Towards Personalized Visualization: Information Granularity, Situation, and Personality

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ABSTRACT

Technology users are collecting data about themselves at an astounding rate. This explosion of data collection has not been matched by users' abilities to assimilate and apply this information. Visualization is a key means of bridging this gap, however, most approaches to visualization neglect individual differences, and focus instead on one-size-fits-all approaches. One proposed solution to this problem is adaptive visualization. To produce appropriate adaptive visualization tools, however, we must understand the relationship between a user's context and the visualization they require. In this paper, we present a study designed to understand the effects of visualizations that are mismatched, in terms of granularity, to user contexts. We show that users are able to interpret data visualizations most accurately and quickly when the information granularity of the visualization they are shown matches their need for detail and we discuss the consequences of mismatching the information granularity of a visualization to a user's information needs.

ACM Classification Keywords

H.5.2 User Interfaces: Evaluation/methodology; H.5.m Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords

Adaptive Visualization; Personality; Visualization; Personal Visual Analytics

INTRODUCTION

The recent data explosion has not been matched by user's abilities to assimilate and apply the information they accrue. We see visualization tools as the most viable candidates for providing users with an ingress to their data. However, most

approaches focus on a one-size-fits-all approach, and neglect individual differences and contexts. Many visualization tools, such as Excel, allow users to modify the presentation of information at run time. These tools are *adaptable*. Unfortunately, these tools require a broad set of skills to use successfully. The promise of *adaptive* software is that it accounts for the context in which it is used, and can modify its behavior to produce an appropriate view of the data available. This idea of adaptive visualization would enable visualization tools to personalize the presentation of information directly for users.

To create useful adaptive visualization tools we must understand the relationship between a user's context and the visualization they require. Other research on adaptive systems has focused on user modeling, individual differences, and near real-time extraction of those parameters [3, 6, 16, 15]. We aim to determine the costs of presenting a user with visualizations that are unsuitable for their needs. This will provide guidelines for creating adaptive visualization tools. We should not produce visualizations that confuse or distract users.

Our research is grounded in the theory of Bounded Rationality (Bounded Rationality Characterizes the Situation), which posits that the capacity to interpret information is constrained by the information and time available to the decision maker. Bounded Rationality provides a framework to understand the relationship between a user's need for detail, and the time they have to interact with a visualization [4]. We focus on need for detail in this work – we have not yet developed a satisfactory way to emulate time constraints.

This work is based on a previous study of adults' daily reports of progress towards health and social goals over 100 days and their use of visualizations of goal progress following each daily session [12]. These findings inspired our turn to bounded rationality as a way to potentially explain when individuals use visual data and how to best support them. In our study of over 1800 participants, we test the extent to which the *information granularity* of visualization must be matched to the users need for detail to allow for accurate and efficient interpretations. In addition, Pham et al. [12] suggested that visualization use may vary across the personality traits neuroticism and extraversion,

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therefore we will examine the effects of these traits in this study as well.

We hypothesize that users are most able to accurately and quickly extract information from a visualization when the information granularity of the visualization matches their need for detail. This hypothesis may seem intuitive; a visualization that is targeted to a question should be more useful than a visualization that presents all available information, and past research supports our view [17]. However, the extent of the cost in mismatching need for detail and information granularity has yet to be identified. This leads to our research questions (RQ):

RQ 1: What is the cost in accuracy of showing a user a visualization that has too much or too little information compared to a user's need for detail?

RQ 2: Are certain analytic tasks more vulnerable than others to mismatched need for detail and information granularity?

RQ 3: Do these costs vary with personality traits or gender?

RQ 1 is our primary focus. For an adaptive visualization system to succeed, the cost of incorrect results should not outweigh the benefits. **RQ 2** allows us look at potential alternative behaviors of an adaptive system. When the system is uncertain of a user's information needs is it better to display a high information granularity visualization or a low granularity visualization? **RQ 3** addresses previous work in the area and further explored the role of personality traits (Neuroticism and Extraversion) in visualization interpretation.

BACKGROUND

Adaptive visualization is one approach for personalizing visual representations to individual user parameters during the course of interaction as the user's interests, desires, motivation, context, and abilities change. Ultimately, then, the question becomes one of *what user characteristics, context, and data attributes are important for inclusion in a model of personalization?*

Adaptive visualization has been a subject of research since the mid 1980's with Jock MacKinlay's work on A Presentation Tool (APT) [10]. Adaptation here is used in the evolutionary biology sense; to mean the ability to change in order to become fit for a given set of circumstances. The use of *adaptive* is an important distinction. Software that provides affordances for modifying its behavior at run time by the user is *adaptable*. Adaptive means that the software is aware of the context in which it is being used, and is able to modify its behavior to fit a perceived purpose. There are four general approaches to adaptive visualization: data centric adaptive visualization [10, 14], design time user modeling [3, 7, 17], intelligent visualization selection [18], and user-adaptive visualization [16, 15].

Data centric adaptive visualization represents 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. Later work on design time user modeling focused on task-specific applications [17, 10], and those user attributes that are most important

for successfully extracting information from a representation [3, 7]. This approach to user modeling was focused on creating a framework for visualization and application designers to produce more effective tools for specific domains. Intelligent visualization selection explores the complete design space from a known set [18], and avoids the difficulty inherent in processes that automatically generate visualizations from data.

User-adaptive visualization employs user modeling and monitoring to adapt visualizations to the user context. Stiechen et al. demonstrated that user's eye-gaze can indicate a user's current task, cognitive abilities, and working memory, which can be used to dynamically adapt a visualization to the user throughout an interaction [15]. 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 effective at communicating the encoded information.

The net result is an evolutionary push forward from data centric adaptive visualization – the production of a visualization using rule systems applied to the data to create an appropriate visualization – toward a more holistic process of user-adaptive visualization. This addresses the shortcomings inherent in considering only the data when constructing a visualization. The requirements placed on the visualization do not originate solely with the data, but rather in a combination of data, context, and user characteristics. In this research we aim to explore the relationship between personality and information granularity as it relates to correctly extracting information and frame this in terms of bounded rationality, using need for detail and time as the basis of our discussion.

Bounded Rationality Characterizes the Situation

In the PULSE project, users were more likely to interact with visualizations (clicking to see a detailed visualization) on days that they made lower goal progress and reported lower subjective well-being. Participants were more likely to interact with the visualizations on days that they spent more time than usual on the daily survey [12]. Taken with the theory of Bounded Rationality, these factors indicate a two-dimensional space characterized by *need for detail* and *time available*. Under this framework, individuals were most likely to interact with visualizations when their need was great or they had additional time to interact with the visualization.

Bounded rationality suggests that the rationality of human decision making is limited by the information the individual possesses and the time they have to make a decision [4]. Here, the visualization is effectively the information the user possesses, limited by their ability to extract it, and the time component is how long they are willing to engage in the sense-making process. Employing this heuristic in combination with the results of the PULSE study, we developed visualizations and questions that simulated an adaptive system against a subset of possible tasks that a user might wish to complete using the visualization. The environment in a web-delivered study, such as ours, is uncontrolled, so we chose to focus on the simulation of need rather than the simulation of a time constraint.

Information Granularity

To describe relationships between multiple visualizations of the same data, we extend the definition of granularity to visualization. The definition of granularity is the scale or level of detail present in a set of data or other phenomenon. When we apply this to visualization, this is the proportion of the source data that can be extracted from a rendered view of the data by visual inspection. A visualization with no granularity would be an empty display; none of the source information is conveyed to the viewer. Low granularity is summarized, aggregated, or some subset of the source information. High granularity visualizations contain more of the source information, and less summary information. The highest possible granularity might be a table displaying all of the available data (we'll neglect the treatment of projections as future work). Discussions of the perceptual "noise" in this process are vital, but beyond the scope of our work (see [2] for an overview).

Granularity has an advantage over using "level of detail" because it represents a well-defined ordinal spectrum of possibilities. Compared to level of detail terminology, low granularity and high granularity are unambiguous – and we avoid overloading an overworked phrase. We use this concept to talk about the relative information content of different visualizations of the same source data.

Neuroticism and Extraversion

A growing body of evidence in the design of user interfaces has acknowledged the importance of personality in guiding how users interact with their visual space. In several current theories of human cognition, personality is used to explain modulations in cognition. Personality can be predictive of goal setting behaviors, how a person rates importance and meaningfulness, and how individuals interpret information [8]. Extraversion and neuroticism have been shown in previous research to differentiate how individuals process and interpret information [6]. Individuals who are high in neuroticism can be characterized as more sensitive to their environments. These individuals are more readily set off track from their goals and may be more sensitive to information overload. Individuals who are higher in extraversion are more outgoing and optimistic. They are more sensitive to rewards and therefore tend to be more outgoing, social, and more likely to explore their environments [9].

There is a substantial body of research exploring the impact of a variety of user characteristics on visualization use [19, 6]. There are some differences between our approach and that taken by Ziemkiewicz et al. Their work was primarily designed to look directly at individual differences, as opposed to looking at the interaction between variations of visual representations and individual differences. We used different personality measures; we measure Big Five Personality traits and we omit locus of control. Rather than the interaction of a user's personality with a single visualization, we manipulate the visualization's information granularity to approximate the moment at which an adaptive system presents a visualization to the user.

USER EXPERIMENT

We examined the effect of matching and mismatching users' need for detail and the visualization's information granularity

on users' abilities to accurately and efficiently complete tasks that require *finding* and *comparing* values. Participants were shown visualizations and asked to complete four find values tasks and four compare values tasks. The granularity of the visualizations was manipulated by displaying either a visualization of high granularity (i.e., time-series) or low granularity (i.e., aggregate performance bar) (Figure 1).

The need for detail was manipulated by the complexity of the task users were asked to complete. Find value(s) and compare values tasks were selected because these tasks occur often as components of compound tasks in pursuit of other high-level goals, as well as occurring as standalone actions [1]. We use the terms *find values* and *compare values* to refer to these tasks.

The experiments examined the cost of mismatching tasks with either too much or not enough detail. In a *too much detail* mismatch, users were asked to complete relatively superficial find (e.g., What was your goal progress today?) and compare values (e.g., Did you make more progress on your health or social goal today?) tasks. The questions in this sequence were paired with visualizations that either *matched* the task with a low granularity visualization or *mismatched* the task with a high granularity visualization (Figure 2). In the *not enough detail* mismatch, users completed find and compare tasks of greater complexity that were either matched with high granularity visualizations or mismatched with low granularity visualizations. User performance was measured in accuracy and in the response time required to accurately complete a task. Users completed 8 tasks in total: 2 find and 2 compare low need for detail tasks, as well as 2 find and 2 compare high need for detail tasks, which were similarly matched and mismatched in information granularity. This allowed for the examination of differences in accuracy and response time of a specific task when matched and mismatched with the visualization's granularity both between and within persons.

Our study addresses three hypotheses: 1) user tasks will be completed more accurately and with quicker response time when the need for detail is matched to the level of granularity. 2) The accuracy and efficiency of completing find value tasks will be more resilient to mismatched information granularity and need for detail than compare values tasks. 3) Individuals who are higher in neuroticism and lower in extraversion will be more susceptible to mismatched granularity and need for detail. With respect to the first hypothesis, users should be better able to complete tasks when the visualization provided to them matches the task they are undertaking [17]. The second hypothesis gets at the complexity of the underlying analytic tasks – find value tasks should require simple visual lookups, whereas compare values tasks require pattern inference. Compare tasks should be more sensitive to insufficient granularity. The third hypothesis is based on the expectation that individuals high in neuroticism are more readily distracted from their target when – by violating their assumptions the mismatched tasks may derail their thought process more easily than individuals higher in extraversion and lower in neuroticism.

Age Group	(both)	Female	Male
18 to 30	50%	39.95%	58.05%
30 to 40	28%	30.39%	26.57%
40 to 50	11%	14.16%	8.10%
50 and older	11%	15.50%	7.28%

Table 1: Participation by age and gender.

Participants

We recruited 1,938 participants from Amazon’s Mechanical Turk (AMT), an online marketplace that provides access to a large and diverse sample of study participants who can complete human intelligence tasks (HITs) for reimbursement [11]. The survey was open to the AMT community for approximately 12 hours. Participants were provided with an informed consent disclosure before completing the survey as required by our Institutional Review Board.

To verify that participants completed the study, we generated a completion code that participants manually copied from our survey interface to the AMT HIT. Participation was limited to United States residents by IP geolocation. The final sample included 1,837 participants.

The participants were 43% female and 50% had completed at least some college. Participant age was well distributed with a mean of 32 (± 11 , [18 - 81]). Compared to the nation, our sample was within the parameters of normal personality for extraversion (46.62 ± 10.42) and neuroticism (46.37 ± 9.95) [5].

Materials

We used the taxonomy of low level analytics tasks to design what we refer to as the the find and compare values tasks [1]. Find tasks involve extracting a single value from a visualization – the distance between the average and the performance on a progress bar (Retrieve Value), or the largest value in a series (Find Extremum). Compare values tasks require the participant to infer trends (Correlate or Characterize Distribution). The questions were designed to simulate a user’s need for detail, and the matched visualizations target these questions. A participant should be able to readily answer a question with a matched visualization.

Question design varied from low need for detail to high need for detail. Find value tasks with a low need for detail involved extracting a single value from a visualization. Find value tasks with a high need for detail included multi-step find operations, such as finding an extremum, which requires first observing the norm, and then finding its exception. Low need for detail compare tasks included comparisons, and high need for detail compare tasks required users to assess correlations or find anomalies (Figure 2).

The visualizations we used for our user experiment were based on previous research on users’ daily use of visualizations of their own data [12]. Performance bars, histograms, and time series visualizations were useful for our purposes because they rely on common underlying visual variables, specifically they used position and length as the primary visual variables and color as a secondary encoding. In contrast to previous

research, our visualizations were not interactive, users were not able to ask for more detail. A non interactive design was necessary to manipulate information granularity.

Procedure

Participants accessed the study by accepting a human intelligence task (HIT) from AMT. After enrolling in the survey, the participant was prompted for informed consent. The informed consent included an affirmation that they were 18 years of age or older. After consenting, the participant answered a series of demographic questions, regarding age, educational attainment, and income. Personality characteristics were measured using the Ten Item Personality Inventory (TIPI) [5] which has established validity across age groups. Since the TIPI is a brief personality measure, it is well-suited to AMT.

Following the demographic questionnaire and the TIPI, we asked participants to consider a hypothetical scenario: they were observing data about their own social and exercise habits near the end of a month. This scenario mimics, but does not replicate, the daily attention to personal data examined in the PULSE project. We asked participants a series of eight questions. Participants selected the correct answer from a set of possible answers, or provided a value using a range slider. Each question was paired with a visualization.

For every question and visualization pair, participants had an “escape hatch” to say that they couldn’t tell the correct answer to the question based on the visualization. In an ideal case, this option would be unnecessary; an an adaptive system would never present a suboptimal visualization to a user. However, in a real world system the “can’t tell” option would be the “big red button” that alerts the system to failure.

The order of the questions was randomized to control for learning effects. Four of the visualizations had information granularity that *matched* the question, and four had granularity that *mismatched* the question. Participants were randomly assigned to a match/mismatch set of questions and visualizations. After completing the questions, participants were provided with a completion code and returned to the AMT interface to receive compensation.

Analysis

We recorded eight observations per participant. To account for dependencies in data collected repeatedly from the same individual, multilevel models were used to analyze the data. Multilevel models disaggregate variance that is between-persons from variance within-persons across repeated measurements. The grouping variable, the person in this study, is similar to a grouping variable in an analysis of covariance (ANCOVA). Manipulations of need for detail and the granularity of the visualization were used as factors to describe variation within-persons, similar to an ANCOVA’s covariates. Therefore, although multilevel models use maximum information likelihood and ANCOVA uses ordinary least squares to derive effect estimates, the two approaches are analogous [13].

We recorded the order that participants completed questions. This order information was used to control for learning effects and quantify the extent to which accuracy and response time

Figure 1: Example visualizations for the granularity levels used in the study. All visualizations display simulated goal progress. These examples show exercise goal progress, but there is a matching set of visualizations that show social goal progress. The static visualizations used in this study were modeled after the interactive visualizations used in the PULSE project [12]

	Low Need for Detail Questions
Find	What was your performance on your exercise goal today? How much above or below average was today's exercise goal?
Compare	Did you make more progress on your goal to exercise or your goal to socialize today? On how many more or fewer days did you make "good" progress on your social goal compared to exercise goal?
	High Need for Detail Questions
Find	Is today's exercise goal progress usual or out of the ordinary? For how many consecutive days was exercise goal progress above average?
Compare	Does performance on you exercise goal appear to be related to your goal to socialize? Is performance improving for health goals, social goals, or both?

Figure 2: Example find and compare questions. Each question was paired with one of the visualizations shown in Figure 1.

change as a function of the number of questions answered. An interaction term combining task and condition was used to test whether find or compare values tasks differed in the susceptibility to mismatching need for detail with the visualization's level of granularity.

RESULTS

Both high need for detail and low need for detail tasks proved to be challenging for participants to complete accurately. Similar to earlier research, accurately interpreting the visualizations proved difficult for many users [19]. When the need for detail was matched to the appropriate level of granularity (the match condition), 60% of the find tasks and 53% of the compare tasks were completed accurately, and this difference was statistically significant ($X^2(1) = 38.05, p < 0.001$). Under the match condition, find value tasks (26.63 ± 0.33 seconds) were also answered more quickly than compare values tasks

(30.37 ± 0.52 seconds, $p < 0.001$). Order effects were non-significant in all models, which suggests that neither accuracy nor response time improved as participants became more familiar with the visualizations. For every task, participants were able to indicate that they did not have enough information to correctly respond. In total, 1,238 participants (67%) used this option at least once while completing their eight tasks.

Characteristics of the Situation: Need for Detail

We model accuracy as a binary variable—users either did or did not answer each task correctly—and it was examined using multilevel logistic models. Results are interpreted as odds ratios (OR), where OR greater than 1 represent higher odds of accuracy and OR less than 1 represent lower odds of accuracy.

Next, we estimate the benefit and cost of matching and mismatching granularity for low need for detail tasks. Under the match condition, participants were more likely to accurately complete a find task than a compare task. When mismatched with high granularity visualizations, the odds of accuracy in completing a low need for detail task were reduced by 73% ($p < 0.001$) for compare tasks and by 66% ($p < 0.001$) for find values tasks. Consistent with our expectations, low need for detail compare tasks are more vulnerable than find values tasks to being mismatched with high granularity visualizations that provided too much detail.

High need for detail tasks also proved to be more difficult to answer when mismatched with low granularity visualizations that did not provide enough detail. In contrast to low need for detail tasks, participants were equally likely to accurately complete find and compare values tasks when matched with high granularity visualizations. When mismatched with low granularity visualizations, the odds of completing a high need for detail task accurately decreased by 73% ($p < 0.001$) for mismatched compare values tasks, but only by 17% ($p < 0.001$) for mismatched find values tasks. As shown in Figure 3, participants were able to complete a mismatched find value task, but few completed a mismatched compare values task. The odds of accurately completing a mismatched high need for detail task were 203% ($p < 0.001$) higher for find values tasks than compare values tasks.

Figure 3: Accuracy across match and mismatch of need for detail and information granularity of the visualization and find vs. compare user tasks. Participants were more likely to answer questions correctly with matched information granularity, and less accurate with mismatched information granularity. Participants were substantially less likely to answer a compare task correctly in the high need for detail situation when shown a mismatched visualization.

We continue with the analysis of response time across correctly completed tasks. Response time was measured in seconds, log transformed to normalize the distribution, and modeled using a linear multilevel model. Unstandardized coefficients are interpreted as the unit change in $\ln(\text{seconds})$ under the mismatch condition.

In addition to compromising accuracy, mismatching the need for detail with the visualization's granularity also increased the time necessary to complete the user tasks. Beginning with low need for detail tasks, when matched with visualizations of low granularity, compare values tasks required more time to accurately complete than find values tasks ($b = 0.07$, $SE = 0.02$, $p = 0.004$). When mismatched with too much detail, however, more time was necessary to accurately find values than to accurately compare values ($b = 0.10$, $SE = 0.04$, $p < 0.001$). In contrast to accuracy, response time was compromised for low need for detail find tasks more than it was for compare tasks when mismatched with high granularity visualizations that provided too much detail. High need for detail tasks were similar to low need for detail tasks under the match condition – compare values tasks required more time to correctly answer than find values tasks when matched with a high granularity visualization ($b = -0.07$, $SE = 0.03$, $p = 0.003$). In contrast to low need for detail tasks, response time was either stable or decreased when high need for detail tasks were mismatched with low granularity visualizations that did not provide enough detail (Figure 4).

Response times for compare values tasks did not significantly vary when mismatched with visualizations of low granularity ($b = -0.04$, $SE = 0.04$, $p > 0.30$) and substantially decreased for find values tasks ($b = -0.29$, $SE = 0.03$, $p < 0.001$).

This suggests that although few accurately completed the mismatched high need for detail tasks, those who did complete the task accurately were quick to do so.

Characteristics of the Person

After identifying the characteristics of the situation – matching and mismatching need for detail with the visualization's granularity – we continued with an examination of whether or not these effects varied across personality and gender. Personality was also somewhat implicated in users' responses to tasks that were matched and mismatched in their need for detail and the granularity of the visualization. First, we found that participants higher in Extraversion were less likely to indicate that not enough detail is available to answer the task ($p < .03$). Those who were higher in Extraversion (+1 SD) were less likely to accurately complete a low need for detail task, regardless of whether it was a find or compare values task ($OR = 0.88$, $p = 0.002$). We also found that respondents higher in Neuroticism (+1 SD) were more likely to correctly identify that a high need for detail task could not be accurately completed when mismatched with a low granularity visualization that did not provide enough detail ($OR = 1.10$, $p < 0.05$). Although the effect of mismatching need for detail with the granularity did not vary across gender, women were on average less likely than men to accurately complete a task ($OR = 0.82$, $p = 0.02$).

DISCUSSION

We addressed three questions in this work. How do users perform when there is a mismatch between their need for detail and the information they have available? Do these reactions vary between different information-seeking tasks? Do characteristics of the person–personality traits and gender–differentiate these behaviors?

Our work provides evidence that a one-size-fits-all approach to visualization design is not optimal, and gives some insight into challenges facing adaptive visualization systems. Users faced with a visualization with information granularity mismatched to the need for detail implied by the task were less able to complete the task correctly, so presenting the appropriate visualization is critical. A useful contribution came from the inclusion of the “escape hatch” for tasks. Users were frequently unable to determine that the information they needed was not present in a visualization and instead developed spurious answers. Additionally, extraversion and neuroticism had direct effects on performance in both accuracy and time, which speaks to the importance of individual characteristics in selecting the appropriate representation. However, matching the task to the visualization appears to have the largest impact on the likelihood of accuracy. Lastly, consistent with our expectations, we found find value tasks to be less susceptible to misinterpretation than compare values tasks.

The Cost of Mismatches

Our findings suggest that mismatching the need for detail with the granularity of the visualization impedes users' ability to accurately and efficiently complete a task. The extent of this effect varied across need for detail. When their need for detail was low and matched with low granularity visualizations, users

Figure 4: Response time across match and mismatch of need for detail and information granularity of the visualization and find vs. compare user tasks.

were more likely to accurately complete find-values tasks than they were compare values tasks. This finding illustrates the potential cost of an incorrect presentation in an adaptive visualization system. It was surprising that users were frequently unable to identify that the information required to correctly complete a task was not present in the provided visualization. More specifically, in these situations, user's attempted to answer the question rather than choose the "Can't Tell" option. Perhaps this is due to visual literacy deficiencies and this lack may be a danger of an adaptive visualization system. That is, in an adaptive system, the user does not have the visualization construction process to use as part of the sense-making process. Without this understanding, users frequently developed incorrect interpretations based on incomplete data – they were not able to recognize when the data presented in the representation was not sufficient to answer the question.

The Effects of Task

Task type was a significant factor in performance between matched and mismatched need for detail and visualization granularity. As expected, find and compare values tasks were equally achievable when high need for detail was matched with a visualization of high granularity. However, mismatching low need for detail with a high granularity visualization that provided too much detail was more detrimental to find values tasks than compare values tasks. When high need for detail was mismatched with low granularity, users were more likely to identify that a find values task did not provide enough detail to answer the question. This was not the case, however, for compare values tasks. For both too much detail and not enough detail sequences, find value tasks were completed more rapidly than compare values tasks when need for detail was matched with the granularity of the visualization.

When users were provided with too much detail, compare values tasks were accurately completed more quickly than find

values tasks. In contrast, when users were provided with not enough information, they were quicker to accurately identify that the visualization did not provide enough detail to accurately complete the task. Together, these findings suggest that providing too much detail may be more of a detriment to efficiently finding a value than it is to making a comparison. Perhaps this is due to the fact that find values tasks require that users interrogate potentially all values, which may be difficult and error-prone when too much data is presented. This may also explain why users are quicker to identify that values are not present (i.e., from scanning all data) than they are to identify that relationships cannot be ascertained from a visualization - which requires additional reasoning beyond scanning for necessary values.

We also found some support for the idea that characteristics of the user – such as her personality – conditions responses to tasks. Personality played out in ways that are consistent with their profiles. Individuals who are higher in extraversion – and therefore more outgoing, explorative, and willing to take risks – were more likely to take information at face value and to take more time in exploring the visualizations. Consistent with the link between neuroticism and sensitivity to the environment, we found participants higher in neuroticism to be less likely to be fooled by spurious correlations.

In our view, there is a significant challenge in mitigating the effect of what we characterize as the tendency of participants to over-generalize or fabricate spurious correlations. We anticipate that this problem's significance will increase as more analytics tools make their way into common use. Health informatics is one domain where we anticipate this challenge to be particularly prevalent. While we cannot directly generalize our results to real applications, most notably because the motivations behind interpreting information in a real-world scenario cannot be replicated in a web delivered survey, we can infer that these users will have similar challenges – looking for specific values of health metrics is key to a number of important activities, including monitoring blood sugar, blood pressure, heart rate, body temperature, oxygen levels, and more. Further, comparing values between these metrics over time is useful for instigating behavioral change, monitoring goal progress, or correlating symptoms.

THREATS TO VALIDITY

Construct

Are we asking the right questions?

As defined, information granularity refers to the amount of the total possible information that is directly available from the visual encoding. By aggregating this information, we effectively reduce the granularity present in order to provide a more abstract view of the information. The visualizations used in the study represent either an instant and average value for a moment in time (low granularity), a histogram view of overall performance decoupled from time plus an instant in time and the average value at that instant (medium granularity), or an overall view of the information situated in time including

derived information (high granularity). This allows us to examine the effects of varying granularity, but this does not allow us to make inferences that generalize to information granularity for visual encodings other than the types that we have tested. A per pixel color encoding of the data values laid out on a single line where the brightness of the pixel encodes the value for a given point in time would also convey this information with high granularity, but it would be challenging if not impossible for most users to extract this information. These values could also be encoded using arc lengths, glyph positions, or a number of other possibilities. Our experiment does not allow us to make inferences about these alternative encodings. We argue that the designs tested make use of a common subset of visual encodings – length and position encodings reinforced with a color encoding – to present information, leaving the primary variation to be the information granularity.

We developed a suite of questions that varied in complexity from finding a single value to comparing trends between two time-series visualizations, treating complexity as a proxy for need for detail. We modeled these questions after the pro forma abstract questions developed by [1]. However, that variation in complexity does not translate directly to a real simulation of the need (Bounded Rationality Characterizes the Situation) – especially given the limited incentive structure provided by AMT (External).

Internal

Are there factors inherent to how we collect and analyze the information that could skew the accuracy of our findings?

The experimental design in the study we have presented is internally balanced in order to allow us to analyze results both across and between individuals. Participants were assigned an order of the tasks randomly. This occurred in the personality inventory as well as the main body of questions.

Reservations about the use of AMT include concerns that participants share information and try to game the system [11]. Because our study was available for only hours, and participants did not know if their answers were correct, our study was less vulnerable to collusion between participants.

The AMT platform is also not limited to any particular device context. Participants used devices ranging from smart phones and tablets to laptops and desktop computers. These differences made it impractical to control for details of the visualizations such as label sizes, the size of visualization, and the color gamut. This precludes analysis of these variations.

External

Are our results generalizable to users interacting with visualization tools that can vary the granularity of information provided?

The scenario presented to the participants was hypothetical, and participants were only motivated to correctly complete the task by the incentive structure provided by AMT. Completion is the metric of worker quality for AMT, so participants were motivated to some degree to accurately complete the tasks required by our study. The results are likely not representative of the participants' behavior were they interacting with their own goals. Hypothetically, if the participants were interacting

with their own data rather than a simulacrum of their data, they may have had a greater investment in understanding the visualizations. This is especially the case for visualizations that require contextual knowledge for accurate interpretation. This design is not sufficient to replicate the experience of real world decision making with data that is contextually situated in an individual's daily life.

As with any web-delivered survey, we had little control over the participant's environment. This is an inherent limitation of web-delivered surveys. However, the experimental paradigm provides a reasonable facsimile of the visual analytics process and allowed us to test assumptions about the importance of matching visualizations to the demands of a task. We performed some filtering on the participant responses to remove participants that took physically unrealistic amounts of time to complete tasks. Participants that took zero seconds to complete a task were either gaming the system, or our timing system failed to capture their actions. This data was not usable and was omitted from our analysis. At the other end of the spectrum, it is possible that participants could walk away from the survey at any time and return, again skewing the timing results.

CONCLUSION

The need for detail – what it is that individuals are looking for in their data – varies within individuals and is essential to understand when designing an adaptive visualization system. In this study we found matching the need for detail to granularity of the visualization to be important across find and compare values user tasks, and for situations where the user is presented with either not enough, or too much information. This impacted both accuracy and response time. Presenting participants with a mismatched granularity visualization resulted in lower accuracy, and was more detrimental for compare values tasks than finding values. Participants were likely to find spurious associations in data in order to complete a given task. In terms of response time, low need for detail tasks were hindered, but this did not hold for high need for detail tasks. This is important because the curation, visualization, and analysis (whether by necessity or for enjoyment) of that data is often entirely in the hands of an end user with unknown levels of visual literacy. For developers creating visualization tools that aim to streamline this process, taking care to present the correct information is key, but they do not yet have the tools to make these determinations on a user by user basis. By continuing to expand our understanding of individual differences, we hope that this gap can be narrowed.

We built on existing work by showing that personality, specifically neuroticism, differentiates how sensitive individuals are to mismatching the need for detail with a visualization's information granularity [6]. Interestingly, participants higher in neuroticism were less likely to be fooled by spurious associations. Extraversion did not differentiate mismatch sensitivity, but participants high in extraversion took longer to complete tasks. We replicated gender differences in overall accuracy. Female participants had overall lower accuracy, but the effect of mismatching information granularity to the need for detail did not vary across gender.

In future work, there should be exploration of the factors that predict appropriate information granularity as a starting point for adaptive visualization tools. The results presented in this study cannot be generalized to a broader set of visualizations from the limited set of visualizations that were used, but the results are indicative of a direction for granularity hierarchies in personalized visualization. Further experimentation is needed to determine a more concrete relationship between individual differences and task appropriate information granularity. Isolating individual characteristics from task type and environmental differences would provide a more detailed perspective on that relationship.

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