explanations of the perceived benefits in terms of visual reasoning. By intentionally both sampling for diversity and analyzing from the perspectives of multiple research disciplines we hope to add richness to this discussion. The contribution of this paper is an exploration the space of alternative explanations to expand our understanding of the value of interaction for visual reasoning.

5.4 Mixed Initative Interaction

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The group defined mixed initiative interaction as a type of interaction for visual reasoning in which the human analyst and the visualization system both are active participants in the interaction. In a traditional interaction scenario, the visualization software is reactive, responding to inputs from the analyst. In MI interaction, the system would play a more active role, for example, making suggestions about appropriate views or next steps in the analysis process. There are then two directions of interaction: human to system, e.g. applying filters, making selections, loading new data; system to human, e.g. suggesting views, suggesting next steps, automatic highlighting of potentially interesting part of a view.

Mixed initiative interaction has been studied for several years, but remains on the periphery of mainstream visualization research. Systems in this area are often called 'smart visualization' or 'intelligent user interfaces'. However, it seems the community is skeptical due to the cost of error: if a smart visualization system suggests a particular representation type, or an analysis process which is inappropriate to the data or current task requirements, then an analyst could become frustrated, or, worse, may come to incorrect conclusions, biased by the underlying interaction model. Other challenges in this research include being able to gather appropriate and sufficient user data to create a model of the user, such as understanding their level of experience, preferences, prior domain knowledge, etc. As this sort of data is difficult to gather and often inconclusive, we focussed our discussion on MI interaction possibilities in scenarios where we do not have prior knowledge about the analyst. Our discussions lead to a list of factors which can be used to evaluate the success of system-initiated interaction prompts:

- Are they timely? Are suggestions provided at the right time or do they interrupt the analyst's flow?
- Does the system take initiative sparingly? If the system takes the initiative too often, the analyst may become fatigued and ignore suggestions.
- Are system suggestions appropriate? Is the system suggesting views, prompts, or other cues which enhance the analysis experience and potential for insight? Or do they lead to incorrect conclusions about the data?
- Is the provenance of system suggestions transparent? Can the human analyst understand why the system makes any given suggestion?

Scenarios where MI interaction may be useful include a new analyst using a system for the first time and requiring tutorial-style guidance. In this scenario, the system may not know much about the characteristics, prior knowledge, interaction styles and preferences of the analyst and has to provide assistance based on characteristics of the data and the current interaction session, and perhaps a crowd-driven model of the way other analysts have used the system.

Human to System Interaction (Human Initiative)

We called the types of traditional interactions, such as selecting data items, panning and zooming a view, "*explicit* interactions". Newer forms of interaction, such as 'model steering' by repositioning items in a visualization to indicate prior knowledge about their relatedness, are also important inputs to a mixed initiative system.

Where we focused our discussion was on new forms of cues which may be gathered by the system in a mixed initiative interaction model to improve the quality and timeliness of prompts and suggestions. We called these inputs 'implicit interactions'. We enumerated the following list of potential 'implicit interactions' which could be tracked by a visualization system and used to decide when and how to take initiative:

- Dwell time (eye gaze, touch, or mouse cursor)
- Facial gestures
- Highlighting / copying behaviour
- Repeated actions
- Body position / gestures (proxemics)
- Thrashing—changing actions / direction
- Emotional indicators
- Physiological indicators
- Mouse signatures
- Keyboard signatures
- Repositioning items on the screen
- The history of what they have explored already (the analysis process)

These implicit interactions could provide a wealth of data to a mixed initiative system, but would also have drawbacks which need to be investigated, including privacy concerns, potential for reinforcing actions (encouraging 'tunnel vision'), or ambiguity of the meaning of the indicators. For example, physiological and behavioural indicators of excitement and annoyance may be quite similar. Which implicit interactions would be most important and how they could work together to create a profile of the analyst state are areas of future research inspired by our discussions.

System to Human Interaction (System Initiative)

Others have researched system-initiated interaction driven by user profiles and data characteristics, so we targeted our discussions on the types of feedback a system could provide based on analysis of implicit interaction data. The timing of system-initiated interaction is crucial: ideally it is timely, does not interrupt the flow of analysis and human-initiated interaction, and is appropriate to the data and task. Design decisions to consider in future work include: (a) how to present interaction and analysis suggestions, (b) how to reveal the provenance of guidance (why a suggestion is made by the system), (c) how to encode the confidence level the system has in a suggestion, etc. We recommended that system feedback could also be subtle or implicit. For example, if the system senses the analyst is "lost" or "stressed", rather than asking "are you stressed?" it could simply provide additional on screen help, adjust or simplify the interface, and suggest alternative views.

We explored a variety of system responses which may be appropriate if the indicators strongly point to the need for system-initiated interaction. Specifically, we looked at possible responses to various detected emotional states, such as frustration, confusion, boredom, interest, and engagement. System responses may include: show more views like the current view, show views different from the current view, show what other people (all people / people like me / experts) did in similar situations, offer help, or simplify the view (remove a data dimension or perform aggregation). MI interaction should be flexible and perhaps system-initiation should be turned off automatically after the analyst does not acknowledge or use system suggestions over a long period of time.

To conclude our meetings, the group brainstormed about a paper outline reporting on our mixed initiative interaction for visual reasoning ideas, and assigned next steps to the participants.

5.5 Conceptual Structures of Interaction for Visual Reasoning

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Interaction is a fundamental element of successful visualization methods and tools. In visualization, interaction can support many low-level and high-level tasks and goals, can support different representation and interaction intends, and can be realized by different techniques. The specific incarnations of the interaction design, however, are driven by the specific application domain, by the tasks being supported, by the type of data being analyzed, by the specific representations being chosen, by potential limitations of computability, and by the needs and requirements of the users. The question that we aimed to analyze is if we can identify general principles of interactions that bridge different domains and are common among tasks, data types, and representations. Can we formulate or propose a language or schema of interaction that is common for most if not all visualization tools and methods, potentially with different dialects?