Considerations for Characterizing Domain Problems

Kirsten M. Winters
Oregon State University
Ballard Hall
Corvallis, Oregon 97330
wintersk@onid.orst.edu

Denise Lach
Oregon State University
School of Public Policy
Corvallis, Oregon 97330
denise.lach@oregonstate.edu

Judith B. Cushing
The Evergreen State College
Lab 1 2700 Evergreen Pkwy
Olympia WA 98508 USA
judyc@evergreen.edu

ABSTRACT

The *nested blocks and guidelines model* is a useful template for creating design and evaluation criteria, because it aligns design to need [17]. Characterizing the outermost block of the nested model—the domain problem—is challenging, mainly due to the nature of contemporary inquiries in various domains, which are dynamic and, by definition, difficult to problematize. We offer here our emerging conceptual framework, based on the central question in our research study—*what visualization works for whom and in which situation*, to consider when characterizing the outermost block, the domain problem, of the *nested model* [18].

General Terms

Design, Experimentation, Human Factors.

Keywords

Evaluation, visualization, software development, participant observation, ethnographic methods.

1. INTRODUCTION

When we ask, *what visualizations work for whom and in which situations,* we are conducting a type of design evaluation. This social science question seeks to define general assumptions about the people and the problems that a visualization tool is meant to serve. In this paper, we overlay our own emerging high-level conceptual framework for answering our social science question onto the *nested blocks and guidelines model (NBGM)* [17] in order to understand what benefit would come from combining the two evaluation methods. While the *NBGM* [17] is aimed primarily at the design and evaluation of *information visualizations* [18], we find it to be conceptually useful in our scientific visualization project where we design scientific visualizations for domain scientists (ecologists), their research problems, and the potential audiences of visualizations resulting from their data.

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The *nested design model* [18] (figure 1) defines four levels for consideration in visualization design and evaluation. In the *nested model* [18], assumptions from the outermost level cascade to affect design criteria at the innermost levels, ideally aligning the design of task abstractions to interaction techniques to algorithms, for example, with the problems in a particular domain (figure 1).

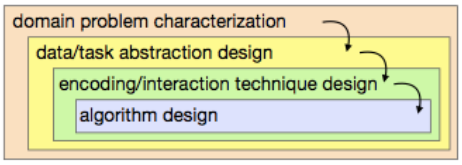

Figure 1: The original four-level nested design model [18].

One refinement of the *nested model* is the addition of "blocks" and "guidelines" [17]. *Blocks* (figure 2) are defined as the potential design outcomes that are chosen and combined at each level (e.g., various interaction techniques) that result in making visualization more targeted [17]. *Guidelines* are statements about the relationships between *blocks* that add detail to design criteria [17]. Meyer et al. [17] note that more studies should provide "examples of blocks at the outermost level of domain problem characterization" (p. 4); however, they also question the nature of the domain problem level, especially to what extent it is definable and applicable to the design process at other levels [17].

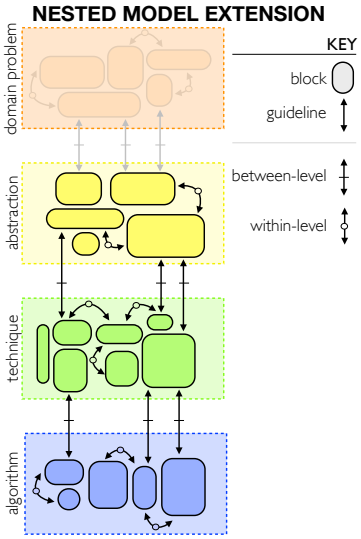

Figure 2: The *extended nested model* [17].

The level of *domain problem* is inherently problematic for many reasons—for example, do we deal with low- or high-level problems [18]? Are we addressing *wicked problems* [21] or

solvable puzzles? To be sure, characterizing *blocks* at the domain problem level is a tall order: how does one create a set of assumptions general enough to translate to other domains, yet specific enough for good design? And yet, developing a deep conceptual model of the domain problem level might profoundly affect design and evaluation criteria ([6, 18]). For example, one threat to the value of visualization, at the domain problem level, is the hammer-without-a-nail problem: does the audience actually have a problem that would benefit from visualization ([18, 19])?

We attempt to understand *what visualizations work for whom and in what situations* during our visualization software design project (VISTAS---the VISualization of Terrestrial-Aquatic Systems). Our conceptual framework for answering this question produced general categories that might contribute to characterizing the domain problem in the *NBGM* [17]. In this paper we present some recent history of the *NBGM*'s development relevant to our project. Next we summarize our project and the domain problem. Then, we give an overview of the conceptual model we developed for characterizing the domain problem. Finally, we overlay our conceptual framework onto the *NBGM* and provide examples that might further concretize the combining of the two models for developing design and evaluation criteria.

1.1 Toward Refining the Design Model

First, we consider some history of the *NBGM* [19] relevant to our project. One research inquiry that led to *blocks and guidelines* being defined within the *nested model* is the QuestVis prototype study [18]. The findings from the QuestVis process, in particular, are relevant to our process of developing a conceptual model to understand *what visualizations work for whom and in what situations.*

The QuestVis tool was designed in order to "promote environmental sustainability and behavior change via community engagement in environmental policy" [19] (p. 255). The QuestVis developers found that creating an all-in-one visualization tool for reaching such goals was difficult. In their reflections on this difficulty, they state that simply providing an information space for end-user exploration required additional facilitation, which was beyond the scope of the visualization's ultimate intent and design [19].

Similar to the QuestVis research finding, we believe that visualization and visual analytics often must be supplemented with other processes such as education, experience, training and better hardware/software, depending on the problem and audience. For example, when questioning what our domain experts meant about the importance of designing *intuitive visuals* for certain audiences and end-users, we found that intuitive visuals were requested so that less expert audiences might understand their complicated visualizations during environmental planning and decision-making processes. We asked the question, "What are intuitive visuals?" What does this mean? Intuition seems to be *fast thinking* [9]. What might make a visualization lead to fast thinking, but also accurate results for solving a problem? Can *intuitiveness* be a design guideline? If so, what makes a visualization *intuitive?* Features of the visualization, itself, or something else?

Determining what was behind this request for intuitive visualizations also meant developing a systematic way to think about problems and the tools contributing to problem-solving: an exercise that might contribute to characterizing the *domain problem* in the *NBGM* [17]. During our initial planning meetings, we set out with the mindset that visualization effectiveness can be determined only with regards to the problems and people being served, hence the inclusion of our domain experts from the beginning of the design process [6]. Additionally, we found that visualization is just one of many tools that someone might use in a problem-solving process, and that it is impossible to evaluate visualization effectiveness without acknowledging a number of variables with which visualization might interact. Our mindset, which is not visualization-centric, helped us to question how much of what we're evaluating and designing for is *visualization effectiveness,* and what the limitations to design might be.

We find it important to highlight the value of the outer *domain problem level* to overcome potential visualization-centric bias in design and evaluation. And toward refining the design model, we contribute our high-level conceptual framework as a way to characterize the blocks of the domain problem level found in the *NBGM* [17]. Perhaps the general categories will be transferable to other design evaluation studies.

1.2 Characterizing the Domain: the VISTAS (VISualization of Terrestrial and Aquatic Systems) Project

We base our conceptual framework on the field data from VISTAS project. VISTAS' environmental science research aims to visualize models that simulate the cycling and transport of water and nutrients as a first step towards achieving science goals—inquiries similar to other environmental science grand challenges [20]. The end users of the VISTAS software tool are the ecologists who develop or use these models, specifically in the fields of biogeochemistry, micrometeorology, and environmental engineering. Visualization is used for understanding ecological processes across spatial and temporal scales, as well as across social and ecological systems. VISTAS scientists also use visualizations in their work with stakeholders and other scientists. With VISTAS, we are trying to understand how visualization and visual analytics might help overcome challenges such as exploring large volumes of data and communicating results. VISTAS' development of visual analytics software answers calls for innovative tools for creating hypotheses and confirming results [28].

Social science is used to evaluate the development process and effectiveness of VISTAS' output. We take a more general view than other human-focused research, such as in the cognitive sciences, human-computer interaction studies, usability research, or psychophysics. In order to study the development process, we use qualitative methods in the field, primarily collecting ethnographic data through participant observation [24]. We've identified themes during field data analysis including challenges in research with high variety and volume of data, and domain experts' specific uses of visualization. Initial analysis of field data produced obvious results that confirmed what the literature says: big data is challenging—both in research and in communication ([11, 12]); domain scientists are using visualization in both their personal research and in collaborative groups ([3, 10, 28]), and scalability is a central problem to both analyzing data and presenting results ([8, 11, 13, 21]). Additionally, we've used a highly iterative process of simultaneous data collection and analysis to create a novel framework for informing design that might be testable and empirically valid [4]. Finally, while many of the visual encoding tasks are intrinsic to our scientists' datasets [18], the use of the *NBGM* [17] is an enlightening exercise, especially as the visualizations produced via VISTAS might be used in a decision-making or public policy process.

2. A HIGH-LEVEL CONCEPTUAL FRAMEWORK

In order to answer our social science question *what visualizations work for whom and in which situations*, we established two general typologies to help with visualization design and evaluation. These typologies include *problem contexts* and *humans-as-viewers, analysts,* or *tool-users* (i.e., how humans approach a visualization experience*)*. These typologies might be taken as building blocks in the domain problem level of the *NBGM.* One might argue the exact details of these typologies, but what is novel here is not each typology exactly as it is, but rather the relationships between the typologies in a design process, especially from a sociological point of view.

2.1 Typology of Problem Contexts

In our study, we set out with the understanding that problems are contextual. A context is simply the circumstance of the situation or the setting in which inquiry occurs. Drawing attention to context of a problem helps research and design teams say, "We can't do that or know that now—in this context, but if circumstances changed, we might be able to tell *x."* For example, acquiring a ladder allows someone to reach a roof more easily than without a ladder. An innovation changes the circumstances or context of problem solving.

By acknowledging the importance of context, one begins to question the circumstances that affect scientific observation and interpretation despite systematized methods for overcoming bias. Problems, in this way, are situated. *How might we characterize domain problems, then?*

A matrix of types of contemporary problems from the literature on planning and design is helpful at this point, even though it is not necessarily novel. This matrix is based on the concept of a *wicked problem* [21], which—applied to the problem domain in environmental science—is defined as a problem where uncertainty is high and consensus is low, as seen in figure 3 (adapted from [21]).

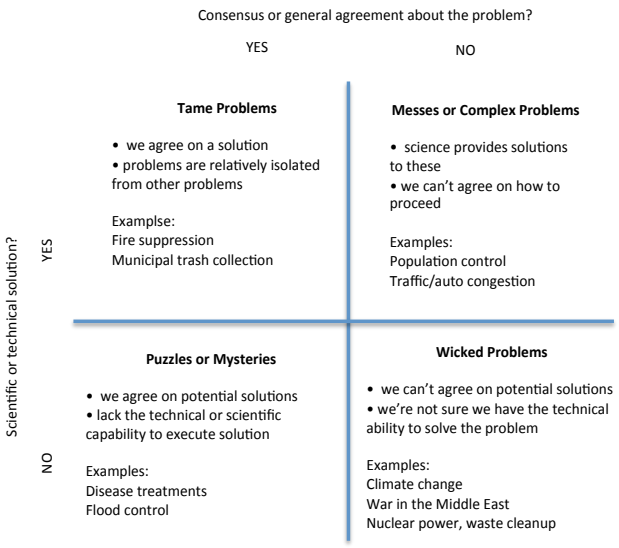

Figure 3: An overview of *wicked problems* [21].

This matrix highlights the importance of two aspects of contemporary problems. First, scientific and technical inquiries (the y-axis) are part of the domain problem. And, second, consensus (x-axis) is also part of the domain problem. The presence of consensus implies a number of factors that affect the context of problems. For example, problems often include scientific and technological aspects, and also sociological and political aspects.

Examples of domain problems similar to those found in environmental science are given in the matrix, including how to deal with diseases, traffic, and war. Many contemporary domain problems include agency and action. They demand: How do we proceed? And where earlier domain problems might have rarely considered irreversible destruction, contemporary domain problems—especially in environmental science—often weigh consequences and the inability of science and technology to find a solution, such as in problems with high uncertainty. For example, consider a past inquiry, which sought to overcome world hunger. During the mid-twentieth century, researchers used science and technology to create new types of seeds and new inputs (fertilizer, pesticides, and herbicides), as well as irrigation methods, to overcome problems such as low-yield crops and infestations. The inquiry included a domain problem, a science and technology inquiry, and a solution.

With hindsight, we can question the ability of technology to solve the hunger problem due to unintended consequences, such as herbicide resistant weeds or genetic drift. We see here, too, that domain problem inquiry is both a scientific problem (the y-axis in our matrix) and a problem of ethics, planning and decision-making (the x-axis in our matrix).

We use the *wicked problems matrix* to show how domain problems are characterized by both the ability of science and technology to produce solutions, and the level of consensus when settling on the 'best' solution. By definition, *wicked problems* are difficult to problematize.

This matrix of problems applies to our study, where the environmental domain problem is tightly coupled with the sociological and political domain. As Batie puts it: *wicked problems*, such as what to do about climate change, move beyond the ability of science to determine clear causal relationships, to predict the future, to control or overcome the unpredictable outcomes, or to establish exactly what is the best outcome [1]. Such *wicked problems* are not only difficult to solve, but they are often controversial. We find *wicked problems* manifest themselves in science during collaborative research—oftentimes with stakeholders who are not domain scientists.

When dealing with certain types of problems—such as wicked ones, the role of science must also range, and this potentially colors aspects of the domain problem for which visualization might be designed and used. For example, four roles for contemporary scientific research inquiry show how information can either limit choices or expand choices within the current problem domain. Briefly, one way to label roles for science might include (1) the pure scientist; (2) the science arbiter; (3) the issue advocate; and (4) the honest broker of policy alternatives [14]. Where the scientist is the *honest broker of policy alternatives*, scientific expertise offers diverse decision alternatives in situations, rather than the one *right* solution [14]. This way of seeing the scientist's expertise presents the balance between features of the problem: that of increasing consensus and that of scientific and technological discovery, providing a means for addressing *wicked problems*. One can see how asking *which visualizations are most effective for whom and in what situation* becomes more complicated here. At times, one wants to generate a variety of visualizations—say to present decision alternatives—with which to explore; at other times, one wants to converge on

the *best* visualization for communicating a solution or a finding. Design of the visualizations, here, is the responsibility of the computer scientist—who designs the software tool based on certain specifications, as well as the domain scientist—who might create a visualization using the software tool or as a result of a visual analytics process for discovery and communication.

Reflecting back onto the *wicked problems* matrix as it contributes to visualization design considerations, we might say that *scientific and technical considerations* and *levels of consensus* could constitute two abstract blocks at the domain problem level of *NBGM* for guiding design and evaluation criteria.

2.2 The Essential Human in the Problem Domain

When we think systematically about design and evaluation criteria from the social science perspective, we find that problems and problem-solvers are tightly coupled, so that both must be considered when evaluating for visualization effectiveness. Our conceptual framework incorporates *the essential human*, but more broadly than other sciences concerned with humans interacting with computers or visualization. Three labels have been contrived here for the purposes of creating a typology of humans using visualization. We believe that *characteristics* of humans who are approaching visualization must be considered within or in relationship to the *domain problem* [17]. It is unclear whether the *essential human* belongs as a type of *block* in the domain problem of the *nested blocks and guidelines* model, or somewhere else; however, we believe that *humans* belong in a high-level conceptual framework in order to understand *which visualizations work for whom and in what situation*.

2.3 Typology of *Humans*

How do we systematically distinguish among the various ways people use and interpret images from a social science point of view? We know that different individuals will experience the same visualization differently. Also, we know that the same individual's visualization experiences vary over time. We borrow here from studies in *visual culture*, as well as other fields dealing with individual sight, interpretation, perception, and cognition, which establish patterns in how individuals approach visualization, make meaning, and use and interpret images ([5, 8, 25, 27]).

We start by broadly characterizing *motivation* [26] when someone is using visualization or conducting visual analytics. For example, the individual might be characterized, at times, as the *viewer* of output; at other times—as an *analyst* of data being visualized; and also, potentially, as a *user* of a visualization tool. Distinctions exist between these typologies, at the same time borders between the typologies are blurry: it matters little the exact point at which a viewer becomes a analyst, and whether an analyst becomes user—just that each type has importantly different traits, and that different disciplines, such as psychophysics, cognitive science and social science, provide insight into these traits.

It should be noted that we refer only briefly to the various studies defining and analyzing human characteristics in this position paper. Critics might find lacking our cursory description of relevant research studies that apply to humans-as-viewers, analysts, and tool-users; however, to do so would be beyond the scope of this paper, which is to present a high-level conceptual framework.

2.3.1 Human-as-Viewer

Humans are, at first, viewers. *Viewing* is a sensory experience. Viewers can vary depending on their ability to sense. Work in psychophysics analyzes the relationship between sight and perception, and pre-attentive vision—or the ability of the low-level human visual system to rapidly identify certain basic visual properties [8]. Through simple visual sensation, the *viewer* sees patterns. And we can use *Gestalt principles,* for example, to create effective visualizations based on what we know about viewers' tendencies during low-level, pre-attentive vision. Some *viewers* vary in their abilities, such as with color blindness, or myopia. Additionally, the *human-as-viewer* often lacks agency, and pre-attentive sensations often lead to unexamined conclusions.

Our goal here is not to engage in cognitive science or psychophysics research, but rather to take a high-level view of someone approaching a visualization event. We are most concerned with level of attentiveness and the level of motivation and purpose of the individual using visualization as part of a problem-solving process. On the continuum of *humans approaching a visualization event,* the *viewer* has the least agency and attentiveness. In terms of previous research, we might categorize *viewers* as *casual* users [26].

2.3.2 Human-as-Analyst

We label the individual who perceives patterns and makes sense of them according to a purpose as *the analyst* of the visualization. Analysts use a visualization to increase action-ability [17] based on their particular purpose. Analysts vary in their visualization experiences. For example, a single *analyst* may return to the same visualization, but with a different purpose, at a later time. A characteristic of the analyst is his or her purpose or *agency* when approaching the visualization. An analyst is more attentive than a viewer, using reasoning (*slower thinking* [9]), and, perhaps, a method for evaluating meaning in the visualization.

Take the example of a visualization of landscape data. A private landowner determining whether to purchase an adjacent lot for grazing cattle has a different motivation and purpose than a transportation official determining the route of a new road on that same landscape. An analyst has unique traits dependent on motivation and purpose. Also, an analyst's visualization experience might be characterized by the use of logic or application of statistics, or a combination of these two ([5], [9]). If the analyst's purpose does not match the purpose of the visualization, we might find that the visualization is not effective for that analyst.

2.3.3 Human-as-Tool-User

A third approach is the *tool-user*. The tool-user is already a viewer and analyst, and more. The tool-user wields a tool to complete a task and interacts with one or more visualizations, depending on purpose. Understanding the traits of *human-as-tool-user* requires considering the visual perception of the viewer, the cognitive and social factors influencing the analyst, as well as a more active approach to visualization.

Tool-users, like *analysts,* are characterized by both their motivation and purpose when they show up to the visualization event. Tool-users may interact with hardware and software in order to manipulate a view for analysis so that they can change the visualization as purpose changes and reasoning dictates. Again, the exact amount of a tool-user's agency and attentiveness during a visualization event is less important than the fact that the tool-user has higher levels of agency and attentiveness than the viewer or the analyst. We view the tool-user as part of design considerations—but in a more social and political way than a cognitive scientist or HCI researcher might. For example, we

might consider design and evaluation criteria with regards to scientific visualization used in a policy-making process with a group of stakeholders. We need to test how other factors such as *levels of expertise* compromise our typologies. For example, we wonder whether expertise is a result of treatments such as education, training, and experience, which may interact secondarily with the effectiveness of the visualization. We might argue that expertise can be held in both the use of the tool and domain of the problem, so that it is beyond the scope of our initial design focus on simply the *levels of attentiveness and agency*. These arguments aside, our typologies are place-holders suggesting how human characteristics *might* be defined as considerations for characterizing blocks in the *domain problem.*

3. DESIGN CONSIDERATIONS

Visualization is not a new method for exploring problems or communicating results. The software that facilitates visual analytics acts like any other tool, extending human capacity to understand—and sometimes simply *perceive*—complex and dynamic data; this is described as allowing for *true discourse* with data [25]. How can we evaluate visualization to tell whether design is aligning to needs? Here we overlay our conceptual framework onto the *NBGM* to see where it might lead.

3.1 Applying a Conceptual Framework as *Domain Problem Blocks*

We have characterized domain problems as situated in political and sociological contexts—pointing out how uncertainty and lack of consensus have increased the need for collaboration among scientists and with stakeholders. We have shown ways that humans can vary in their visualization experience. We are still applying project data to continue building and refining this high-level framework (summarized in figure 4). What follows are some initial findings from our social science inquiry that might demonstrate the framework's usefulness.

TYPOLOGY of PROBLEM CONTEXTS (problems vary by…)	Level of technology and science to address
	Level of consensus
TYPOLOGY of HUMAN-AS-viewer, analyst, or tool-user (humans vary by these in their approach to visualization)	Level of attentiveness
	Level of agency

Figure 4: Our emerging conceptual framework.

We give examples here using the language of the *NBGM* with regards to our conceptual model (see Figure 4 for names of potential *blocks)*, which includes the *ability of science and technology to solve a problem, levels of consensus,* and the *levels of attentiveness and agency* of the humans involved in the domain problem inquiry as *blocks* through which design *guidelines* might emerge.

Example #1—A Focus on Consensus and Humans with Varying Levels of Agency and Attentiveness

In VISTAS, we often consider the role consensus plays in applying solutions to problems to the extent that finding a solution is a part of the *domain problem*. We can imagine how visualization of environmental models affect science communication—and possibly even the construction of scientific 'fact' [5].

In some cases, *level of consensus* becomes a key feature in the domain problem, perhaps having the effect of a *block* from which to develop design *guidelines*. Consensus denotes agreement and accord. Low consensus can occur for any number of reasons. For example, when a collaborative group comes together, if *humans-as-analysts* have high levels of agency, but also vary in what that agency is (i.e., the direction of their various purposes), consensus will likely be low. Consensus occurs when the members of a group converge in agreement over a solution. In this way, *consensus* may be marked by low variance in individual agency, and divergence as high variance. If individuals have *low attentiveness, consensus* might occur simply because those in the group may not care. *Levels of agency* and *attentiveness* affect *consensus*, despite the complexity of the problem, and may affect *guidelines* for how *data* might be best abstracted into a fitting visualization.

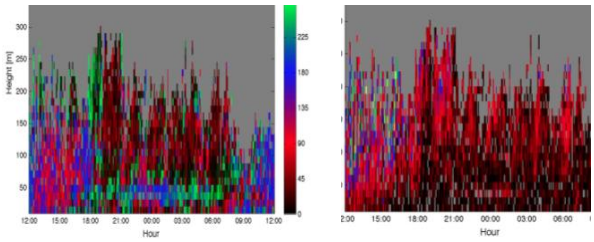

Figure 5: Technically complicated visualization (from SODAR) from a project partner. This visualization, while useful to a domain scientist, may not be effective to a group of stakeholders in a policy planning process.

For example, we might decide that a design *guideline* would be for visualization to build *consensus* among group members with varying levels of *attentiveness and agency,* to convince of findings, or to present a variety of scenarios for discussion, rather than to provide a sophisticated visual analytics process for exploring a technically challenging *problem*. For example, figure 5 shows a visualization that may not work for the purposes of consensus building, depending on the stakeholders involved. Additionally, this view would help us define how other factors outside of visualization, such as cultural values and level of scientific expertise, would interact with the visualization if consensus is seen as a barrier to problem solving. In this case, the *domain problem* takes into account political and sociological features of problem solving when developing criteria for visualization design.

Example #2: A Focus on Scientists Working Alone or Together to Achieve Insight into Problems

We found with VISTAS—as the literature echoes—that domain scientists are not often data-limited, but insight-limited [15]. In VISTAS, researchers are looking outside their normal, discipline-oriented boundaries to understand how their particular model, process or system might interact with other models. The *domain problem* often includes one scientist's model in relation to other systems and other problems. In this case, the *ability of technology and science to address the problem* becomes the central focus for design criteria.

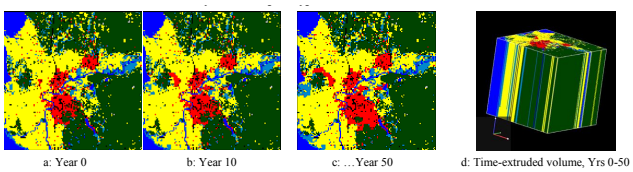

Figure 6: Data extrusion used to explore changes over time (from project partner).

One design *guideline* would be to increase the ability of domain scientists, who have *high attentiveness* and *agency,* to visualize various aspects of terabytes of data. For example, one *data abstraction* might be in the form of a 3D volume extrusion that stacks graphs and compresses information for finding the proverbial needle in the haystack (figure 6).

Perhaps another *guideline* derived from this example is integrating cross scale visualizations, which is important for understanding how various phenomena interact or how systems are coupled [22]. Unlike in *Example #1,* design *guidelines* are less concerned with vertical communication between stakeholders with various backgrounds. Additionally, scientific *consensus* is systematic, and while challenging at times, methods for establishing consensus are relatively consistent across scientific disciplines. *Guidelines* for designing for *consensus* as a *block* differ here from *Example #1*. Instead, the ability for scientists to set parameters for *technically sophisticated* visualization, and boosting collaboration, exploration and discovery would guide design. The ability to create a visualization that externalizes a complicated thought experiment for others to consider might also constitute a *guideline* in this example [16]. In contrast to *Example #1,* visualizations needed in this type of collaboration or process are more often for the purpose of *exploration of potentially wicked problems* by various sophisticated tool-users who are homogenous due to their institutional status and disciplinary training, rather than for communicating complicated findings or a range of findings within a non-institutional, heterogeneous group.

4. LIMITATIONS

There are a number of limitations to be mentioned here. First, one might say that our conceptual framework for categorizing the domain problem is too coarse or vague, and that it overlooks fine-grained technical considerations that might be supplied by sharing more study-specific findings, such as in Kang & Stasko [16]. Additionally, other studies have tested or summarized visualization evaluation in a more particularly focused way than what we offer here. For example, a recent state of the art report from 2014 [2] compiles and analyzes the myriad studies on dynamic graphs, and summarizes the types of evaluation conducted such as task evaluation, user-study driven evaluation, and algorithmic evaluation. This report is very useful and complete in its taxonomy of dynamic graph types, among other topics; however, it summarizes evaluation as dealing with different topics such as the importance of mental maps or the innermost part of design—algorithms—according to *the nested blocks and guidelines model*, rather than offering a broader and higher level position on evaluation, as we do here. Conversely, one might say that our framework is too domain-specific, and that this conceptual framework actually constitutes the beginnings of a specific domain model [6] rather than considerations for *blocks and guidelines* that might be transferred to other design and evaluation processes, or that it does not accurately represent what the *NBGM* intends as a *block* or *guideline*. Or perhaps our question of *which visualizations work for whom and in what situations* may not be a valid inquiry for creating a conceptual framework that applies outside of a social science domain. Additionally, our conceptual model is preliminary and needs more testing. To be sure, visualization design and evaluation are domain specific, and the time and cost of robust and long-term research processes are essential to good design.

5. CONCLUSION

We presented here considerations for characterizing domain problems with regards to the *nested blocks and guidelines model (NBGM)* [17] based on our social science inquiry during a visualization software development project. The model that we are developing considers the features of *wicked problems* [21], which, by definition, are difficult to problematize. We find that the problem domain must take into account not only scientific and technological considerations, but also political and sociological considerations, so that typifying how individuals approach visualization events in relation to the *domain problem* becomes an important design-evaluation consideration. We highlight the essential human in the *domain problem*, but at a higher level than other research studies in the fields of cognitive science or user studies. Additionally, we question a visualization-centric focus for design, and believe that by identifying human factors in a visualization event—such as levels of agency and attentiveness—we might better understand how factors such as education, training, and experience interact with visualization, and craft design criteria accordingly. We use the language of the *NBGM* with regards to the typologies developed in our project, and believe this is an enlightening exercise for not only software development, but for evaluating design and targeting visualization use. Finally, we continue to develop our framework with the hope that it might be refined enough to test in future studies. Our contribution to shaping visualization design and evaluation theory is our attempt to generalize the framework we used for understanding *what visualizations work for whom and in what situations*, especially with regards to the *domain problem* level in the *NBGM* [17].

6. ACKNOWLEDGMENTS

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