nAble Adaptive Scaffolding Agent– Intelligent Support for Novices

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Abstract

Scaffolding techniques allow human instructors to support novice learners in critical early stages, and to remove that support as expertise grows. This paper describes nAble, an adaptive scaffolding agent designed to guide new users through the use of an analytic software tool in the 'nSpace Sandbox' for visual sense-making. nAble adapts the interface and instructional content based on user expertise, learning style and subtask. Bayesian Networks and Hidden Markov task models provide the agent reasoning engine. An experiment was conducted in which participants were provided with one of: an adaptive scaffold, an indexed help file or a human guide. Users of the adaptive scaffold outperformed users of the indexed help and more quickly converged with the performance of users with the human guide.

1. Introduction

Regardless of our experience or years in various industries, we are all novices. Platforms change, applications develop, techniques improve, and new ones are invented. In fact, it often seems that the only difference between apprentices and masters of a trade is that the apprentices have more time to learn the new tools and methods which are constantly emerging. True expertise is not a goal, but a constant re-investment of time in new skills and techniques [1].

Literature on adult learning theory and expertise development offers hints on how agents can be incorporated to guide us through new tools. Intelligent tutoring systems (ITS) are successful at facilitating learning [7],[8], as they can offer some of the advantages of one-on-one tutoring. Educational scaffolds provide structures and frameworks for learning based on an ongoing diagnosis of the learner's current level of understanding. Scaffolding enables learners to perform at more advanced levels than their current skills would allow [2] and presents a useful construct for an adaptive tutoring system.

User interfaces based on adaptive recommender agents also try to enhance user performance and have seen recent attention in the literature [3],[4]. Adaptive systems attempt to optimize user experience by changing the interface, content, or processes based on user preferences, experiences and abilities.

We propose nAble: a set of principles and techniques for an adaptive scaffolding agent that guides novice users in software tools and tradecraft methodologies. In this paper we focus on testing nAble adaptive scaffolding techniques by examining how they can be applied to a challenging task in a creative tool for visual sense-making. The scaffolding agent supports users in conducting an Analysis of Competing Hypotheses (ACH) [5] in the nSpace Sandbox [6]. The Sandbox makes use of 'put-this-there' cognition to support information visualization for both formal and ad-hoc analysis and problem solving. As users become proficient, the interface provides less support for operating the ACH tool and explaining ACH methodology. In addition, richer tool capabilities and methodologies are revealed for more expert users. Figure 1 shows an example of the ACH tool and the nAble adaptive scaffold in the Sandbox.

Analysis of Competing Hypotheses is a methodology to help intelligence analysts work with noisy evidence and overcome cognitive biases in judgment and decision making [5]. A systematic approach is used to create multiple hypotheses and then to decide which hypothesis is most likely based on evidence and explicitly stated assumptions.

2. nAble adaptive techniques

nAble adaptations are summarized below and their application to the scaffolding agent is illustrated in
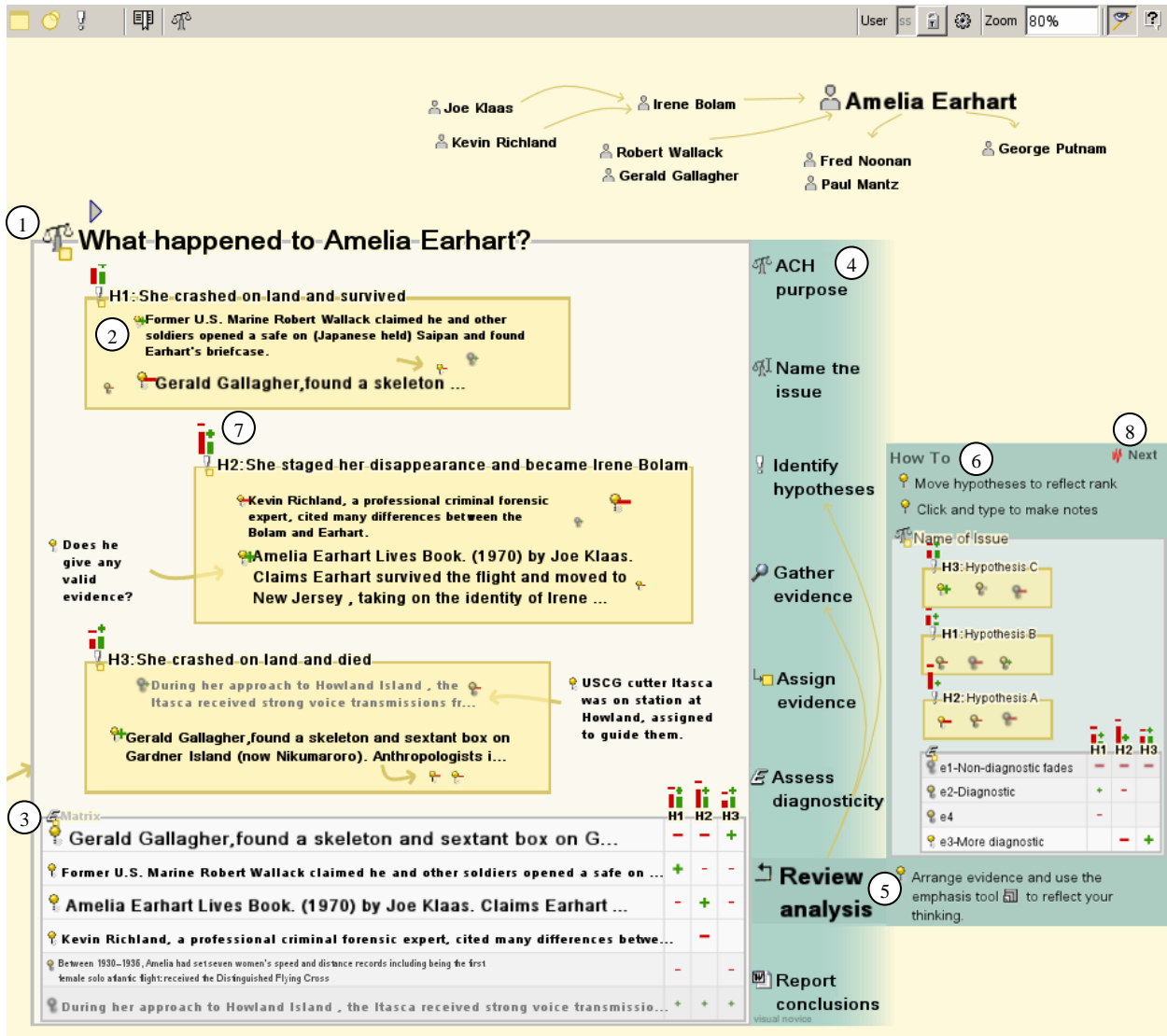
Figure 1. nSpace Sandbox for visual sense making. The ACH tool is shown (1) containing the competing hypotheses (2) and the ACH matrix (3), which is a grid representing evidence strength across each hypothesis, The attached scaffold (4) provides a task overview (5) and details on the mechanics of the subtask (6) recommended by the task model. Evidence strength indicators are enhanced (7) to clarify meaning based on expertise. Participants used the nSpace gesture system (8) to navigate the nAble content.

Figure 1. Adaptations were provided in the descriptive content as well as in the saliency of user interface controls and explanatory features.

- *Order of content*. The scaffold adapts the order in which it presents content based on user expertise. Novices receive basic theory and information, while experts get advanced methods and a summary.

- *Presentation style*. The scaffold adapts presentation style to expertise [1] and learning style [9]. Expert scaffolds are less intrusive while degree of graphical expression is based on learning style preferences.

- *Bootstrapping*. Novice users are introduced to the system by an instructional note shortly after opening the Sandbox. Also, key menu options are highlighted and scaffold content is open by default.

- *Task guidance*. nAble detects the current sub-task using a task model. The scaffold emphasizes relevant steps in the current subtask to provide instruction and momentum to the user.

- *Varied visual saliency*. The visual saliency of key indicators changes according to expertise and is used to clarify meaning. Adaptive indicators of hypothesis support scores are enhanced for novice

users, presenting a larger scale, as well as +/- symbols for further clarification.

- *Attention management.* Attention management techniques include tool highlighting and dialogue alerts. Popup warnings are reserved for important notifications such as during novice bootstrapping and timeout warnings for all users.
- *Introduce functionality.* Visual feedback on key components was modified to introduce new functionality to novice users. For example, feedback buttons appear on mouse-over to highlight the ability and location for tuning evidence weight.

2.1 Decision Making Agent

Decisions about which adaptation to employ are made using a Bayesian network for the user model and a Hidden Markov Model for task recognition (see Figure 2). The Hidden Markov Model (HMM) tracks the user's progression through ACH subtasks and a Bayesian network is used to make adaptation decisions based on the user's current expertise and learning style (as measured by the Felder-Silverman model of learning styles). Models are implemented using a layered agent approach, with sensors monitoring user performance which in turn influence adaptive
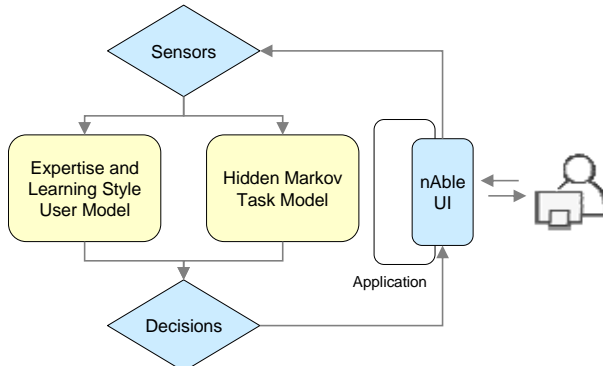

Figure 2. nAble Recommending Scaffold

decisions. Sensors for both models include explicit initial entry of learning style and expertise as well as implicit detection of user behavior and preferences throughout the task. Examples of sensors include the number of times a user has logged in, the number and type of objects currently in the Sandbox, the frequency of assistance requests and dismissals, and the errors in tool use. The Bayes net has a hidden layer consisting of learning style and expertise, while ACH subtasks and bootstrapping nodes comprise the hidden layer of the HMM. Connections between subtasks were not strictly linear, allowing for flexibility in the order in which tasks were undertaken.

The Bayesian network and the HMM work in conjunction to select appropriate adaptations given the current task and user information. The agent makes suggestions for any decision which reaches sufficient utility based on the user's current learning style and state of expertise. For example, it could suggest that relevant scaffold content be presented, and in a style suited for a visual novice. The contribution of the task network is to recommend which subtask the current assistance should focus on. Thus, if assessing evidence diagnosticity is detected as the sub-task, the scaffold would be presented with suggestions on assessing diagnosticity automatically opened.

As this was the first experiment using these models, initial connections and weights were assigned using expert knowledge of the task domain and literature on expertise and learning style. Networks were initially tuned to user survey results for learning style and set at novice for expertise, but these could be adjusted by the networks within a single day or across multiple sessions. For example, a user could have tested for a visual learning style preference, but showing repeated preference for verbal scaffolds, the networks would adjust the engine's recommendations to compensate. The Hidden Markov task model used primarily user observation as sensors, including the number and type of objects created in the Sandbox, the number of hypotheses formed, the amount of evidence assigned and whether key features like ACH diagnosticity sorting had been discovered. The Bayesian network and HMM were implemented with the SMILE/Genie Bayesian tool [10].

3. "Into the deep end" experiment

A study was conducted to examine the potential of adaptive scaffolding techniques to facilitate rapid progression towards higher levels of expertise. Our primary objective was to show that our scaffolding user group would create better analyses than non-scaffold participants. Participants were given the task of completing an ACH for a controlled problem in the nSpace Sandbox. Participants had no prior knowledge of ACH methodology or the Sandbox tool environment. They were literally thrown into the "deep end" and expected to complete a significant analysis task. Three groups of participants each received one of the following support types: 1) nAble adaptive scaffolds, 2) indexed, searchable help and 3) human guidance. There were 27 participants on the first day of the experiment, and 10 participants were brought back for four additional days for a total of five days to examine the development of expertise over time.

Participant results were blind rated by a group of three experts for the completeness and quality of the final analyses. Included in this measure were the number and applicability of hypotheses, the

appropriateness of rated evidence and stated assumptions and the completeness of the final report. The presented quality score is based on the mean from the three experts. Significance level was set to .05 for all results.

3.1 Performance results

There were significant results and observations in the day one group on the interaction of learning style, adaptive technique and performance. These results are beyond the scope of this paper and will be covered in detail in a future paper. This discussion will focus on key results for the five day longitudinal study.

As expected, participants performed better as they participated in more sessions. Figure 3 shows that our scaffold users were able to match human guided performance by day two, while indexed help users did not reach parity until day five.

To put the previous data in perspective, these novices were literally thrown 'Into the deep end'. They were given a one minute demo in the nSpace Sandbox software (a complex, albeit intuitive program to support visual thinking) and only a ten-second description of how to access their instruction/guide before the experiment began.

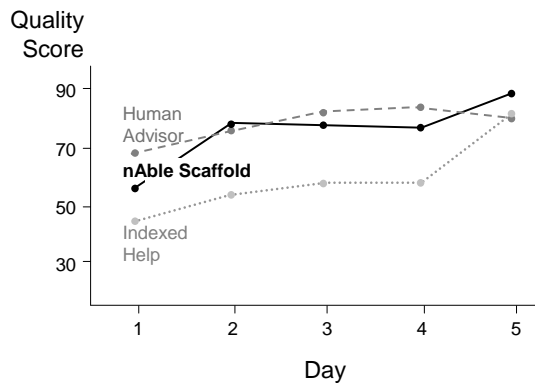During the experiment, they had one hour to perform each analysis task which required learning the

Figure 3. Scaffold participants matched users with one-on-one advisors by day two.

The ACH Tasks over five days:
1. What happened at Roswell in 1947?
2. What happened to Amelia Earhart?
3. What is causing global warming trends?
4. What life exists outside of this planet?
5.What effect do video games have on youth?

ACH methodology, using the ACH tool within the Sandbox, and putting it all together to answer a complex question. Given these challenges, our participants did exceptionally well. Many scaffolding participants were able to create a number of reasonable

hypotheses from the evidence, assign the evidence as either supporting or refuting, explore the diagnosticity of evidence and use the ACH matrix to come to a reasonable conclusion regarding the likelihood of each hypothesis. This demonstrates an impressive gain in understanding of methodology, tool and environment

4. Conclusions

The goal of the nAble project is to discover principles and techniques for adaptive systems that guide novices through software capabilities, and facilitate immediate productivity on the first tasking. The 'Into the Deep End' experiment tested initial adaptive scaffold techniques and demonstrated that scaffolds can match human tutoring twice as fast as traditional indexed help systems. Future work includes broadening the task models, further technical exploration of new adaptive user interfaces and visualizations, and extensions of adaptive scaffolding into Web 2.0 and synthetic world domains. Further experiments are planned to refine nAble principles for adaptive techniques to assist novices.

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