Adaptive Information Visualization - Predicting user characteristics and task context from eye gaze

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Abstract. Our research aims to design information visualization systems that adapt to each individual user's characteristics and task context. In order to provide such *Adaptive Information Visualizations*, the first step is to predict these characteristics and context from a number of real-time measures. In particular, this paper presents initial results from an eye tracking user study, providing evidence that a user's *eye gaze* can indeed be used for predicting a user's task context and cognitive abilities.

Keywords: Information Visualization, Eye Tracking, Machine Learning

1 Introduction

While Information Visualization systems have gained in terms of general usage and usability, they have traditionally followed a one-size-fits-all model, typically ignoring an individual user's needs, abilities and task context. However, recent research has shown that such characteristics can indeed have a significant impact on user effectiveness during visualization usage [1][2]. It is therefore crucial to design information visualization systems that can dynamically adapt to individual task and user characteristics in order to best support each individual user.

Adaptation and Personalization have long been established as effective techniques to support individual users in information seeking tasks, in particular in areas such as Personalized Information Retrieval and Adaptive Hypermedia [3]. However, only very recently researchers have started to apply similar techniques to support users of Information Visualization systems. Such adaptive systems (e.g. [4]) typically monitor users' actions (e.g. mouse clicks) in order to infer their current intent/task. If suboptimal user patterns are detected, alternative visualization techniques are then recommended that better support the inferred task.

The research presented in this paper differs from such systems in a number of aspects. Firstly, in addition to recommending different visualization techniques, we also aim to provide adaptive interventions within the current visualization. Secondly, we are interested in adapting to different user characteristics, in particular a user's cognitive abilities such as working memory and perceptual speed. We are interested in such characteristics as they have previously been found to significantly affect a user's performance with different visualizations [2]. Thirdly, instead of purely focusing on interaction data, our work aims to also capture task, user and visualization characteristics based on a user's eye gaze behavior. We argue that this fine-grained data provides a more detailed insight into the low-level processing of visualizations.

Only recently, eye tracking technology has been used successfully in Information Visualization studies, for example to identify pattern differences for different visualization techniques [5]. However, while related research on desktop interfaces and intelligent tutoring systems has provided evidence for different gaze patterns depending on different tasks and/or users (e.g. [6], [7]), Information Visualization studies have typically not focused on detecting such characteristics. By contrast, the work presented in this paper is specifically focused on using eye gaze data to classify different task contexts and user characteristics.

In summary, this paper proposes to provide *Adaptive Information Visualizations* through the use of real-time eye tracking in combination with machine learning techniques to predict and adapt to task, user and visualization characteristics. In particular, the paper presents preliminary results from an initial user study, showing that eye tracking data can indeed be used for predicting such different characteristics.

2 Preliminary User Study and Classification Results

The first step in an Adaptive Information Visualization process consists of the prediction/classification of current task, user and visualization characteristics. In order to investigate this step, an initial user study was conducted that captured a number of such different characteristics along with corresponding user eye gaze behavior. Due to space limitations, we provide only a brief overview of the experimental design (a more complete description can be found in a related study [2]): 32 participants completed a series of different types of tasks with bar and radar graphs while stationed in front of a Tobii T-120 Eye tracker. Each of the tasks consisted of answering a question about student performance scores (e.g. *"Is Andrea stronger in Biology or in Painting", "Find the courses in which Andrea is below the class average and Diana is above it"*). The eye tracking data collected during these tasks consisted of user fixations, saccades, as well as transitions from/to specific Areas Of Interest (i.e. regions of the screen that carry a particular purpose, such as the question text or graph legend). For each participant, we also collected the following cognitive measures (using standard tests available from the literature): *Perceptual Speed*, a measure of speed when performing simple perceptual tasks; *Verbal Working Memory*, which measures the working memory for manipulation and maintenance of verbal information; and *Visual Working Memory*, which measures the storage and manipulation capacity of visual and spatial information.

Using this data, we performed a number of classification experiments to predict visualization, task and user characteristics from eye gaze features (i.e. fixations, saccades and transitions). The experiments were run with different classifiers available in the Weka workbench (e.g. Support Vector Machine, Decision Tree based, Logistic Regression), using feature-selection and 10-fold cross-validation. The baseline for each of these experiments was selecting the most common class value in the training set. Paired t-tests were performed to check for statistical significance.

Overall, Logistic Regression (LR) produced the highest classification accuracy, with preliminary findings being shown in Table 1 (all of the reported results are statistically significant with $p<0.001$). As can be seen from this table, the accuracy on predicting the current visualization type (i.e. bar graph vs. radar graph) is very high at 91%. In terms of predicting different task characteristics, we ran a number of classifiers for task difficulty (i.e. easy vs. difficult) and different task types (e.g. *find extremum, compute derived value*). On each of these task characteristic classifications, LR was found to be significantly more accurate than the baseline classifier. Lastly, in terms of predicting different user characteristics, i.e. low vs. high values for each of the characteristics (determined through a median-split), LR again outperformed the baseline system, albeit with lower accuracy.

Table 1. Classification accuracy

	Baseline	**LR**
Visualization Type	52.76%	91.19%
Task Characteristics		
Task Difficulty	68.51%	78.18%
Task Type	27.90%	57.59%
User Characteristics		
Verbal WM	52.21%	58.54%
Visual WM	50.27%	58.75%
Perceptual Speed	52.21%	57.45%

3 Conclusions and Road Ahead

This paper has presented initial steps towards *Adaptive Information Visualization*s, by predicting various task, user and visualization characteristics solely based on a user's eye gaze. Results from a user experiment have shown initial evidence that eye gaze data can indeed be used as a predictor of such characteristics, which could then be used to drive an intelligent adaptation engine to produce visualization interventions (albeit certain accuracies needing some improvement if such a classifier is to be used in a live system). In addition to improving the accuracy of the classifiers, we plan to investigate the subsequent steps necessary to provide Adaptive Information Visualizations, namely *adaptation decisions*, i.e. when to adapt, and the *intervention execution*, i.e. how to change the visualization to assist individual users for specific tasks.

References

1. Velez, M.C., Silver, D., Tremaine, M.: Understanding visualization through spatial ability differences. Proceedings of Visualization 2005, (2005).
2. Toker, D., Conati, C., Carenini, G., Haraty, M.: Towards Adaptive Information Visualization: On the Influence of User Characteristics. Proc. UMAP 2012, (2012).
3. Steichen, B., Ashman, H., Wade, V.: A comparative survey of Personalised Information Retrieval and Adaptive Hypermedia techniques. Information Processing & Management, 48 (4), pp. 698–724, (2012).
4. Gotz, D., Wen, Z. Behavior-driven visualization recommendation. Proc. 13th intl. conf. on Intelligent user interfaces, pp. 315-324, (2009).
5. Goldberg, J.H., Helfman, J.I.: Eye tracking for visualization evaluation: Reading values on linear versus radial graphs. Information Visualization 10(3), pp. 182-195, (2011).
6. Iqbal, S.T. and Bailey, B.P.: Using eye gaze patterns to identify user tasks. The Grace Hopper Celebration of Women in Computing, (2004).
7. Kardan, S., Conati, C.: Exploring Gaze Data for Determining User Learning with an Interactive Simulation. Proc. UMAP 2012, (2012).

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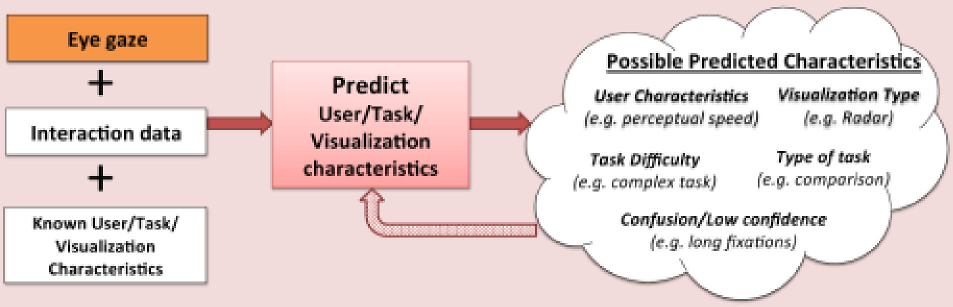
MOTIVATION:

- While **current Information Visualization systems** have gained increasingly in terms of general usage and usability, they have traditionally followed a **one-size-fits-all model**, typically ignoring an individual user's needs, abilities and task context.
- However, recent research shows that such characteristics can indeed have a significant impact on the efficiency and effectiveness of visualization usage.

***PROPOSED SOLUTION**: Adaptive Information Visualization*

- Adapt to user, task and visualization characteristics through **visualization interventions**, such as recommendations for **alternative visualizations** or slight **visualization modifications**.
- First step of this adaptation process consists of the **prediction of such characteristics** through real-time user modeling.

REAL-TIME USER/TASK/VISUALIZATION PREDICTION

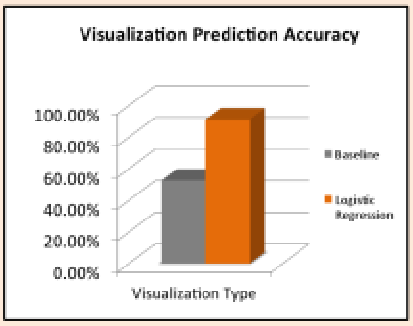


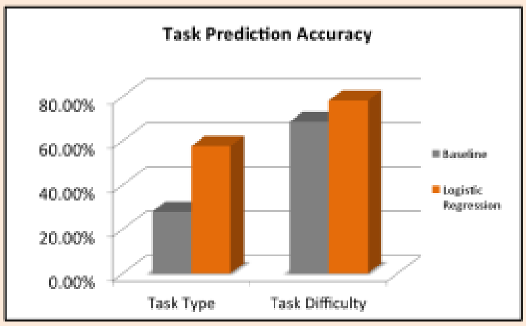
GENERAL PREDICTION QUESTIONS

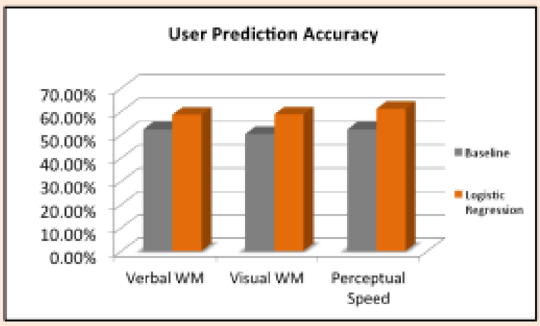
- **What predictions** are possible & what is the prediction accuracy?
- **Which** properties are part of the **input**?
- **How many "iterations"** of predictions?

INITIAL PREDICTION RESULTS BASED ON EYE TRACKING DATA

- User study to capture **user eye gaze behavior during bar and radar graph usage** (while stationed in front of a Tobii T-120 Eye tracker).
  - Each user engaged in different standard visualization tasks, once with each visualization type.
  - Each task consisted of answering a question about student performance scores (e.g. "*Find the courses in which Andrea is below the class average and Diana is above it*")
- Collected eye tracking data: **fixations, saccades** and **transitions** from/to specific Areas Of Interest .
  - A total of 48 different features were extracted from this data (e.g. *number of fixations, fixation rate, mean angle between fixations*)
- For each participant, we also collected the following cognitive measures:
  - **Perceptual Speed**, a measure of speed when performing simple perceptual tasks.
  - **Verbal Working Memory**, which measures the working memory for manipulation and maintenance of verbal information.
  - **Visual Working Memory**, which measures the storage and manipulation capacity of visual and spatial information.
- Using this data, we performed a number of **classification experiments** (incl. Support Vector Machine, Decision Tree based, Logistic Regression)
  - **Logistic regression performed best, with accuracies up to 90%** (statistically significantly higher than the baseline most-likely classifier)







NEXT STEPS

- Perform **scan path analysis** (i.e. use fixation sequences)
- Use additional interaction data (e.g. mouse clicks)
- Investigate **adaptation decisions** (context-to-intervention matching)
- Design & Implement **Interventions** (e.g. highlighting, signaling)