, that Glaser and Strauss intended grounded theory to be used with both qualitative and quantitative data. For them, the data used is not important as long as the researcher aims to construct rather than verify theory:

Our position in this book is as follows: there is no fundamental clash between the purposes and capacities of qualitative and quantitative methods or data. What clash there is concerns the primacy of emphasis on verification or generation of theory—to which heated discussions on qualitative *versus* quantitative data have been linked historically.

We believe that *each form of data is useful for both verification and generation of theory*, whatever the primacy of emphasis. Primacy depends only on the circumstances of research, on the interests and training of the researcher, and on the kinds of material he needs for his theory. (1967:17–18)

For Glaser and Strauss, verification is the hallmark of positivism and assumes that (1) there exists a real and objective social world independent of our thoughts and ideas about it and (2) the purpose of research is to test the validity of our ideas to determine how accurately they represent this “real” world (see Glaser and Strauss 1967:chap. 8). Therefore, what researchers do is (a) construct a theory about the world (which they operationalize as a set of hypotheses); (b) collect data through rigorous methods meant to secure objectivity and impartiality—which usually comes in the form of quantitative data—and then (c) use this data to test (verify) the legitimacy of their theory. If the data collected verify the theory, then it is a legitimate understanding of social reality. If not, the theory is discarded.

If Glaser and Strauss succumb to positivism, they do so only inasmuch as they hold true the first of the above two assumptions. Grounded theory, as originally articulated, relies on the idea that, through a rigorously close analysis of the data, researchers can “discover” the “hidden” and “underlying” theoretical framework holding the data together. But this is as far as their positivism goes. They cannot be

accused of the second error in thinking. They do not believe that theorization should be removed from or take place prior to the collection of data. Instead, they believe that the rules of verification should be softened so that grounded theorists can examine quantitative data in a manner similar to the analysis of qualitative data. They state, "When the sociologist consciously starts out to suggest a theory plausibly, rather than test it provisionally, then he can relax many of the rules for obtaining evidence and verification that would otherwise stultify or squelch the generation of theory" (1967:186). Because of their "softened" approach to quantitative data analysis, we can think of Glaser and Strauss as postpositivists. They do away with the linear model, regression coefficients, t-tests of significance, and verification in general. From this perspective, the analysis of qualitative and quantitative data does not differ. Both are textual statements, albeit of different types. Neither provides a more direct window into social reality than the other. As such, they can both serve the purpose of generating theory.

Although Glaser and Strauss originally intended grounded theory to be used with both qualitative and quantitative data, the reality—thirty-six years later—is that these boundaries still stand. The techniques of statistical analysis are too embedded in the verificationist paradigm to prove useful. As Ragin (2000) and others (e.g., Capra 1996; Cilliers 1998; Kosko 1993) have pointed out, by definition statistics confines researchers to linear, probabilistic thinking. Using these techniques to understand qualitative difference, let alone the complex interactions between variables, has therefore proven too difficult. Even Strauss and Corbin (1994) concede this point. They state that not only was *The Discovery of Grounded Theory* subtitled *Strategies for Qualitative Research*, but "we ourselves wrote specifically for qualitative researchers" (p. 277). But all of this was before the SOM. With the SOM the rules of verification are no longer an issue. Not only does the SOM blur the boundaries between qualitative and quantitative data, it is "soft" enough to be used as a qualitative tool for the analysis of large and complex quantitative databases. Equally important, following the logic of Charmaz (2000)—and in contradistinction to statistics—the models of "best fit" generated by the SOM are not verified against an objective reality. Instead, they are open-ended, qualitative models localized to the data at hand. As such, with each new piece of conceptual information added, the SOM changes what it knows. This is why it is called a form of artificial intelligence. It is for these reasons, then, that the SOM is part of the new moment in grounded theory, where the possibilities for "new strategies and styles of quantitative analysis, with their own rules yet to be discovered" can take place (Glaser and Strauss 1967:186).

### THE SOM: A BASIC REVIEW

As a technique useful for the discovery of grounded theory, it is best to think of the SOM as a qualitative conceptual modeling technique that is compatible with the general aims of grounded theory. However, the main difference is that the SOM,

unlike grounded theory, can handle large and complex databases comprised of quantitative and qualitative data.

### The SOM as a Conceptual Modeling Technique

In their essay “Conceptual Modeling as a Toolbox for Grounded Theorists,” Soulliere, Britt, and Maines (2001:266) argue that “issues of theory construction and modeling are generic to all social scientific inquiry.” Regardless of the methods used or the audience sought, at some level “scholars are dependent on some sort of model” to make their descriptions and ideas plausible and intelligible (2001:266). This is particularly true for grounded theory, given its emphasis on theory construction.

Conceptual modeling aids the construction of grounded theory in two important ways: diagrammatic and procedural. The goal of diagramming is to help researchers map and discuss the development of theory by breaking theory construction into three basic, iterative, and interdependent processes: deciding which concepts are important, determining the nature of these concepts, and modeling the relationships between them. The purpose is to provide researchers with a framework for dialoging with complex data, not to end with reified theory. Better yet, the goal is to develop the comparative method of grounded theory by disciplining researchers to constantly reexamine their assumptions “about how and why patterns exist in the data” (Soulliere, Britt, and Maines 2001:267).

The second benefit of conceptual modeling is its threefold process of theory construction. In grounded theory, the basic procedure is discovery and development. In conceptual modeling, it is discovery, assessment, elaboration, and refinement. Soulliere, Britt, and Maines (2001:267) state, “For grounded theory, development implies ‘inductive theory building.’ Discovery comes first, then, development.” For conceptual modeling, however, “development implies continuous dialogue of discovery, assessment, elaboration and refinement” (p. 267). Again, the purpose is to develop the comparative method. Soulliere, Britt, and Maines state, “the impulse of conceptual modeling is in encouraging constant comparison rather than in rote rule-following, as may be the temptation in some practices of grounded theory procedures” (p. 267).

Although conceptual modeling aims to enhance the comparative method of grounded theory, the tools and techniques associated with it vary in function and purpose. For analyzing quantitative data, the most useful technique is the SOM.

### Overview of SOM

The SOM is one of the newest modeling techniques to emerge from the distributed artificial intelligence literature (also known as neural networking) and derives from the field of complexity theory (see Cillier 1998; Garson 1998; Strübing 1998). The study of complexity is, apropos, a complex field, with ties to ecology, biology, systems theory, computer science, physics, neuropsychology, and sociology (e.g.,

Capra 1996; Mathews, White, and Long 1999; Rasch and Wolfe 2000; Strübing 1998). In his groundbreaking book, *Complexity and Postmodernism* (1998), Cilliers explains that despite diverse approaches in the field of complexity, they share the same basic goal. All seek to understand how complex, self-organizing systems form, develop, operate, change, and inevitably transform into something else.

The most important concept for understanding complex systems is self-organization (see Cilliers 1998:2–5). This concept resembles Strauss's (1978, 1993) concept of negotiated order: a self-organizing system's patterned regularity depends on and emerges out of the complex set of negotiated interactions that constitute it; conversely, these negotiated interactions depend on and are conditioned by the larger system of which they are a part. This self-organizing negotiated order exists in time, follows a series of trajectories, and evolves and adapts to internal as well as external changes and conflicts.

The SOM's effectiveness for modeling complex, self-organizing systems derives from its internal architecture, which is built on the connectionist principles of the brain (see Garson 1998). As Cilliers (1998:25) states, "Neural networks conserve the complexity of the systems they model because they have complex structures themselves." The nuts and bolts of the SOM's internal architecture, as shown in Figure 1 below, consist of a complex web of interconnecting artificial neurons and nodes and mathematical synapses. They combine to form a self-organizing, geographic output space that looks like a one-dimensional grid (Garson 1998:25). The strength of this neural architecture for grounded theory is twofold. First, it helps grounded theorists to "discover" knowledge (generate theories) about the nonobvious patterns and relationships in complex quantitative databases through a comparative process of assessing, elaborating, and refining which concepts are important, what these concepts mean, and how they relate to one another. Second, it allows the SOM to "discover" nonobvious patterns and relationships in a manner similar to traditional grounded theory method.

## SIMILARITIES BETWEEN THE SOM AND GROUNDED THEORY

The SOM is methodologically similar to grounded theory in five important ways. Like grounded theory, the SOM relies on the comparative method, is a diagrammatic tool, strives for saturation, uses theoretical sampling, and is exploratory in orientation.

### Comparative Method

Like grounded theory, the SOM relies on a comparative method of analysis referred to as the training process (Garson 1998:87–90). During the training process, the SOM repeatedly passes through a complex set of data—sometimes several hundred times—in search of nonobvious patterns and relationships. As the SOM becomes familiar with the data, it does three things. First, it decides which conceptual

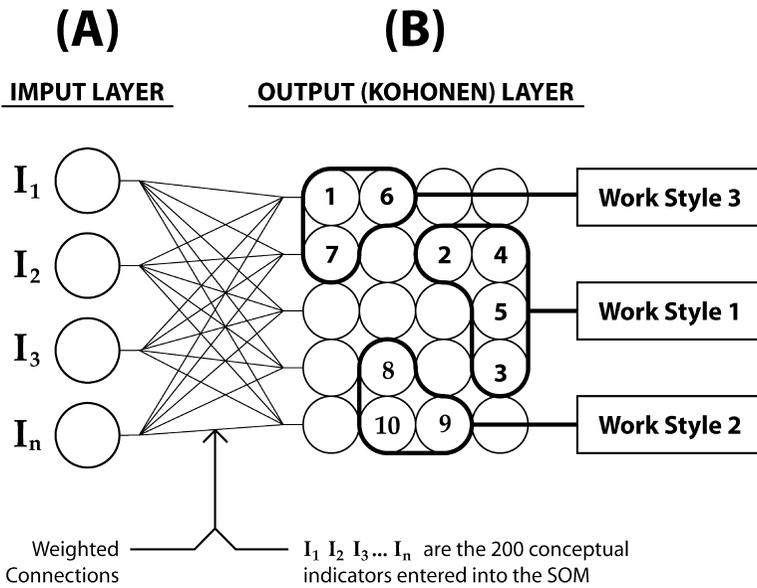


FIGURE 1. Diagram of the SOM for the First Ten Interviews

domains are the most important. To do this, the SOM, like the comparative method, begins to organize the data according to particular sites in the database. Like the comparative method, these sites help the SOM to determine which conceptual domains are the most important and which indicators best represent these domains. This step leads to the next: by making hundreds of passes through the data, the SOM begins to decide which conceptual domains best represent the data (indicators) and, conversely, which data (indicators) best represent the conceptual domains. Finally, the SOM models the relationships between the conceptual domains themselves through the production of an output layer: the Kohonen layer (Fig. 1).

### Diagramming

The SOM helps researchers to diagram their model as it develops. As Kohonen (2001:106), the creator of the SOM, states, “The Self-Organizing Map (SOM) is a new, effective software tool for the visualization of high-dimensional data. In its basic form it produces a similarity graph of input data.” The SOM produces this map by reducing the conceptual indicators presented to it onto a smaller output layer (grid) that represents the best set of conceptual domains explaining the indicators. Once the SOM produces this output layer, the researcher can literally remove and then use it to map the data. In other words, as a conceptual modeling technique, the SOM gives grounded theorists a map that they can use to generate theory. The researcher, however, must construct the theory. The researcher has to go back to the original data and, using standard grounded theory procedures, figure

out how to interpret the map, that is, determine which conceptual domains are the most important, what they mean, and how they relate to one another (Bigus 1996; Shalvi and DeClaris 2001).

### Saturation

The third similarity between the SOM and grounded theory is saturation. Like grounded theory, the validity of the SOM lies in its utility (see Cilliers 1998). The purpose of the SOM is to produce “useful” theory, not “true” theory. Usefulness, as always, relies on both the researcher and the subjects in the study deciding when and how well a theory “fits” their experiences. In neural networking, this is called convergence: the SOM settles on the model of “best fit” when, comparatively, the researcher and subjects learn less on each successive pass of the data (Garson 1998:35).

### Theoretical Sampling

Because its creators built the SOM to solve local problems, like grounded theory, issues of generalization do not directly concern it. The SOM relies on theoretical, as opposed to random, sampling to build and develop its model. In neural networking terms, theoretical sampling is defined as data mining (Berry and Linoff 2000; Bigus 1996; Cios 2001; Han and Kamber 2001). Like theoretical sampling, data mining allows the model, while being developed, to guide what information the researcher collects next. In addition to establishing core concepts, defining them, and specifying how they relate to one another, each time the researcher runs and analyzes the SOM he or she decides what information needs to be collected next, what new or different indicators are necessary, and what needs to be discarded through a process of discovery, assessment, elaboration, and refinement.

### Exploratory Knowledge Discovery

As the SOM’s approach to data collection suggests, researchers use this technique, like grounded theory, to engage in exploratory, inductive knowledge discovery. The SOM is most useful when the researcher cannot identify patterns in a large, complex database. Neural networking terminology refers to pattern discovery as *unsupervised learning* (Garson 1998; Kohonen 2001). However, the researcher remains involved in the process of knowledge discovery. “Unsupervised” means that the SOM does not require the researcher to impose a predefined theoretical model or set of hypotheses on the data, in contrast to traditional statistics and other, more positivistic modeling techniques. Like grounded theory, the SOM works best when the researcher is trying to arrive at a new and yet unknown interpretation of the data.

This concludes the basic overview of the SOM. But we end this article with a final exercise. We apply the SOM to a hypothetical example to demonstrate how

grounded theorists, applying traditional techniques, can use the SOM to generate theory from a complex database consisting of qualitative and quantitative data.

## APPLYING THE SOM TO THE STUDY OF PHYSICIAN WORK STYLES

Consider the following hypothetical example. As a medical sociologist who studies the work styles of primary care physicians, you know that the biggest challenge physicians face today is successfully adapting their work styles to meet the demands of the managed health care system and its new rules for practicing medicine. These demands include, among other things, increased concerns about health care costs, evidence-based medicine, team-based approaches to care, salaried employment, and increased patient sophistication. Based on your previous research and the literature, you also know that not all work styles are equal. Some primary care physicians handle today's complex system better than others: they provide better care and are happier in their work. You therefore decide to interview and collect data on primary care physicians to determine the different ways they deal with the complex health care system. You hope to use this information to construct a typology of primary care physician work styles, so that physicians can learn about the strengths and weaknesses of their different approaches to practicing medicine.

### Constructing the Interview

Because you are at the beginning of your study, you decide to conduct a series of informal interviews with a list of ten primary care physicians. Several interviews into your study, however, you realize that rather diverse and complex factors influence these physicians' work styles. Applying the conditional matrix to the data you have so far collected, you map what amounts to eight major conceptual domains: (1) the organization of the physician's practice; (2) the physician's relations with staff and other health care providers; (3) the physician's involvement with third-party payers; (4) the physician's increased visibility and accountability (e.g., physician profiles, utilization reviews, chart review); (5) the physician's patient population and approach to patient care; (6) the physician's use of pharmaceuticals and biomedical technologies; (7) the physician's approach to malpractice and legal issues; and (8) key social psychological characteristics, such as locus of control and flexibility. Other key indicators you find important are gender, ethnicity, and age.

Using these eight domains and the additional key indicators as your guide, you construct a rather exhaustive semistructured interview format and call it the Primary Care Work Styles Interview (PCWS-I). For each domain, you have ten to fifteen key indicators. You also decide to collect an extensive list of quantitative information about each physician, including patient demographics, utilization rates, and so

on. You then interview several more physicians to validate the utility of the PCWS-I. In total, you have more than two hundred conceptual indicators.

Because the SOM requires that the information it analyzes be in numerical form, even though it is a qualitative technique, your next task is to crudely quantify your two hundred indicators, some of which are already quantified. To quantify your indicators, you follow Glaser and Strauss's (1967) basic argument:

When the discovery and generation of theory is the goal of a survey [or quantified interview format], "crude" or "general duty" indices (as described in detail by Lazarsfeld) suffice to indicate the concepts of the theory and to establish general relationships between them, which in turn become the basis for suggesting hypotheses for the emerging theory. (1967:190)

As Glaser and Strauss argue, when the goal of quantifying qualitative data is modeling and not verification, the rules of positivism do not apply. Your only goal is to generate a set of basic concepts and to present a qualitative interpretation of relationships between these concepts and their indicators. As such, crude quantification of your indices is sufficient. And so, following this logic, you quantify your two hundred indicators.

### Collecting the Data

After you have constructed and quantified the PCWS-I, you are ready to ask your two basic grounded theory questions: What are the different types of primary care physician work styles? And which conceptual indicators seem to account for these differences? To answer these questions, you begin collecting data. Following the basic procedure of theoretical sampling, however, you arbitrarily decide to interview only ten physicians, after which you will pause to begin analyzing the data using the SOM. Before you do this, however, you apply the comparative method to your ten interviews to determine, initially, what the potential work styles in your small but current database might be. After completing this initial pass through the data, it is time to run the SOM.

### Running the SOM

The purpose of running the SOM is simple. You want to determine which set of work styles, given your two hundred indicators, best represents the physicians you have interviewed. The SOM helps you accomplish this process in two ways. First, it clusters your ten physicians into the best set of work styles. Second, it does so while maintaining the complexity of your data.

The procedure for running the SOM is as follows. First, all two hundred conceptual indicators need to be entered into the SOM, creating "the input layer." In this input layer, all the indicators are connected to one another in the form of a large interaction term. The next step is to tell the SOM how many work styles it should look for. Although the SOM is a form of unsupervised learning, it needs guidance from the

researcher. Because the SOM has no predefined theoretical model to use, it depends on you, the grounded theorist, to have a basic idea of what you are looking for. This is why, before running the SOM, you used the comparative method to initially determine the work styles you thought might be present in your database of ten physicians. Given your preliminary analyses, you tell the SOM to look for three work styles, which it does. After a series of iterations through the data, the SOM tells you that it has clustered the physicians the best it can. If it performs any further analysis, you will have passed the point of saturation. And so you stop to see how the ten physicians are clustered on the output layer (see Fig. 1).

### Interpreting Results Using the Comparative Method

As shown in Figure 1, the output layer has organized your ten physicians as follows. Included in the first cluster, Work Style 1, are physicians 2, 3, 4, and 5; in Work Style 2 are physicians 1, 6, and 7; and in Work Style 3 are physicians 8, 9, and 10. At this point the SOM has done all it can as a conceptual modeling technique. It has given you a map and located the three conceptual domains (work styles). It has shown you, visually, the theoretical proximity that these three styles have to one another: Style 3 and Style 2, for example, are the farthest apart. And by locating which physicians belong to which identified style, it has given you the opportunity to return to the database to determine the patterns associated with the three groups of physicians.

### Engaging in Comparative Analysis

Now that the SOM'S work is completed, at least initially, you use the map to begin generating theory. The logic of conceptual modeling requires you to do the following: (1) decide on the relative importance of the three conceptual domains you found, (2) further examine what these three concepts (work styles) mean, and (3) given their proximity, determine the relationships the three conceptual domains—and the indicators and physicians comprising them—share with one another.

For example, after examining the data from the ten physicians, you conclude that you can make sense of the first two work styles but not the third. You may therefore decide to discard the third style; or perhaps you will interview more physicians to see if it becomes clearer.

You might also find that Work Style 2 is clearly defined, even though you need to interview more physicians. After having combed through the data, you realize that the following conceptual indicators are shared by the three physicians in this group. These indicators are *gender* (the physicians are all women), *flexibility* (they can adapt to the new demands of managed care), *age* (they are all under thirty-five), *teamwork* (they work well in team activities), *salaried employment* (they prefer to work for someone else to avoid the hassles of self-employment), *lifestyle* (personal and professional life equally concern them; they do not want to work eighty hours a week), and *patient-centered care* (they promote patient responsibility for care and

work with patients rather than for them). Tentatively, you decide to name the second work style New School Female Physicians. To confirm your findings, you have the female physicians review your concept. If it fits, you can feel confident to develop your ideas further. If not, you begin again.

### Starting the Process Over Again

Obviously, given that you have interviewed only ten physicians, your results are limited. But following the logic of grounded theory and conceptual modeling, it is a start. And so you next interview more physicians, run the SOM again, review your output map, go back to the data to engage in the process of assessment, elaboration, and refinement, share your information with those whom you studied, and then start the process all over again until you reach a level of saturation. In the end, you hope that you have arrived at a useful typology of physician work styles.

### CONCLUSION

We have aimed to introduce researchers to the SOM and to make a case for using it in the grounded theory process. The basis for our argument is threefold. First, the SOM, unlike grounded theory, can handle complex databases comprising qualitative and quantitative data. Second, as a conceptual modeling technique, the SOM helps grounded theorists to understand which concepts in their data are the most important, what those concepts mean, and how they relate to one another. Third, as an exploratory approach to knowledge discovery, the SOM works in a manner similar to the techniques of grounded theory. Given these three strengths, we recommend it be added to the toolbox of grounded theorists.

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### REFERENCES

- Berry, Michael J. A. and Gordon S. Linoff. 2000. *Mastering Data Mining: The Art and Science of Customer Relationship Management*. New York: John Wiley and Sons.
- Bigus, Joseph. 1996. *Data Mining with Neural Networks: Solving Business Problems from Application Development to Decision Support*. New York: McGraw-Hill.
- Capra, Fritjof. 1996. *The Web of Life*. New York: Anchor.
- Charmaz, Kathy. 2000. "Grounded Theory: Objectivist and Constructivist Methods." Pp. 509–36 in *Handbook of Qualitative Research*, 2d ed., edited by N. Denzin and Y. Lincoln. Thousand Oaks, CA: Sage.
- Cilliers, Paul. 1998. *Complexity and Postmodernism: Understanding Complex Systems*. New York: Routledge.

- Cios, Krzysztof, ed. 2001. *Medical Data Mining and Knowledge Discovery*. Denver: Springer-Verlag.
- Denzin, Norman K. and Yvonna Lincoln, eds. 1994. *Handbook of Qualitative Research*. Thousand Oaks, CA: Sage.
- . 2000. *Handbook of Qualitative Research*, 2d ed. Thousand Oaks, CA: Sage.
- Garson, David G. 1998. *Neural Networks: An Introductory Guide for Social Scientists*. Thousand Oaks, CA: Sage.
- Glaser, Barney and Anselm L. Strauss. 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Chicago: Aldine.
- Han, Jiawei and Micheline Kamber. 2001. *Data Mining: Concepts and Techniques*. San Francisco: Morgan Kaufmann.
- Kohonen, Teuvo. 2001. *Self-Organizing Maps*, 3d ed. New York: Springer-Verlag.
- Kosko, Bart. 1993. *Fuzzy Thinking: The New Science of Fuzzy Logic*. New York: Hyperion.
- Mathews, K. Michael, Michael C. White, and Rebecca C. Long. 1999. "Why Study the Complexity Sciences in the Social Sciences?" *Human Relations* 52(4):439–62.
- Ragin, Charles C. 2000. *Fuzzy-Set Social Science*. Chicago: University of Chicago Press.
- Rasch, William and Cary Wolfe. 2000. *Observing Complexity: Systems Theory and Postmodernity*. Minneapolis: University of Minnesota Press.
- Richards, Thomas J. and Lyn Richards. 1994. "Using Computers in Qualitative Research." Pp. 445–62 in *Handbook of Qualitative Research*, 1st ed., edited by N. Denzin and Y. Lincoln. Thousand Oaks, CA: Sage.
- Richardson, Laurel. 1993. "Interrupting Discursive Spaces: Consequences for the Sociological Self." Pp. 77–84 in *Studies in Symbolic Interaction: A Research Annual*, vol. 14, edited by N. Denzin. Greenwich, CT: JAI Press.
- Shalvi, Doron and Nicholas DeClaris. 2001. "A Data Clustering and Visualization Methodology for Epidemiological Pathology Discoveries." Pp. 119–51 in *Medical Data Mining and Knowledge Discovery*, edited by K. Cios. Denver: Springer-Verlag.
- Soulliere, Danielle, David W. Britt, and David R. Maines 2001. "Conceptual Modeling as a Toolbox for Grounded Theorists." *Sociological Quarterly* 42(2):253–69.
- Strauss, Anselm L. 1978. *Negotiations: Varieties, Contexts, Processes, and Social Order*. San Francisco: Jossey-Bass.
- . 1993. *Continual Permutations of Action*. New York: Aldine de Gruyter.
- Strauss, Anselm L. and Juliet Corbin. 1990. *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*. Newbury Park, CA: Sage.
- . 1994. "Grounded Theory Methodology: An Overview." Pp. 273–85 in *Handbook of Qualitative Research*, 2d ed., edited by N. Denzin and Y. Lincoln. Thousand Oaks, CA: Sage.
- . 1998. *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*. Thousand Oaks, CA: Sage.
- Strübing, Jörg. 1998. "Bridging the Gap: On the Collaboration between Symbolic Interactionism and Distributed Artificial Intelligence in the Field of Multi-Agent Systems Research." *Symbolic Interaction* 21(4):441–63.
- Weitzman, Eben. 2000. "Software and Qualitative Research." Pp. 803–20 in *Handbook of Qualitative Research*, 2d ed., edited by N. Denzin and Y. Lincoln. Thousand Oaks, CA: Sage.