Adaptive and Personalized

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Abstract
Adaptive visualization has the potential to improve the accessibility of information in personal informatics systems while reducing the effort required of developers and designers to target data visualizations to specific use cases and specific users. Users have many widely differing needs, and they vary equally in their ability to understand visualizations. That ability is based on individual differences in personality and circumstances among others. We aim to demonstrate that adaptive visualization is a viable direction for designing personalized visualizations, and that it has benefits for both users, designers and developers. We present issues in personalized visualization, how adaptive visualization may be used to address them, and our view for moving a research agenda forward in this domain.

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Personalized Visualization, Adaptive Visualization

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

General Terms
Personal Visualization, Quantified Self, Visualization Evaluation

Introduction

Adaptive visualization is in essence the holy grail of information visualization. Adaptive visualization represents crystallizing the theories and best practices of information visualization into a structure that is capable of ingesting data and constructing visualizations that convey information as effectively as possible. Personalized visualization as a concept has a significant amount to gain from adaptive visualization especially as the amount of data that a single person can aggregate about themselves grows from a trickle into a flood. With this growth there has been an explosion of special purpose applications that help users track their exercise routines, finances, productivity, weight, location, driving habits, diets, and just about any other aspect of life that can be quantified. This is the data that drives the quantified self movement and visualization is the *lingua franca*.

To paraphrase Jock MacKinlay, with an adaptive system, the problem of generating a good representation is no longer the problem of a developer or design team to anticipate all of a user's needs, but is instead the responsibility of the adaptive system[4]. From a research perspective the problem area is rich with possibilities for incorporating, formalizing, and evaluating current ideas on user modeling and effective visualization strategies into an adaptive visualization system.

In the remainder of this paper we will focus on how adaptive visualization has developed over the last 30 years, examine how these results apply in the case of personalization, and discuss potential avenues for future work as well as our perspective from ongoing projects in our group. We will use the five stage model of personal informatics[3] to ground the discussion.

Background

Adaptive visualization has been a subject of research in some form or another since the mid 80's with Jock MacKinlay's work on APT[4] and has progressed steadily. We have identified four general approaches:

- Data centric adaptive visualization[4, 5]
- User Modeling to inform adaptation[1, 2, 8]
- Intelligent visualization selection[9]
- User-adaptive visualization[7, 6]

Data centric adaptive visualization was the earliest work, and focused on selecting an appropriate representation based solely on data attributes and a heuristic model of how well a representation would be interpreted by users. APT for example was able to select theoretically correct visualizations. Later work that focused on user modeling focused on task specific applications [8], and which user attributes are most important for successfully extracting information from a representation [1, 2].

Intelligent visualization selection is a promising direction as it acknowledges the difficulty of automatically generating good visualizations by exploring the complete design space, opting instead to suggest appropriate representations from a known set[9]. Another recent trend is the union of adaptive visualization concepts and user modeling. Stiechen et. al. demonstrated that user's eye-gaze can indicate a user's current task, cognitive abilities, and working memory. This could be used to dynamically adapt a visualization to the user throughout the duration of interaction[6]. The inclusion of user modeling in the adaptive framework is critical, as the key problem in visualization is not mechanically creating representations that encode data, but creating visualizations that are useful, efficient, and accurate at communicating the encoded information.

Incorporating Adaptive Visualization into the Personal Informatics Model

In personalized visualization, the important aspect of visualization comes in the *reflection stage* of the five stage model. Li et. al.[3] found a number of problems faced by users in the overall personal informatics process. We will not treat all of the problems examined in their work, but instead focus on those relevant to visualization. The first we will address was termed simply *visualization* where the amount of data displayed was mismatched with the user's needs. *Interpretation* issues occurred when the representation was inappropriate for the user's level of visual literacy, or was overly complex. The final problem we will examine was *data was not useful*. The spirit of the issue was that the user already knew the data well, and found no additional utility in examining the visualization.

For problems of *visualization*, adaptive visualization should prove beneficial by examining information about the user to infer the most useful representation. Toker et. al. noted that there are significant differences in user performance depending on the representation chosen, the user's cognitive abilities (most importantly perceptual speed), and their experience level[7]. Issues with visualization go hand in hand with issues of interpretation, and we suspect adapting visualizations to conform to users expectations will reduce issues both in *visualization* and in *interpretation*. *Data was not useful* is a more challenging issue; it speaks to a dearth of data, or a lack of user engagement. An intelligent representation should be able to indicate to a user that there is insufficient data to use for reflection or decision making. That said there is little to be done for a disinterested user.

Lessons from our Work

In a recently completed study run via Amazon Mechanical Turk we examined some factors that influence user speed and accuracy when performing visualization related tasks. Empirical results from the study illustrate the benefit and cost in speed and accuracy of mismatching the complexity of a visualization with the complexity of the user's inquiry in order to examine differences in personality, education, and occupation. The study used a 4 (2 simple vs. 2 complex visualizations) $\times$ 2 (find value vs. relate values tasks) $\times$ 2 (match vs. mismatched complexity) design. We examined participants' accuracy and response time for interpretation tasks under two sequences: a simple inquiry mismatched with a complex visualization (s2c) and a complex inquiry mismatched with a simple visualization (c2s). The results indicate that providing too much information increases accuracy at the cost of speed. Over simplification can lead the participant to misinterpret information. Users were, in general, more accurate at completing find tasks compared to relate tasks, though they took more time to find values, especially with complex inquiries.

Personality traits also played a role. Neuroticism (characterized by increased sensitivity and emotional reactivity to perturbations in the environment) is associated with higher likelihood of accuracy for simple inquiries (s2c) but not for complex tasks (c2s). When answering simple inquiries, neuroticism decreased the difference in the likelihood of accuracy between find and relate tasks. In contrast, when completing complex inquires, neuroticism dampened the advantage of find compared to relate tasks.

These findings suggest that a visualization is most effective when it matches the complexity of inquiry. This advantage varies across user characteristics. Therefore, an adaptive visualization system would be sensitive to within-user variation in context, and also user-specific norms and preferences.

Conclusion

Successfully meeting the challenges of designing for a small audience (an audience of one) is difficult. Designing for each individual directly is not feasible. Adaptive visualization with ongoing advances in user modeling and interaction presents opportunities to improve visualizations both before and during user interactions. There are several strategies to pursue for incorporating adaptive components in personal visualization and informatics applications. We argue that this is a fruitful area for further exploration.

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