ALIDA: Using Machine Learning for Intent Discernment in Visual Analytics Interfaces

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Abstract

In this paper, we introduce ALIDA, an Active Learning Intent Discerning Agent for visual analytics interfaces. As users interact with and explore data in a visual analytics environment they are each developing their own unique analytic process. The goal of ALIDA is to observe and record the human-computer interactions and utilize these observations as a means of supporting user exploration; ALIDA does this by using interaction to make decision about user interest. As such, ALIDA is designed to track the decision history (interactions) of a user. This history is then utilized to enhance the user's decision-making process by allowing the user to return to previously visited search states, as well as providing suggestions of other search states that may be of interest based on past exploration modalities. The agent passes these suggestions (or decisions) back to an interactive visualization prototype, and these suggestions are used to guide the user, either by suggesting searches or changes to the visualization view. Current work has tested ALIDA under the exploration of homonyms for users wishing to explore word linkages within a dictionary. Ongoing work includes using ALIDA to guide users in transfer function design for volume rendering within scientific gateways.

Keywords: artificial intelligence, cognition, intent discernment, volume rendering.

1 Introduction

Intuitive interactive visualizations are designed to scaffold human cognition. However, cognition, especially the higher processes such as reasoning, tend to be combinatorial and dynamic. As such, these processes are difficult to standardize. Furthermore, there are no operational models of human reasoning, thus such interactive visual interfaces often encounter difficulties when trying scaffold what is not known or understood. One effort to define an intuitive visualization system that would incorporate an ongoing comprehension of holistic cognition is the Human Cognition Model (HCM) [3]. The HCM outlines the primary interactive processes during interface-enabled analysis.

One of the agenda items that the HCM outlined is the need to make visual analytics more intuitive by creating interfaces that pay attention to what information or data the user is exploring in order to provide clues to what related information the user might be interested in [3]. This fits well with the definition of visual analytics in general as the use of interactive interfaces to support analytical reasoning. By capturing the analyst's focus, interfaces are able to be automatically tailored to a user's needs, enabling the data analysis and visualizations to have enhanced contextual information directly related to the analysts needs. This paper outlines ongoing research toward the interface-human collaboration envisioned in the human cognition model through use of an intelligent, autonomous agent that sits underneath a simple data visualization prototype.

2 Related Work

Work in determining a users interest during interaction has largely focused on web interfaces. Recent examples include Godoy and Amandis [1] personal agents for web experiences, which tracks user behaviour and provides a user profile to aid in future web navigation. Another example, MASHA is a multi-agent architecture for multi-modal web interaction [5]. In visualization related research, machine learning has been used on user annotations to attempt to classify user goals [6]. Our work focuses on adapting this concept of a personal agent into the visual analytics pipeline.

3 ALIDA: Active Learning Intent Discerning Agent

This section describes our personal agent (ALIDA) and the current application domain. The current ALIDA prototype was developed in the Processing prototyping language. Processing does not easily support highly interactive visualizations (such as direct interaction), but does support the rule based decision function ALIDA uses.

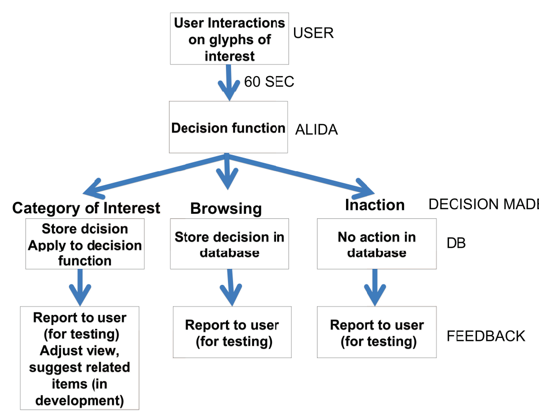

Figure 1: The flow of intent discernment with ALIDA, from user interaction until ALIDA provides feedback.

ALIDA sits underneath the interactive visual interface, continuously recording and analyzing user behaviour in real-time. The agent uses low-level interaction information, such as mouse clicks and movements, to make decisions about current and future intent. During this observation ALIDA does not disturb the user or ask for direct feedback. Instead, ALIDA is designed to be autonomous; every 60 seconds, the agent makes a decision by using the captured interactions to calculate a decision function. The results of ALIDA's decisions are provided as feedback to the user in a variety of ways and stored in ALIDAs memory for future use.

The decision function currently returns three categories of decision: area of interest, browsing, and inaction. (Please see Figure 1.) To return a decision about an area of interest, a comparison of means of interaction behaviors and decision history are both used to determine the current base category of interest. If no single category stands out (interaction is scattered in a statistically insignificant way), the agent decides the user is browsing. In the last case, the user has ceased (or almost ceased) all interaction with the visualized glyphs. In this way, ALIDA uses these decisions as part of ongoing research to make interfaces aware of what the user is exploring in order to direct the interface which context or related data to display.

ALIDA uses a MySQL database to store a history of intent decisions for each user. This history is currently used in two ways. First, the history is incorporated into the decision function. If past intent discernment decisions are similar to previous decisions, the probability of accuracy is increased. Second, it allows the user to take advantage of interface capacity to return to previous states the user has visited. This is also part of an emerging capacity for user profiling as ALIDA becomes a learning agent. Feedback, for testing purposes, is done through direct decision reporting in an ambient overlay. (See Figure 2.) Other forms of feedback are less direct, such as making areas of user intent more visible in the view. All of ALIDA's features are currently being user tested for accuracy and ease of use by comparing ALIDA's decision to the self-reported intent of the users during interaction.

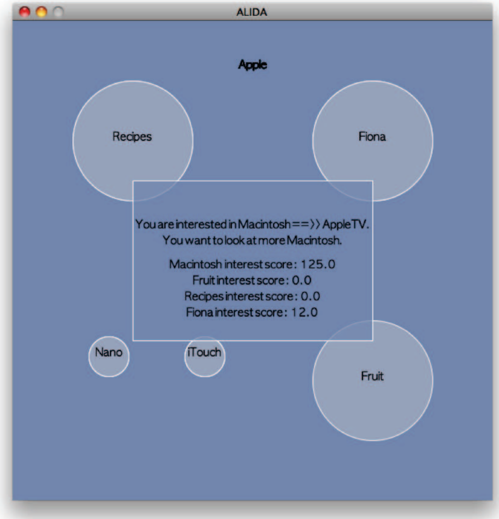

Figure 2: ALIDA direct reporting through ambient overlay.

4 Applying ALIDA for Lexical Ontology

The testing and evaluation phase of ALIDA is being performed using interactive visualization tool for exploring lexical ontologies. The interface prototype visualizes a multiple hierarchical dataset where each level, or cluster, is visualized as a sphere within the spatial context of the base node (or categorization) in the hierarchy, Currently, we utilize a lexical ontology of homonyms as the test dataset. This dataset was chosen to support more advanced semantic testing in future work. The name of each category is used to label each spherical glyph. All category labels had fewer than three words, and the glyphs were organized such that there was sufficient space between glyphs to make the labels easily legible.

Interaction with the glyphs is *direct*, that is, users click directly on the glyph of interest. *Drill down* is discrete. The clicked-on glyph disappears to reveal all subcategory glyphs. Right-clicking supports a discrete *drilling up*.

To support the "reset" and "go back" functionality, associated icons float on the periphery of a highlighted glyph. Reset allows the user to return to initial view. *Go back* takes the user back to the glyph, or area, of last interest based on ALIDA s memory of the last intent decision.

5 Ongoing and Future Work

This agent is only successful insofar as it "understands" and responds to the human user. To some degree, this agent will allow us to test certain research questions that have arisen during our research of human complex cognition during analytical reasoning in interface interaction, such as the impact of human individual differences on use of visually enabled interfaces (e.g. [2]). We will use what we have learned about complex cognition during the agent development, and use the agent as another method of evaluating the human cognitive models such we are currently developing, such as aspects of the HCM.

In addition, as part of future research, we plan to extend ALIDA to be used in volumetric rendering. Multi-dimensional transfer functions have long been established as a powerful means for interacting with volumetric data [4]. However, efficiently designing transfer functions has turned out to be a non-trivial problem. Typically, multi-dimensional transfer functions are shown as a two-dimensional (2D) scatterplot, the axes of which represent two variables of the feature space of the data. Users interact in this space, assigning optical properties (color and opacity) to the voxel data. In this dual-domain interaction (volume data space and transfer function feature space), users are able to select data properties in the feature space and see the resultant rendering in the volume space. This interaction improves the user's ability to understand how the feature space of the data is reflected in the volumetric data. However, much of the user interaction tends to be a hunt-and- peck approach as they modify and refine the transfer function based on their knowledge of the dataset or general intuition. Through the addition of an intent discerning agent where the agent unobtrusively observes the overt behavior of the user and generates transfer functions across combinations of feature space, suggesting potential areas of exploration to the user based upon the user's own interactions. The goal of the agent would be to direct the visualization with respect to underlying statistical properties that the user may or may not be utilizing in their exploration. Thus, the agent becomes part of a continuous feedback loop which is fed by continuing human interaction (or lack thereof).

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