Interaction Junk: User Interaction-Based Evaluation of Visual Analytic Systems

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ABSTRACT
With the growing need for visualization to aid users in understanding large, complex datasets, the ability for users to interact and explore these datasets is critical. As visual analytic systems have advanced to leverage powerful computational models and data analytics capabilities, the modes by which users engage and interact with the information are limited. Often, users are taxed with directly manipulating parameters of these models through traditional GUIs (e.g., using sliders to directly manipulate the value of a parameter). However, the purpose of user interaction in visual analytic systems is to enable visual data exploration – where users can focus on their task, as opposed to the tool or system. As a result, users can engage freely in data exploration and decision-making, for the purpose of gaining insight. In this position paper, we discuss how evaluating visual analytic systems can be approached through user interaction analysis, where the goal is to minimize the cognitive translation between the visual metaphor and the mode of interaction (i.e., reducing the "*interaction junk*"). We motivate this concept through a discussion of traditional GUIs used in visual analytics for direct manipulation of model parameters, and the importance of designing interactions the support visual data exploration.

Categories and Subject Descriptors
H.5.2 User Interfaces

General Terms
Design, Human Factors

Keywords
Interaction, visual analytics, evaluation

1. INTRODUCTION
The ability for users to interact with a visualization is critical in enabling visual data exploration [1]. As such, the study (or science) of interaction is particularly important as underlying analytic models increase in computational ability, but also complexity [2]. It can be argued that designing user interaction is as important as designing the visualization itself.

The model for designing these interactions is in large part focused on giving users direct, graphical controls over specific, complex parameters. The visualization pipeline, shown in Figure 1, models how these interactions are typically designed. Such a model is reasonable, given the design of the complex mathematical models underlying many visual analytic systems require setting numerous parameters, thresholds, and other assumptions that can be varied. However, we contend that such user interactions are designed around the particular mathematical models, as opposed to designed to support the user's analytic process. This leads to the challenge of determining to what extent these interactions are optimized to produce insight and support sensemaking, rather than clutter that may produce "interaction junk" (similar to how "chartjunk" refers to unnecessary visual clutter that may obscure true data in visualizations [3]). Thus, the goal of reducing interaction junk is accomplished through reducing interaction clutter that may interfere with the analytic process of the user.

Evaluating visual analytic systems based on the user interactions provided is an open challenge [4, 5]. In this position paper, we approach this challenge by providing a brief overview of previous work describing user interaction in visual analytic tools. We present our concept for evaluating these interactions based on minimizing the amount of cognitive translation required between the visual metaphor (i.e., the visualization) and the method for interacting with the visualization (e.g., sliders, menus, and other graphical components) – reducing the "*Interaction junk"*. Instead, the goal of interaction-based evaluation is to open the design of user interactions that maintain as close to the visual metaphor being manipulated. This idea is conceptually similar to traditional usability research, where the purpose of usability is to increase the amount of progress a user can make in their task while minimizing the amount of effort they expend. We conclude by discussing the open challenges for a more formal methodology for interaction-based evaluation of visual analytic systems.

2. RELATED WORK
The role of interaction for information visualization is difficult to classify [6]. This is in part due to the ability for humans to "interact" with even a static image, where patterns are formed and insights are gained purely via cognitive manipulations [7]. As such, one of the challenges for information visualization is to gain a deeper understanding of how users interact with visualizations,

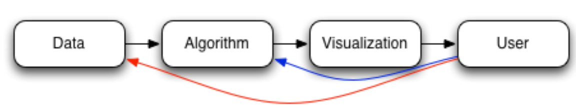

Figure 1. The visualization pipeline, with arrows indicating the modes of interaction users can engage in to explore the information.

and more importantly how these interactions integrate into the analytic process [1].

Yi et al. have presented an extensive categorization of types of user interactions available in popular exploratory visualization tools [8]. They categorize user interaction in visualization based on user-intent (i.e., select, explore reconfigure, encode, abstract/elaborate, filter, and connect). Further, Dou et al. have shown that logging such low-level interactions of users analyzing a dataset can enable researchers to extrapolate portions of a user's analytic process, and in turn validate the importance of user interaction for successful visual analysis.

Further work has been done to explore and understand how the design of user interaction can impact the analytic process. Green et al. proposed that user interactions should be designed so as not to drive users out of their "cognitive zone" [9]. Their work emphasizes the need to maintain engagement with their task, rather than become distracted with navigating a tool, etc. Similarly, Elmqvist et al. propose the design of "fluid interactions" that promote users to stay in the flow of their analytic process [10]. Lam presented a framework for interaction costs that can be used to measure the cognitive and physical costs associated with a user's task of forming a plan of action to execution [11]. The metrics by which this can be measured are [11]: (1) Decision costs to form goals, (2) System-power costs to form system operations, (3) Multiple input mode costs to form physical sequences, (4) Physical-motion costs to execute sequences, (5) Visual-cluttering costs to perceive state, (6) View-change costs to interpret perception, and (7) State-change costs to evaluate interpretation.

User interaction in visual analytic systems has the added complexity of not only interacting with a view, but also manipulating underlying analytic models. As such, model steering is becoming a popular concept in visual analytics. Figure 2 shows how users can interact with the Galaxy view in IN-SPIRE [12]. As system designers are becoming more aware that the domain expertise of users is critical to the success of these systems, the ability to steer the models is important. The challenge in doing so is designing user interactions that are both usable by the domain expert analyzing information, as well as maintaining the expressiveness necessary to manipulate the analytic models [13].

3. INTERACTION-BASED EVALUATION

Interaction-based evaluation enables users to evaluate user interaction within a visual analytic system based on the utility and effectiveness of producing insight. As such, the high-level definition of interaction-based evaluation is described by:

$$Interactionjunk = \frac{Distance\ from\ Visual\ Metaphor}{Insight}$$

Based on this formula, the objective of designing user interactions is to minimize the amount of "*Interaction junk"* by providing interactions in tools that minimize the distance from the visual metaphor they control.

Fundamentally, the goal of interaction junk is to encourage visual analytics designers to consider the implications of creating specific interactions. Analogous to chart junk emphasizing the minimization of visual clutter, Interaction Junk emphasizes the reduction of interaction clutter. Interactions should allow users to progress through their analytic task, rather than deviate from it to control a tool.

3.1 Insight

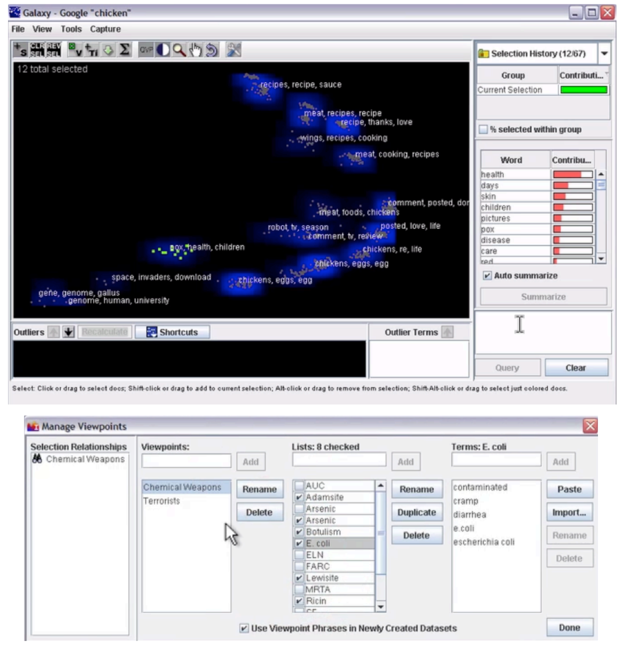

Figure 2. The model generating the Galaxy in IN-SPIRE (top) can be controlled via directly adjusting the contribution of specific terms in GUIs (bottom).

We define *Insight* based on previous work by Saraiya et al., who propose insight-based evaluation as a means for evaluating visualizations [14]. Insight-based evaluation presents a means for recognizing moments of insight during an investigation, and pinpoint the advantage of a visualization in doing so. Further, the authors outline methods for determining the relative importance of insights, so as to point out specific insights that are more valuable than others.

3.2 Distance from Visual Metaphor

Defining the *Distance from Visual Metaphor* for the purpose of interaction-based evaluation is more complex. Fundamentally, this concept is based on how disjoint the visual metaphor used to represent the information (i.e., the visualization) is from the method for users to interact with the tool. (It does not represent physical distance of mouse movements, or virtual distance such as pixels.) For example, interactions for a spatialization for text documents (such as the one shown in Figure 2), can be designed as follows:

Menus Directly Adjusting Model Parameters Values: Parameters of the dimension reduction models can be directly controlled. Examples include menus, or other textual interfaces where users are required to translate their insights or hypotheses from the spatial metaphor into interactions designed to steer the models (e.g., directly biasing dimensions, choosing different Eigenvectors, etc.). These types of interactions would be considered to require a high amount of cognitive translation, as they typically do not map to the spatial metaphor created.

Graphical Controls of Model Parameters: Similar to the adjustments described above, these interactions are designed to directly manipulate models underlying the visualizations. While the graphical interfaces (e.g., sliders, knobs, etc.) decrease the amount of translation required, users are still required to perform a moderate amount of cognitive translation to modify the visualization and explore the dataset.

Direct Visual Manipulation: User interactions that leverage the visual representation as a medium for user interaction require a low amount of cognitive translation between the insights and interaction (e.g., [13, 15, 16] [17]).

Another factor impacting the amount of cognitive translation a user must perform is how distant from the domain of the user the interaction is. For example, if a domain expert is trained in topics such as political science, history, and related classics fields, designing interactions based on knowledge in dimension reduction algorithms results in a longer distance. However, designing interactions the leverage the abilities of expertise in the domains of the user, such as highlighting phrases of text, jotting annotations about how a portion of text reminds them of similar past events, etc. is preferred.

4. FUTURE DIRECTIONS

Assessing visual analytic systems by their ability to maintain user interaction within the visual metaphor can lead to more usable and effective tools. This position statement briefly describes the concept of interaction-based evaluation, and through the discussion opens research questions that, in the future, can enable a more formal evaluation methodology for visual analytics.

5. ACKNOWLEDGMENTS

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6. REFERENCES

[1] Thomas, J. J. and Cook, K. A. Illuminating the path. IEEE Computer Society, 2005.

[2] Pike, W. A., Stasko, J., Chang, R. and O'Connell, T. A. The science of interaction. Information Visualization, 8, 4 2009, 263-274.

[3] Tufte, E. R. Visual Display of Quantitative Information. Graphics Press, Cheshire, CT, 1983.

[4] Scholtz, J. Beyond Usability: Evaluation Aspects of Visual Analytic Environments, 2006.

[5] Scholtz, J. Developing guidelines for assessing visual analytics environments. Information Visualization, 10, 3 (July 1, 2011), 212-231.

[6] Card, S. K., Mackinlay, J. D. and Shneiderman, B. Readings in information visualization: using vision to think. Morgan Kaufmann Publishers Inc., 1999.

[7] Spence, R. Information Visualization: Design for Interaction. Prentice Hall, 2007.

[8] Yi, J. S., Kang, Y. a., Stasko, J. and Jacko, J. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. IEEE Transactions on Visualization and Computer Graphics, 13, 6 2007, 1224-1231.

[9] Green, T. M., Ribarsky, W. and Fisher, B. Building and applying a human cognition model for visual analytics. Information Visualization, 8, 1 2009, 1-13.

[10] Elmqvist, N., Moere, A. V., Jetter, H.-C., Cernea, D., Reiterer, H. and Jankun-Kelly, T. Fluid interaction for information visualization. Information Visualization, 10, 4 (October 1, 2011 2011), 327-340.

[11] Lam, H. A Framework of Interaction Costs in Information Visualization. Visualization and Computer Graphics, IEEE Transactions on, 14, 6 2008, 7.

[12] Wise, J. A., Thomas, J. J., Pennock, K., Lantrip, D., Pottier, M., Schur, A. and Crow, V. Visualizing the non-visual: spatial analysis and interaction with information for text documents. In Proceedings of the Readings in information visualization: using vision to think (1999). Morgan Kaufmann Publishers Inc.

[13] Endert, A., Fiaux, P. and North, C. Semantic Interaction for Visual Text Analytics. In Proceedings of the ACM CHI (2012).

[14] Saraiya, P., North, C., Lam, V. and Duca, K. A. An Insight-Based Longitudinal Study of Visual Analytics. IEEE Transactions on Visualization and Computer Graphics, 12, 6 2006, 1511-1522.

[15] Brown, E. T., Liu, J., Brodley, C. E. and Chang, R. Dis-function: Learning Distance Functions Interactively. In Proceedings of the IEEE VAST (2012).

[16] Endert, A., Han, C., Maiti, D., House, L., Leman, S. C. and North, C. Observation-level Interaction with Statistical Models for Visual Analytics. In Proceedings of the IEEE VAST (2011).

[17] Endert, A., Fiaux, P. and North, C. Unifying the Sensemaking Loop with Semantic Interaction. In Proceedings of the IEEE Workshop on Interactive Visual Text Analytics for Decision Making at VisWeek 2011 (Providence, RI, 2011).