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A conceptual model for characterizing the problem domain

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Abstract
Defining characteristics of a problem domain continues to challenge developers of visualization software although it is essential for designing both tools and resulting visualizations. Additionally, effectiveness of a visualization software tool often depends on the context of systems and actors within the domain problem. The nested blocks and guidelines model is a useful template for informing design and evaluation criteria for visualization software development because it aligns design to need. Characterizing the outermost block of the nested model—the domain problem—is challenging, mainly due to the nature of contemporary domain problems, which are dynamic and by definition difficult to problematize. We offer here our emerging conceptual model, based on the central question in our research study—what visualization works for whom and in which situation—to characterize the outermost block, the domain problem, of the nested model. We apply examples from a 3-year case study of visualization software design and development to demonstrate how the conceptual model might be used to create evaluation criteria affecting design and development of a visualization tool.

Keywords
Evaluation, visualization, software development, social science methods

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 article, we overlay our own emerging high-level conceptual model for answering our social science question onto the nested blocks and guidelines model (NBGM). We then explain how we find it to be conceptually useful in our scientific visualization project, where we are developing a software tool for domain scientists (ecologists), their research problems, and the potential audiences of visualization resulting from their data.[1] The nested design model, originally developed for information visualization design, defines four levels for consideration in visualization design and evaluation, where 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.[2]

The nested model uses the metaphor of "blocks" and "guidelines" to describe potential design outcomes (blocks) that are chosen and combined at each level (e.g. various interaction techniques) that result in making visualization more targeted. Guidelines are statements about the relationships between blocks and add detail to design criteria.

In ecological research problems and related policy processes, domain problems are problematic for many reasons, especially those involving wicked problems.[3] We asked the question *what visualizations work for*

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whom and in what situations during our visualization software design project (VISTAS—the VISualization of Terrestrial-Aquatic Systems). Our conceptual model for analyzing this question has produced general categories that might contribute to characterizing the domain problem in the NBGM, specifically how a visualization software tool and visual analytics might contribute to problem-solving.

In this article, we introduce the VISTAS project and VISTAS case study. We situate our case study with regard to recent history of the NBGM's development, as well as other information visualization studies and frameworks for domain analysis relevant to our conceptual model. Then, we give an overview of the conceptual model characterizing the domain problem at a high level, describing the typologies and showing how other studies contribute to our understanding of those typologies. Finally, we overlay our conceptual model onto the NBGM and apply examples from case study analysis of the VISTAS development process. We hope that applying examples from the VISTAS case study might further demonstrate how others could use the conceptual model for developing design and evaluation criteria, especially for developers and designers who might want a general overview of where to begin evaluating visualization design or visual analytics software products for problem-solving in settings where complex models are presented for the purposes of decision-making.

Characterizing the domain: the VISTAS project

We based our emerging conceptual model related to the NBGM on the field data from the VISTAS project. VISTAS' environmental science research aims to visualize remote sensing data and models that simulate land-use changes or the cycling and transport of water and nutrients as a first step toward achieving science goals—inquiries similar to other environmental science grand challenges.[4] The target 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 by Thomas and others for innovative tools for creating hypotheses and confirming results.[5]

The propositions central to the VISTAS project are that visualization tools will increase the ability of scientists to (1) analyze data at multiple spatial and temporal scales; (2) gain insight into more complex problems spanning coupled human and natural systems; and (3) deal with new challenges and opportunities presented by data. Reducing problems to a crisp set of tasks is a difficult but essential goal for achieving functioning software and automation of visualization techniques; however, we have found that it is also critical to take a holistic approach and a broader view provides insight into design effectiveness of both software tools and resulting visual output.[6–8] The nested model suggests that the highest level—the domain level—should guide visualization design. Our project considers the domain level, and we found that taking this broad view of problems impacts the outcomes of our design work.

VISTAS case study

A case study approach was used to evaluate the development process and primary users' intentions for producing and using visualization (e.g. for what purposes, for which settings, and for which audiences).[9] Over the course of 3 years with the members of the group (n = 21 participants, with varied attendance at meetings over the course of the study), key informants (n = 7 participants) were interviewed formally at least once. These key informants were the scientists (primary users) and computer scientists (primary developers) involved in the software design and development. In addition to the transcripts from interviews, field notes were produced via follow-up emails and informal conversations about the project and topic with members of the group. Data collected from VISTAS weekly meetings from 2011 to 2014, and field notes and transcriptions of audio recordings from these meetings and annual all-hands meetings, were used in the analysis. Meetings varied in subject matter and included both scientific discussions and technical details. Observation of secondary users of the visualization output is planned for future research, so the findings presented here are based on primary users' experiences and perceptions, as well as their ideas for design requirements and development requests. While analysis of secondary users' experiences with data visualization is an important part of evaluating visualization use and usefulness in multiple contexts, we note that incorporating the secondary user group is an emerging consideration to the VISTAS research rather than a central design focus. Additionally, the VISTAS research initiative was focused on giving domain scientists a tool; however, we discovered that along with the functionality of this tool, it might be important to guide users in what visualization techniques would be best-suited for the many purposes for which they would be producing visualizations. In other words, the tool comes with the capability to produce a wide range of visualizations, but does not suggest which visualization is the best to use for which setting. Other studies have recommended ways to give the user ideas for how to best construct visualizations, but a thorough discussion on this topic is outside the scope of this article.[10] The contribution of this article is to conceptualize the relationship between general categories of user types with regard to general features of the domain problem at a high level.

Toward refining the design model for VISTAS

First, we consider some history of the NBGM relevant to VISTAS design. One research inquiry that led to defining blocks and guidelines within the nested model is the QuestVis prototype study.[11] The findings from the QuestVis process are particularly relevant to our own process of developing a conceptual model to understand what visualizations work for whom and in what situations.

The QuestVis tool was designed to “promote environmental sustainability and behavior change via community engagement in environmental policy” (p. 255). 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. This finding is similar to the findings in Grammel et al.’s study on the way novices construct information visualizations in that the barriers to the process include “translating questions into data attributes, constructing visualizations that help answer these questions, and interpreting the visualizations” (p. 949), which we view as requiring some sort of verbal explanation or articulation as support.[10,11]

Similar to the QuestVis (2011) and Grammel et al.[10] research results, we found 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, our domain experts continually referred to the need to create intuitive visuals for certain audiences and end-users. When analyzing transcripts and field notes, we found that—across participants—intuitive visuals were requested so that less expert audiences might understand complicated ecological processes during environmental planning and decision-making. We asked the question, “What are intuitive visuals?” and found that intuition seems to be fast thinking.[12] What makes a visualization lead to thinking fast, but also result in accurate thinking for complex problem-solving? 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 visualization 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. The term intuitive was used when participants discussed creating a visualization for a specific type of user. According to VISTAS case study participants, intuitive visuals often appeal to what they termed tough critics of their scientific findings. Intuitive visuals were desired, too, to simplify difficult concepts and data transformations. In order to address this desire for intuitive visuals and reasons behind it, our conceptual model attempts to capture and characterize the different users and viewers of VISTAS visualization. This attempt to distinguish between different types of users and their characteristics is similar to the way Pousman et al.[13] distinguish between traditional users of InfoVis and a proposed category of the casual user.

We believe the outer domain problem level can be conceptualized in such a way to identify the extent to which visualization design contributes to problem-solving and to use by a range of people. Other frameworks that are domain-driven identify how problem-solving and information behavior occurs within a particular context, recognizing the various systems already in place, and other factors such as the personal, social, and organizational aspects.[14] And related methods for development, such as domain-driven theory, take this broad approach. Also, the fields of anthropology and sociology have a long history of using methods, such as ethnomethodology, to analyze the practices of scientists in their workspaces.[15,16] We situate our study as more narrowly related to visualization use and effectiveness than these broader domain problem studies in that we refer to concepts unique to viewers or visual analysts, and yet we acknowledge that other factors relevant to the work- or problem-solving activities might interact with visualization. Or, more importantly, we acknowledge and seek to understand the unique role visualization plays in problem-solving at a high level.

In the following section, we present our high-level conceptual model as a way to characterize the blocks of the domain problem level found in the NBGM. Visualization design and evaluation is domain-specific, and the time and cost of robust and long-term research processes are essential for good design. In addition to past visualization studies focused on problem-solving in the environmental science and policy domains, theories for understanding both how a tool-user and systems co-evolve, such as domain theory and cognitive work analysis, inform the conceptual model presented here, especially with regard to acknowledging how visualization complements and/or supplants current tools and techniques within a problem-solving ecosystem of actors and problems.[14,16]

A high-level conceptual model

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 types include problem characteristics and humans as viewers, analysts, or tool-users (i.e. how humans approach a visualization experience). These types 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 broader point of view.

Typology of problems

We characterize problems broadly using a matrix of types of contemporary problems from the literature on planning and design. Although not necessarily novel, this matrix helps to define types of problems with reference to wicked problems.[3] The concept of wicked problem applied to the problem domain of environmental science is defined as a problem where uncertainty is high and consensus is low, as seen in Table 1.

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 not only scientific and technological aspects, but also sociological and political aspects that affect problem framing and solution acceptability.

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 need to weigh consequences of bad decisions as well as the inability of science and technology to find solutions to unique and emerging problems.

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[17] 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 the best outcome is. Batie reminds us that such wicked problems are not only difficult to solve, but they are also often controversial. We find wicked problems often manifest themselves during collaborative research—oftentimes with stakeholders who are not domain scientists.

Table 1. An overview of wicked problems.[3]

Scientific/technical solution available?	Consensus or general agreement about the problem?	
	Yes	No
Yes	*Tame problem* Isolated, agreement on solution Examples: fire suppression, municipal trash collection	*Mess or complex problem* Science can provide solution but no agreement on how to proceed Examples: population control, traffic congestion
No	*Puzzle or mystery* Agreement on solution, but lack technical/ scientific capacity Examples: disease treatments, flood control	*Wicked problem* No agreement on problem or solution, lack of technical/scientific capacity for full solution Examples: climate change, nuclear power waste clean-up

When dealing with certain types of problems—such as wicked ones—the role of science must also range, and this potentially affects how visualizations 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.[18] In situations where the scientist is an honest broker of policy alternatives, scientific expertise offers diverse decision alternatives, rather than the one right solution. This way of seeing the scientist's expertise helps balance the distinguishing features of the problem: increasing consensus and scientific/technological discovery, and provides 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 with which to explore —say to present decision alternative; at other times, one wants to converge on the best visualization for communicating a solution or a finding. Responsibility for the design of visualization, here, is jointly shared by the computer scientist, who designs the software tool, and the domain scientist, who might create a visualization using the software tool or as a result of a visual analytics process.

We acknowledge the importance of understanding how visualization design fits within a greater problem-solving process, where scientists and stakeholders are currently using other systems and tools, and function within an environment or organizational structure where there are barriers between stakeholders and the scientists, who are trained in a particular discipline and charged with a particular role in analyzing problems.[14] We use the wicked problems matrix as a frame for characterizing current problem-solving processes and systems relevant to those involved in environmental science and policy, suggesting that both scientific and technical considerations and consensus building affect design and evaluation criteria.

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. During our initial planning meetings, we set out with the mindset that visualization effectiveness can be determined only with regard to the problems and people being served, hence the inclusion of our domain experts from the beginning of the design process.[16] Our conceptual model incorporates the human user, acknowledging and combining the concepts developed by studies that distinguish and define experts and novices, or analysts and casual users.[10,13,19,20]

Three labels related to prior work on the differences between users of visualizations and actors solving problems have been used here for the purposes of creating a typology of humans using visualization. We believe that characteristics of humans who are using visualization must be considered within or in relationship to the domain problem. This view helped us to delineate for whom we are evaluating and designing visualization effectiveness, and what the limitations to visualization design might be within a system and with regard to particular actors involved in problem-solving.

Typology of humans in the domain problem

How do we systematically distinguish among the various ways people use and interpret images? We know that there is a temporal aspect to visualization use,[13] so different individuals may experience the same visualization differently, or the same individual's visualization experiences may vary over time. Additionally, studies in visual culture, as well as other fields dealing with individual sight, interpretation, perception, and cognition, have established patterns in how individuals approach visualization, make meaning, and use and interpret images.[21–24]

In conceptualizing a typology of humans or actors, we start by broadly characterizing motivation when someone is using visualization or conducting visual analytics.[25] 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. While distinctions exist between these types, the borders between the types are blurry: it matters little the exact point at which a viewer becomes an 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 article. 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 article, which is to present a high-level conceptual model.

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.[26] Through simple visual sensation, the viewer perceives 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 may 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 find that viewers are similar to casual users.[13,25]

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 based on their particular purpose.[2] 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), and perhaps a method for evaluating meaning in the visualization.[12]

Consider the example of a visualization of landscape data. A private landowner determining whether to purchase an adjacent lot for grazing cattle has a different purpose than a transportation official determining the route of a new road on that same landscape. An analyst has unique traits dependent on 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.[12,21] 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.

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. With regard to the cognitive work analysis framework, we might say that the task of the tool-user is to interact with a visualization tool to conduct visual analytics.[14]

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 level 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 regard 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 typology. For example, we wonder whether expertise as a result of treatments such as education, training, and experience may interact secondarily with the effectiveness of the visualization.[10] One 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 levels of attentiveness and agency. These arguments aside, our types are place-holders suggesting how human characteristics might be defined as considerations for characterizing blocks in the domain problem.

Design considerations: example of VISTAS case study application

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.[5] Initial analysis of transcripts produced obvious results that confirmed what the literature says: big data are challenging—both in research and in communication;[27,28] domain scientists are using visualization in both their personal research and in collaborative groups;[29,30] and scalability is a central problem to both analyzing data and presenting results.[27,31] Additionally, over the course of the project, we found that like in other studies, visualization often plays a complementary rather than central role in data analysis and communication.[32]

How can we evaluate visualization to tell whether design is aligning to needs? Below we overlay our conceptual model using VISTAS case study examples onto AQ5 the NBGM to see where it might lead.

Applying a conceptual model for characterizing 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 discussed ways that humans can vary in their engagement with visualization. What follows are some initial findings from our social science inquiry that might demonstrate the model's usefulness.

It should be noted that our empirical work was designed to focus on the experiences of software users who are both conducting visual analytics and engaging others using software output. In contrast to a similar development project associated with the Vismon tool, which was developed to help managers conduct data analysis, we did not set out to evaluate visualization for secondary users, such as managers.[19] The managers in the Vismon project are characterized as having a particular set of knowledge, but not as having expertise in statistical analysis and simulation software as our primary users do. One goal of the Vismon project was to enable managers to do data analysis. Results of analysis were used for communication of complicated scientific models with policy makers for decision-making. Similarly, our work and conceptual model highlight how visualization tools such as Vismon and our own VISTAS visualizer can connect scientists and stakeholders; however, the VISTAS case study set out to evaluate effectiveness from the point of view of our primary tool-users—expert scientists—who will be creating visualizations of varying effectiveness, rather than evaluating visualization effectiveness by directly observing interactions with and experiences of secondary users.

Next, we give examples from VISTAS case study analysis using the language of the NBGM with regard to our conceptual model, 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.

Consensus building

Participants in the VISTAS case study present their scientific models to stakeholders and community leaders in decision-making processes where consensus may be low, and agency and attentiveness both high among most visualization users. In such a setting, a viable design guideline would be for the visualization(s) to present several scenarios for discussion among group members with varying levels of attentiveness and agency; this would provide a live visual analytics process for exploring a technically challenging problem and building consensus. Visualization can contribute to consensus building, where visualization might be used as a way to make complicated scientific models more accessible, as exhibited in this statement characteristic of VISTAS participants' experiences:

> [My audience] is more results-oriented. They ask: How will these management decisions affect my livelihood? In the case of our forest simulations: How will forest harvest over a 50 or 100 year period affect the flow of timber into the mills and how does that affect jobs? How does it affect the water supply? People's interests might be different as you talk to different groups, of course, but you want to be able to address all those things in a very clear way. I think it would be rare to get the question: How did you create that visualization? (Scientist 1, 2011 Interview)

Another desirable feature of visualization is to build consensus through engaging viewers in a live analytics event, as exhibited in this statement characteristic of VISTAS participants:

> But once you get into this visualization scenario mode, someone else [not the scientist] is articulating scenarios, and some of the burden is off of us at that point, because the deniers are part of the process. (Engineer 2, All-hands meeting, November 2013)

These examples of visualization used in settings with multiple types of viewers and analysts highlight the need to (1) make scientific findings accessible and (2) provide a means to engage highly attentive viewers with potentially low consensus through visual analytics. To be sure, visualization is just one aspect of the problem-solving process so that understanding how visualization works to build consensus also helps us identify how other factors outside of visualization, such as cultural values and level of scientific expertise, might interact with the visualization if consensus is seen as a barrier to problem-solving. The demand for creating intuitive visuals, as often mentioned in interviews and meetings over the course of the VISTAS case study, is related to the process of visualization for appealing to non-scientist audiences, where terms such as uncertainty and variability may be perceived differently. By identifying and characterizing types of actors, their characteristics, and levels of consensus, the domain problem takes into account political and sociological features of problem-solving, which might also help define guidelines for visualization design effectiveness and software tool development.

For example, levels of consensus might determine design guidelines. Consensus denotes agreement and accord. Low consensus can occur for any number of reasons. 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. If individuals have low attentiveness, consensus might occur simply because those in the group may not care or feel as strongly about their competing interests. 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, such as through showing audiences a familiar landscape and projecting data-driven visual changes onto that landscape based on different land-use decisions.

Exploration of complex problems

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.

One technical challenge described by all the scientists in the study was the ability to integrate models producing big data; and one design guideline the VISTAS group was testing was the ability of visualization to integrate the research of the VISTAS scientists, who work at multiple temporal and spatial scales. In this example, the participants all have high agency and attentiveness, and the focus is on tackling a technical and scientific problem with high systems uncertainty, such as understanding the interaction between processes of different scales that might occur on the same landscape.

Over the course of the VISTAS case study, discussion about exploration and discovery within the domain problem was focused on one hypothesis of the VISTAS project articulated at the first meeting: Can visualization help these scientists integrate their research and make new discoveries or hypotheses by doing so? As a result, suggestions for how to integrate research were mentioned during meetings, such as certain features of data that might be common across scientific domains. For example, at the initial meeting participants discussed the possibility of connecting across different disciplines by analyzing carbon dioxide (CO_2), a major research focus in environmental science. One scientist suggested intersecting their work through visualizing different processes:

> You know, having the biogeochemical model (scientist #1's data) in the background to atmospheric data (scientist #2's data) adds value to this by showing where the air flows and how it flows, or how it's trapped, and being able to explain some of the variability that you cannot explain with variability in temperature or stream or so forth. (Project PI, All-hands Meeting, 2013)

As described in the statement above, the development team was encouraged to take risks with technically sophisticated visualization. Another example includes integrating cross-scale visualizations, which is important for understanding how various phenomena interact or how systems are coupled.[33] Project data confirmed the importance of integrating science across scales and potential design features developed for visualizing these interactions; however, designing a visualization and visual analytics process for conducting cross-scale, interdisciplinary analysis continued to be a challenge. That said, the use of visualization in this discovery-based activity is noticeably different than the example where consensus was the primary goal. We found that collaboration and data integration occurring early in the data pipeline was necessary to using visualization for developing insights.

In this discovery-based example from the VISTAS case study, guidelines are less concerned with communication between scientists and non-scientists. 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 building in this example differ from building consensus with stakeholders. Instead, the ability of 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.[20] In contrast to using visualization for consensus building among public stakeholder groups, visualizations needed in this type of collaboration or process are more often for the purpose of exploration of problems by various sophisticated tool-users with similar institutional status and disciplinary training, rather than for communicating complicated findings to non-scientists.

Nested model's value

Standardizing a design format to respond to such context-dependent needs for visualization might seem difficult.[34] That said, characterizing visualization users by considering the unique aspects of visualization from a cognitive science and psychophysics point of view, then considering the degree to which visualization users care and are directed by a purpose, seem like good first steps. Then, one might consider how the various types of actors (tool-users, analysts, and viewers) might plug into the problem domain, including the relationships between the number of actors involved in the various stages of problem-solving and the levels of systems uncertainty and consensus. These design considerations take into account both the level of technical and scientific complexity and the potential political and cultural aspects related to the problem context. The nested model can be useful for then talking about the necessary guidelines in the other levels of design—such as which interaction techniques work best for whom or which data abstraction might be AQ6 most appropriate for integrating models.

In addition, a domain-driven study might acknowledge how tool design affords tool-users a full array of visualization options based on initial design. This array of options allows primary users to choose which story or narrative to present to others, depending on the problem context, in addition to an array of techniques for using visualization for exploration. As Danziger[34] highlights, data narratives using visual and verbal elements are more likely to appeal to non-scientists (or non-expert users) than the statistical transformations behind the data story. One related finding from our case study is the distinction between design for software users as analysts and design for software users as tool-users creating artifacts to be used in other settings. While we were limited in having the resources to observe our primary users interacting with various audiences, we find the limitation useful in that it helps us conceptualize evaluation phases that are separate and may have different criteria for effectiveness at the different levels of the nested model and may even be conducted by different evaluators (e.g. by a specialist in visualization who is developing a software tool, or by a future tool-user on a case-by-case basis with regard to the many settings in which visualization is presented, as a poly-centric evaluation practice). This finding confirms past work that identifies two strains of visualization research—one that is grounded in design for visual communication and other that is grounded in design for human users.[34] Visualization evaluation and design criteria may be affected by the use of techniques, other tools, and language to build data narratives. The data, visual, and verbal displays all work together in the act of perceiving and processing information.[21] This finding complicates the software design and development process. Our high-level conceptual model attempts to elucidate these complications by presenting a system for understanding the relationships between the types of humans and problems that might affect problem-solving, with specific reference to visualization use.

Limitations

There are a number of potential limitations to application of our conceptual model to the problem domain of the NBGM. First, one might say that our conceptual model 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 and Stasko.[20] 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 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.[35] 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 NBGM, rather than offering a broader and higher level position on evaluation, as we do here. Conversely, one might say that our model is too domain-specific, and that this conceptual model actually constitutes the beginnings of a specific domain model rather than considerations for blocks and guidelines that might be transferred or generalized to other design and evaluation processes, or that it does not accurately represent what the NBGM intends as characterizations of the problem domain. Or perhaps our question of which visualizations work for whom and in what situations may not be a valid inquiry for creating a conceptual model that applies outside of a social science domain. Finally, terms like "levels of attentiveness" and "levels of agency" imply the ability to somehow quantify these concepts. More research into how to operationalize quantification—or whether quantification is even necessary or desirable—might help test the usefulness and refine our conceptual model.

Recommendations

Applying the NBGM to our project and as we characterized the domain problem helped us derive a conceptual model for design considerations. Based on this exercise, we recommend identifying and including both primary and secondary users in design making. For example, the results of VISTAS data led us to distinguish between primary users of the visualization tool and the secondary users to whom scientific results would be presented. Understanding how VISTAS scientists as tool-users perceived their audiences and their role in presenting findings in various settings helped us specify design requirements. We thus recommend that our conceptual model be used to identify differences in how tool-users, analysts, and viewers interact with visualization and how they might be affected by other types of users during exploration and communication events. This distinction between types of users might be compared to the consume and produce tasks in Brehmer and Munzner's multi-level typology of abstract visualization tasks.[36] The multi-level typology was built through extensive meta-analysis of previous studies and focuses more specifically on the mechanics of visualization tasks than our typology does. In comparison, we see similarities between the two schemes where high-level visualization tasks of consumption in Brehmer and Munzner's work include presenting, discovering, and enjoying. Our tool-user type would potentially present, discover, and enjoy visualization more than those visualization consumers with less agency or attentiveness.

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Additionally, as a problem-driven study, we recommend articulating how visualization might be applied to different types of problems. The visualization is used to build consensus and engage different types of users, in addition to solving a puzzle. Such an analysis of the problem domain offers insight into the standard metrics for evaluating visualization effectiveness (such as the typical time-to-task or error-reduction evaluation) and offers the benefits and limitations of taking a holistic view of effectiveness in design versus a purely reductionistic view.[37] The holistic view we propose might be helpful in addition to technical design of visualization when solving puzzles or exploring novel problems; however, we believe that evaluating design for wicked problems requires different indicators of success than typical time-to-task and error-reduction evaluation.

Conclusion

We presented an extension of considerations for characterizing domain problems with regard to the NBGM based on our social science inquiry during a visualization software development project, uniting the aims of various past studies into a birds-eye view of characterizing the problem domain. We find that the problem domain must take into account not only scientific and technological considerations, as described by the wicked problems matrix, but also political and sociological considerations so that typifying how actors approach visualization events in relation to the domain problem becomes an important design-evaluation consideration.

We highlight the importance of human actors in the domain problem, incorporating and aggregating characterizations of users from some previous studies. Additionally, we discuss the importance of identifying human factors in a visualization event—such as levels of agency and attentiveness—in order to 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 regard to the typologies developed in our project and believe this is an enlightening exercise for not only software development, but also for polycentric evaluation of design effectiveness by tool-users, suggesting that effectiveness depends not only on the actor or system, but also on who is evaluating effectiveness. Finally, our contribution to shaping visualization design and evaluation theory is to present relationships between general categories for analyzing what visualizations work for whom and in what situations, especially with regard to the domain problem level in the NBGM.

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