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Towards User-Adaptive Information Visualization

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Abstract

This paper summarizes an ongoing multi-year project aiming to uncover knowledge and techniques for devising intelligent environments for user-adaptive visualizations. We ran three studies designed to investigate the impact of user and task characteristics on user performance and satisfaction in different visualization contexts. Eye-tracking data collected in each study was analyzed to uncover possible interactions between user/task characteristics and gaze behavior during visualization processing. Finally, we investigated user models that can assess user characteristics relevant for adaptation from eye tracking data.

Introduction

Research in Information Visualization (InfoVis) has traditionally followed a one-size-fits-all approach that does not account for user differences. In recent years, however, researchers have started showing that user-adaptive interaction, i.e., interaction adapted by an intelligent interface to suit each user's specific needs and abilities, has the potential to improve users' experience during visualization processing (e.g., Gotz and Wen 2009, Ahn and Brusilowsky 2013). Still, despite these initial results, the effects of both user differences and different forms of adaptation remain largely unexplored. This paper summarizes the results of ATUAV (Advanced Tools for User-Adaptive Visualizations), an ongoing multi-year project aiming to uncover further knowledge and techniques for devising user-adaptive visualizations.

Three main questions should be addressed in any research involving intelligent interfaces that deliver user-adaptive interaction: *What* user differences should be considered for adaptation? *How* to adequately adapt to these differences? *When* to adapt, in order to maximize adaptation effectiveness and reduce intrusiveness? To address these questions, we conducted three studies designed to achieve the following objectives:

- Objective 1: investigate whether a variety of user and task characteristics impact user performance and satisfaction in different visualization contexts. Essentially, we wanted to identify which characteristics have enough impact on user visualization experience to justify adapting to these characteristics (*what to adapt to*).
- Objective 2: Provide eye-tracking data to be analyzed to understand if/how users and tasks characteristics affect user attention patterns to specific elements of a visualization to identify possible targets for adaptation (*how to adapt*).
- Objective 3: Investigate if eye-tracking data can inform *user models* to predict, in real-time, characteristics relevant for adaptation (*how* and *when to adapt*).

Related Work

Our work on user-adaptive visualizations draws from research in three related areas: analyzing influences of user traits on visualization effectiveness, user modeling, and the use of eye-tracking to build user and task models.

The influence of user traits on the effectiveness of information visualizations has been studied for both cognitive abilities and personality-based traits. The cognitive abilities of perceptual speed, visual working memory, and verbal working memory were found to influence both performance with and preferences for visualizations (Conati and Maclaren 2008, Velez et al. 2005, Toker et al. 2012), while capacity of attention was found to modulate the effectiveness of visualizations (Haroz and Whitney 2012). The locus of control personality trait was found to influence performance on visualization tasks (Ziemkiewicz et al. 2011, Green and Fisher 2010).

Studies linking user traits to visualization effectiveness motivate the need to estimate those traits during visualization use. Several researchers have approached this task by tracking user interface actions. For instance, Grawemeyer (2006) and Mouine and Lapalme (2012) recorded user selections among alternative visualizations to

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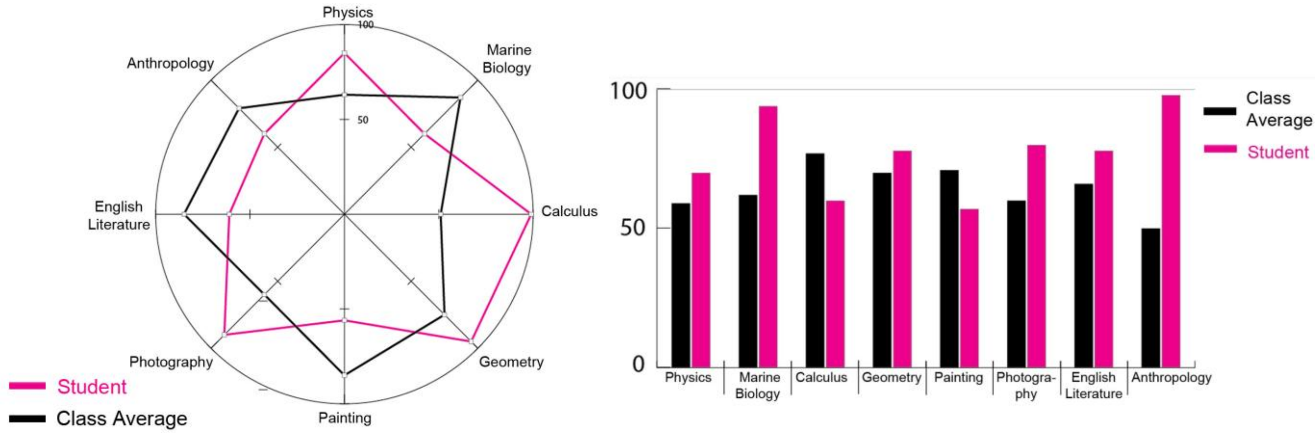

Figure 1*. Sample radar and bar graph used in the Bar/Radar study.*

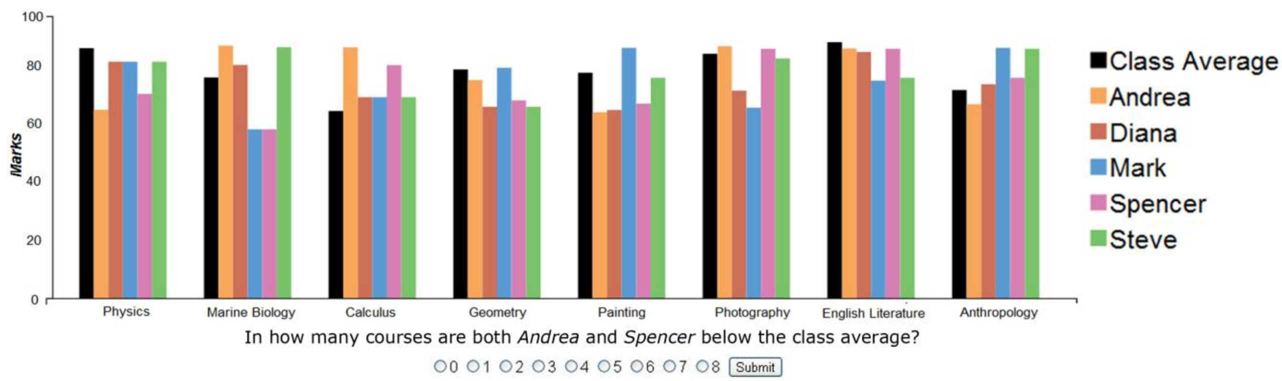

Figure 2*. Sample bar chart used in the Intervention study.*

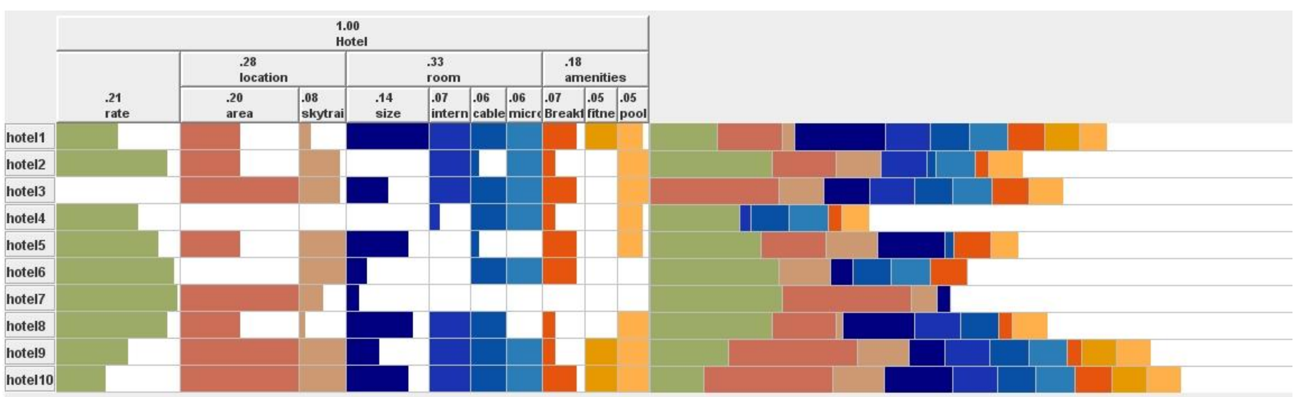

Figure 3*. Sample ValueChart from the VC study, shown in horizontal layout.*

recommend visualizations in subsequent tasks. Gotz and Wen (2009) track suboptimal user interaction patterns to recommend alternative visualizations for the current task. Ahn and Brusilovsky (2013) track a history of user search terms to customize the display of exploratory search results. Nazemi et al. (2013) track users' interaction data (mouse/keyboard) to customize the visualization of bibliographic entries.

Gaze data has been shown to be a valuable source of information for user modeling in various domains. For instance, Eivazi and Bednarik (2011) used gaze data to predict user strategies when solving a puzzle game. Kardan and Conati (2013) and Bondareva et al. (2013) use gaze to predict student learning with educational software, while Jaques et al. (2014) and D'Mello et al. (2013) leverage it for affect prediction. Liu et al. (2009) predict skill level differences between users in collaborative tasks, while

Tang et al. (2012) detect domain expertise. In HCI, Iqbal et al. (2005) track pupil sizes to detect cognitive workload during task execution. Jang et al. (2014) use gaze and pupil sizes to identify human implicit visual search intention. Finally, Plumlee and Ware (2006) use eye movements to investigate differences in user accuracy between alternative visualization interfaces.

User Studies

Our first study (Toker et al. 2012) looked at the three objectives above in the context of using two InfoVis techniques: bar graphs and radar graphs (*Bar/Radar study* from now on – see Figure 1). The second study (Carenini et al. 2014) extended the first study by evaluating four different visual prompts (see Figure 4) designed to help users process bar graphs, with the long term goal of understanding which, if any, of these visual prompts could be suitable as adaptive interventions under specific circumstances (*Intervention study* from now on – see Figure 2). While the first two studies involved visualizations that could only be processed visually, the third study (Conati et al. 2014) extended our investigation to *interactive visualizations*, i.e., visualizations that provide users with a variety of functionalities to explore the visualized data interactively. We refer to this study as *VC study*, because it targeted an interactive visualization called ValueChart (see Figure 3), which is designed to support users in decision making tasks involving preferential choice (i.e., the process of selecting the best option out of a possibly large set of alternatives based on multiple attributes).

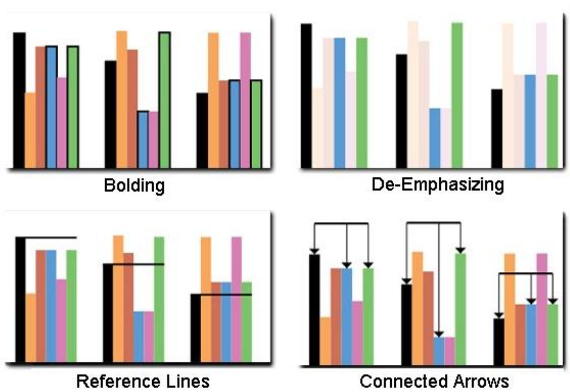

Figure 4. *Visual prompts evaluated in the Intervention study, aimed at facilitating visualizaton processing using various highlighting techniques.*

In all three studies we collected information on a variety of user characteristics that could affect a user's visualization experience. These include *visualization expertise*, as well as three cognitive measures*: perceptual speed (PS)*, *visual working memory (visWM)* and *verbal working memory (verbWM)*. The Intervention and VC study also included *locus of control*, a personality trait that other studies have shown to impact visualization effectiveness (Ziemkiewicz et al. 2011). The VC study also includes measures of *task expertise*, i.e., expertise in making preferential choices in general and by using visualization aids.

All three studies considered different task types and varied task complexity, to investigate if and how these task characteristics influence the impact of user differences on visualization experience. The Bar/Radar study (Toker et al. 2012) included 5 different task types, chosen from a set of *low-level* analysis tasks identified as largely capturing people's activities while employing information visualization (e.g., retrieve the value of a specific datapoint, find the datapoint with an extreme value in the dataset) (Amar et al. 2005). The study also varied task complexity by visualizing two datasets of different size (i.e., consisting of either two or three data series respectively). The Intervention study (Carenini et al. 2014) and VC study (Conati et al. 2014) also varied task type and complexity, but in order to limit the number of experimental conditions, complexity was varied by selecting task types that were, respectively, among the simplest and the most complex in Amar et al. (2005) rather than including multiple datasets of different complexity. In addition to low-level visualization tasks derived from Amar et al. (2005), the VC study also included a *high-level* task of using ValueChart to explore at will a set of alternatives (e.g., movies to watch), and select the preferred item.

Dependent measures were collected in terms of both performance (e.g., logged task completion time), as well as subjective measures of user satisfaction. In addition, in each study users' gaze was tracked via a Tobii T120 eye-tracker.

We analyzed the data collected in the studies in three different ways. To investigate the impact of user and task characteristics on visualization experience (Objective 1), we ran linear mixed-effects model (Mixed Model) analyses with user and task characteristics as factors/covariates, and performance and satisfaction measures as dependent variables (Toker et al. 2012, Carenini et al. 2014, Conati et al. 2014). To investigate the impact of user/task characteristics on gaze behavior (Objective 2), we ran similar mixed models where the dependent variables were a variety of summative statistics on gaze measures, e.g., rate of gaze fixations, average fixation length, percentage of gaze transitions between salient areas of the visualization known as Areas of Interest, or AOI (Toker et al. 2013, Toker et al. 2014). Finally, to investigate whether gaze data can help build user models that predict relevant user/task characteristics during visualization processing (Objective 3), we conducted machine learning experiments that leveraged different feature sets based on gaze data to predict user performance and cognitive/personality traits, as well as task type and difficulty (Steichen et al. 2013, Steichen et al. 2014, Gingerich and Conati 2015). We have completed all types of analysis for both the Bar/Radar study (Toker et al. 2012, Toker et al. 2013, Steichen et al. 2014) and the Intervention study (Carenini et al. 2014, Toker et al. 2014, Gingerich and Conati 2015), whereas for the VC study we have so far performed only the analysis related to Objective 1 (Conati et al. 2014).

In the next section we summarize a selection of results from the analyses. All results reported are statistically significant at the .05 level (adjusted for multiple comparisons), unless otherwise qualified.

Overview of Results

Impact of user characteristics on performance

Bar/Radar study (Toker et al. 2012). For simple tasks (i.e., tasks performed with the simpler dataset) we found, not surprisingly, that higher PS corresponded to faster completion time with both visualizations. However, we also found an interaction effect between PS and visualization type, there was larger difference in time performance between bar and radar graphs for users with low PS than for users with high PS. This result is important because it confirms the finding in (Conati and Maclaren 2008) that PS is a cognitive measure that can impact the *compared effectiveness* of two different visualizations, at least when one of them is a radar graph.

For more complex tasks, the main effect of PS becomes marginally significant, but still has a medium-large effect size. Individual differences also impacted user subjective preferences. Users with high visWM gave higher preference ratings to radar graphs than users with low visWM, and users with low verbWM found bar graphs easier to use than users with high verbWM.

Intervention study (Carenini et al. 2014). While there was no impact of cognitive abilities or locus of control on task performance with simple tasks (i.e., tasks asking users to retrieve a specific value from a bar chart), for more complex tasks (requiring users to compute aggregate measures over a subset of the data) all three cognitive abilities (PS, visWM, and verbWM) had an impact[1]: users with higher values of these abilities performed significantly better in terms of a performance measure combining accuracy and completion time. These results indicate that task complexity can significantly impact user performance depending on cognitive abilities, and suggests that users with lower cognitive abilities would benefit from adaptive interventions when tasks get harder. It should be noted that while the result for PS aligns with results in previous work (Toker et al. 2012), for visWM and verbWM the Intervention study is the first to connect these two cognitive traits to objective task performance (as opposed to subjective user preferences) with a visualization, possibly because previous studies relied on tasks that were not complex enough to detect these effects. In terms of possible influences of individual differences on the effectiveness of the different visual prompts (interventions) tested in the study, none were found for task performance: all interventions had a similar positive impact on users' performance, and were better than receiving no intervention (except for the "Reference Lines" intervention with complex tasks). Individual differences however, affected users' subjective measures of intervention *usefulness*. Specifically, differences in visWM affected the usefulness ratings for "Bolding" and "Reference Lines" interventions. This finding confirms the influence of visWM on subjective ratings found in (Toker et al. 2012).

VC study (Conati el al. 2014). We investigated the effect of user characteristics on performance for low and high level tasks, mediated by two visualization layouts (vertical and horizontal[2]). These layouts can be considered as a possible form of personalization since previous studies with ValueChart suggest that they are not equivalent in terms of user performance. For low-level tasks, interaction effects were found between task type and each of: visualization expertise, PS, visWM, and verbWM. Once again, no effect was found for locus of control. Users with lower visualization expertise are significantly slower in more complex low-level tasks, suggesting that personalized support should be available to non-experts for such tasks. In general, as we found for the Intervention study, lower levels of user PS and verbWM negatively impacted performance on specific task types. However, for all low-level tasks, users with lower visWM were significantly faster than users with higher visWM when they worked with a horizontal layout, contrary to previous findings showing that lower visWM users are at a disadvantage. This result is important because it indicates that giving users the appropriate visual artifacts for their cognitive abilities (e.g., a horizontal layout for low visWM) can compensate for limitations in these abilities.

For high-level tasks, users with low self-rated frequency of using visualizations to make preferential choices spent significantly less time making decisions with the vertical layout than with the horizontal layout, while maintaining similar levels of decision confidence or decision

[1] No effect was found for locus of control.

[2] Figure 3 shows the horizontal layout. The vertical layout corresponds to the horizontal one rotated counter clockwise by 90 degrees.

satisfaction as with the horizontal layout. This suggests that personalization based on layouts could increase efficacy on high-level decision making tasks.

Table 1 summarizes all the main significant effects of user characteristics found in our analyses.

	Perceptual Speed	VerbalWM	VisualWM	Visualization Expertise
Bar /Radar study	Task performance	Ease-of-use ratings	Bar vs. Radar preference ratings	-
Intervention study	Task performance	Task performance	Task performance Ease-of-use ratings of interventions	-
VC study	Task performance	Task performance	Task performance	Task performance

***Table 1.** Features on which each user characteristic has a significant impact per experiment.*

Analysis of eye-tracking data

We investigated (i) if user characteristics impact gaze behavior during visualization processing tasks, and (ii) which gaze features are the most influenced by user characteristics *(Objective 2)*. We summarize here some of the results that can be leveraged to understand how to provide user-adaptive interventions.

In the Bar/Radar study (Toker et al. 2013) we found that PS significantly impacted gaze behavior, influencing fixation rate and gaze measures relating to the *legend*, *labels* and *graph* regions (Areas of Interests, or AOI, from now on). For instance, users with low PS spent more time and transitioned more often to the labels AOI and legend AOI regions of the visualization. This effect was more pronounced when performing difficult tasks. This finding suggests supporting users with low PS (e.g., older adults and people with autism) in terms of legend/label processing, especially for more difficult tasks, given that these users have lower performance, as discussed in the previous section (Toker et al. 2012). Similar results and conclusions for label processing were found in the Intervention study, i.e., users with low PS had lower performance and spent more time processing the labels AOI region of the visualization with complex tasks (Toker et al. 2014).

The Intervention study, in addition, uncovered analogous finding for visVW and verbWM. Users with lower levels of these measures tended to have worse task performance, as discussed above, which can be explained by the impact that these measures were found to have on different elements of the Intervention study visualizations. For instance, users with low visWM spent more time and transitioned more often to the *answer input* AOI region of the visualization on complex tasks, suggesting that these users likely have difficulty connecting the answer options in the input area with the information in the graph. This, in turn causes them to go back and forth between the input and the other graph areas more often than high visWM users do. This behavior can explain why in this study low visWM users were found to be slower at solving the tasks than their high visWM counterparts. This combination of findings suggest that we may want to experiment with designing adaptive support for low visWM users that focuses on facilitating processing of the input options in relation to the task (e.g., experiment with different input methods or visual representations of radio buttons). Similarly, users with low verbWM spend more of their time reading the textual elements of the visualization (legend, labels, and question AOIs). This effect can explain the increase in task response time that we found for low verbWM users, indicating that it is worthwhile to investigate adaptive interventions that aid the processing of a visualization's textual components for these users. All the above results provide evidence that users with lower cognitive abilities could benefit from adaptive interventions that can help them process visualizations components that may affect their task performance, and that eye gaze analysis can help identify these components.

Classification experiments based on gaze data

We investigated if user characteristics, task complexity, and user performance can be predicted solely based on eye tracking data (Objective 3) for both the Bar/Radar and Intervention studies (Steichen et al. 2103, 2014; Gingerich and Conati 2015).

For both datasets, we were able to build classifiers that predict each of the above measures with accuracy significantly better than majority baseline classifiers, relatively early on from the start of a target visualization task. Classification accuracy for predicting task type reaches 79-81% after observing only 10% of the gaze data for that task. This result has direct implications for a system's ability to provide useful adaptive support to users, given the strong influence that task type/complexity has on user performance, as discussed above. For instance, using gaze data, a user-adaptive module built for these two visualizations (i.e., bar and radar graphs) would be able to distinguish whether a user is engaged in an easier or more complex task, and then consider suitable adaptations accordingly. User performance classification (i.e., predicting if a user will finish a task quickly/slowly) complements task type classification by identifying occasions in which users are most in need of support, and in our experiments it reaches accuracies in the range of 78-85% after seeing 10% of the gaze data. Classification of user cognitive abilities, which can be useful for the finegrained tailoring of visualization support, has lower accuracies in the 60-64% range, indicating that task type and user performance have a stronger impact on user gaze behaviors than these cognitive measures. Still, it should be noted that these accuracies are achieved after seeing user gaze for only one task, and tasks in these two studies are basic short ones (on average less than one minute). As users completed multiple tasks in each study, higher classification accuracies could likely be achievable by allowing the system to track user gaze across many tasks.

Discussion and Conclusions

The long-term goal of the research discussed in this paper is to devise intelligent user-adaptive visualizations that can adapt in real time to the specific needs and abilities of each individual user. Based on the results found in the three user studies overviewed in this paper, we can identify two broad categories of adaptive support.

The first category consists of *delivering adaptive interventions* that can help the user process a given visualization. For instance, findings from the Intervention study suggest that in the presence of complex tasks:

- Users with low perceptual speed may benefit from interventions that help them process the labels in the visualization
- Users with low visual working memory should be given support with how their answers are submitted (e.g., using radio buttons vs. drop-down menus)
- Users with low verbal working memory can be helped by adaptive interventions that emphasize any or all textual elements of the visualization.

The second category of adaptive support consists of *selecting the best visualization or visualization layout* among a set of alternatives. For instance, findings in the Bar/Radar study suggest that:

- Users with low perceptual speed should be given bar graphs instead of radar graphs when working with information seeking tasks, because they are faster with them.
- Users with high visual working memory or expertise with radar graphs should be given this type of visualization because they are likely to prefer it to bar graphs.

Similarly, the VC study findings suggest that:

- When performing low-level visualization tasks with ValueChart users with lower visual working memory should be given a horizontal layout, which allows these users to compensate for their visual working memory limitations.
- When performing high-level decision-making tasks with ValueChart, users with limited expertise in using visualizations for decision making should be given a vertical layout, as they spent less time making their decision with this layout at no cost of decision confidence and satisfaction.

In order to provide adaptive support as described above, an adaptive visualization needs to be able to assess in real time when interventions are needed and why. We have presented promising results with two different datasets (from the Bar/Radar study and from the Intervention study) showing that classifiers based solely on tracking gaze data can predict early on during a task whether the user may need help because they are showing low performance with the current visualization set up. We also showed early accurate prediction of type/complexity of the visualization task a user is working on, which affects the type of support the user may need. Accurate information on the user's cognitive abilities that can further qualify the type of adaptive support to be provided is harder to obtain using solely gaze data on the current user task, although our classifiers still perform significantly better than majority class baseline classifiers. One of our threads for future work involves investigating ways to increase prediction accuracy for a user's cognitive abilities, for instance by (i) classifying over more than one task; (ii) looking at additional features for classification such as pupil-based measures and action-based features when available (e.g. in the ValueChart dataset). A second thread involves designing some of the different adaptation strategies identified in this paper, and evaluate their effectiveness first via Wizard of Oz studies and then by implementing the actual adaptive cycle. Finally, we are looking at practical applications of our approaches. For instance, we are looking at using existing corpora of multimodal documents (e.g., articles from the Economist) which contain graphs, text that describes different aspects of the graphs, and explicit links between related sentences and graph elements. Our goal is to build mechanisms that track when a user is reading sentences that require attention to the graph and solicit attention to the relevant graphical elements in an adaptive manner.

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