

An agent-based methodology for analyzing and visualizing educational assessment data

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ABSTRACT

We examine data collected from on-line assessments of the numeracy and literacy skills of young students in order to construct probabilistic agent-based controllers. We demonstrate the value of this methodology as an effective means for both analyzing and visualizing aspects of large data sets that are difficult to capture with traditional equation-based statistics and static graphics.

Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence; K.3.1 [Computers and Education]: Computer Uses in Education

General Terms

Design, Human Factors

Keywords

learning, training, education, simulation

1. INTRODUCTION

The motivation for the work outlined here is the formulation of a methodology for simulating human learners, as a means toward better understanding of the human learning process. The work discussed here is designed to take advantage of a specialized, detailed data set collected from human learners to build data-backed, agent-based *simulated learners*. Using computational techniques, we define the knowledge base being acquired by the learners and we represent the learners as artificial agents. The behavior of the individual agents, and their interactions, can be guided in various ways. Related work has explored the use of both an abstract

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theoretical control mechanism [3] and a mechanism based on pedagogical theory [4].

The work described here builds a probabilistic control mechanism backed with data collected by an on-line multi-dimensional assessment tool called the Children's Progress Academic Assessment, or CPAA¹. The CPAA covers concepts that are essential to early childhood development. It is grouped around "core concepts" in language arts and mathematics, such as alphabet knowledge, phonemic awareness, quantities and patterns. These concepts were chosen to reflect US national and state academic standards for language arts and mathematics for ages 4–8. The scoring rubrics for these core concepts are calibrated to state standards regarding end-of-year expectations for each grade. The core concepts are divided into "prime questions" which address specific concept components. For example, phonemic awareness is comprised of prime questions related to rhyming, initial sound, blending, and syllable counting. The prime questions are organized within the assessment in an adaptive manner. That is, if a child answers a particular prime question correctly, then she would receive a more difficult prime question. An example is shown in figure 1.

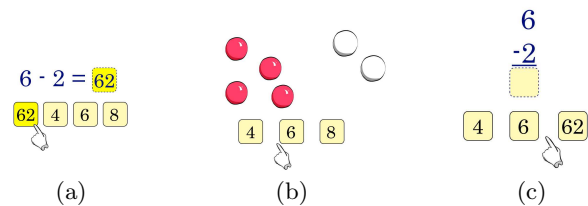


Figure 1: CPAA example. The initial question is (a): $6 - 2 = ?$. If the child answers correctly, she moves ahead. However, an incorrect response generates "hints" to guide the child to the correct answer. If the child answers (a) $6 - 2 = 62$, then the child is presented with a concrete hint: (b) "Here are six balls. If I take away two balls, how many balls would you have?" If the child responds $6 - 2 = 8$, then the child is presented with (c) a particular hint that is designed to direct the child's attention to the fact that this is a subtraction problem.

¹<http://www.childrensprogress.com>

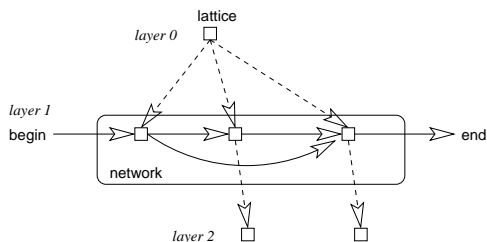


Figure 2: Database architecture.

The content of each assessment inside the CPAA is organized using a *lattice* data structure [2]. Essentially, this is an overall schematic of the theoretical organization of the questions that comprise an assessment. This underlying lattice structure is similar to the notion of a *concept graph* [3], where a “concept” is defined as an atomic bit of knowledge within a domain, and theoretically, an entire domain can be represented as a graph of concepts, where each concept is illustrated by a node in the graph. Links connect the nodes and have real-valued weights associated with them, where the weights indicate the strength of the relationship between the concepts. Directionality of the links provides a “curriculum”, i.e., an ordering for the presentation of concepts by a human teacher or an automated tutoring system.

The difference between a typical on-line evaluation system and the CPAA is the unique way that the knowledge domain is organized as a hierarchical lattice and the ability of the system to adapt on-line, automatically, to the needs of each human user. To allow maximum flexibility for the adaptive assessment too, we designed a multi-layered database architecture (shown in figure 2) which is organized as a tree at the top layer and as networks at the lower layers. The “core concepts” are shown in layer 1, and layer 2 contains networks representing “prime questions”. The edges connecting the nodes in layer 1 can be re-ordered in any fashion to suit the evaluator, as can the nodes in layer 2—and so on. The design allows creation of additional layers without loss of data integrity or run-time access.

2. AGENT MODEL

In order to construct a model of learner behavior within the CPAA, we analyzed the student log data for a particular instance of the assessment given to first grade (age 7) students in Spring 2005. First, we performed some preliminary analysis on a small portion of the data in order to help design our agent behavior model. Then we used the full data set to construct a probabilistic agent control model.

Our preliminary analysis examined the data for 183 students from the same school district. Figure 3a shows the variation in paths taken by the students traversing the lattice. The vertical axis contains the index number of each node in the lattice. The horizontal axis shows the passage of time. All the students start at the same node (index number 2)² but rapidly diverging by the 10th time step. Figure 3b shows the scores accumulated by the same set of students. For easy comparison, all students started with a score of 0. If a student gets the answer to a question

²An anomaly in the data had some students starting at node index number 149.

right, then her score increases by 1; if a student gets the wrong answer, her score decreases by 1. Note that this is not how scoring is computed within the assessment, but was adopted to simplify the illustration here. Again the disparity amongst the students—all of the same age from the same school district—is marked.

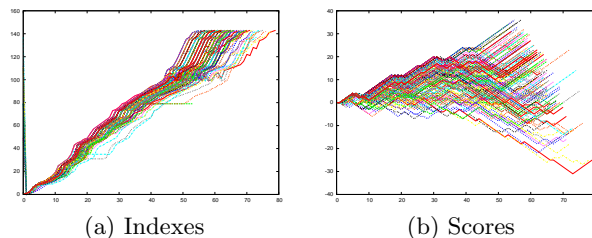


Figure 3: Snapshot of student logs.

Next, we examine the construction of a probabilistic agent controller for modeling the behavior of a learner using the CPAA assessment. We overlay the notion of a *concept graph* onto the structure of the *lattice*, such that for every node a list of the possible “next nodes” is defined. This is a Markovian process, wherein each subsequent state in the assessment is reached based on an action performed in the previous state, but the number of actions that can transition the learner from her current state to another state are limited by the inherent content of the lattice. We can assign the probability of going from one node to another solely based on the opportunity to do so, using textbook Bayesian techniques, which would give us a behavioral model of *legal* moves within the network.

However, we have more data available than just the structure of the assessment lattice. We also have the complete student logs (878 students). We can use this probabilistically by counting, for every student, every traversal from node to node in the assessment. This gives us a *frequency*-based method for defining an agent-based controller. The probability that any student in the data set will go to node c_j next, given that she is currently at node c_i , is:

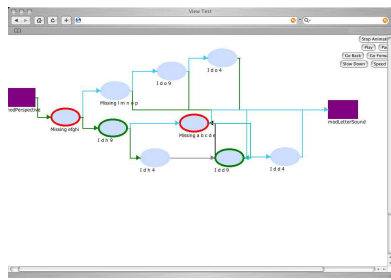
$$Pr(c_{i,j}^{\rightarrow}) = v_{i,j}/n_i$$

where $v_{i,j}$ is the number of times c_j was visited after visiting c_i and n_i is the total number of times c_i was visited.

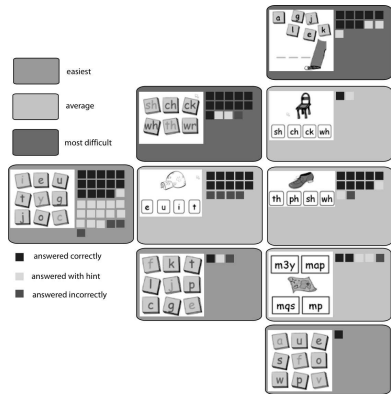
The problem with using a strictly Bayesian method is that we have more information available to us and would prefer to build a controller that takes advantage of the experience stored in the data set of student logs. The Bayesian method provides a model of what is *possible*. The problem with using a strictly frequency-based method is that it will only be able to model what is *probable*. Thus, we need to be able to combine possible and probable in order to result in a comprehensive behavioral model; and our current work is exploring the application of possibilistic techniques [1].

3. VISUALIZATION FOR ANALYSIS

Classroom teachers are interested in having access to the wide range of data collected by the CPAA, but find they lack the tools or skills or experience to manage all the data that has been collected. We have constructed a browser-based “video” reporting tool that allows teachers to replay the



(a) Structure-based



(b) Content-based

Figure 4: CPAA visualizations.

assessment of any of her students. The tool is interactive in order to allow maximum flexibility for examining individual, or groups of, students. A set of VCR-like controls allow the user to “play”, “stop”, “pause” and even “fast forward.” When “play” is pressed, an animation begins that highlights, over time, which nodes a user has visited. Each oval in the figure represents a “prime question” in the assessment tool. The border of an oval is drawn in green when the student has gotten the answer to a question right, and red otherwise. In the figure, the ovals without borders are those which the student never visited.

We take advantage of the fact that the underlying structure of the assessment is hierarchical in order to display logically the entire content of the assessment, split over several screens. The structure represented in figure 4a contains nodes from layer 2 of the assessment. The dark rectangles at the far left and right of the diagram indicate entry and departure points for the concept covered by this network. Clicking on the leftmost rectangle sends the user to the previous network in the layered hierarchy; the rightmost rectangle shifts the user to the next network in the hierarchy.

This visualization works well for showing the underlying structure of the CPAA assessment and demonstrating how a single student progresses from one sub-concept to the next. However, for viewing the progress of multiple students at a time, or even an entire class, the visualization is limited. An informal focus group held with in-practice classroom teachers provided feedback that the visual representation of nodes and transition links was too abstract for the typical, technically challenged early elementary school teacher. Additionally, we noted that the agent-based approach, where we

explained to teachers that each of their students was being represented as an individual agent, worked very well. The teachers saw that as a natural way to connect their students to the large data set they were exploring with our tool.

A second visualization has been designed and is illustrated in figure 4b. This drawing illustrates a set of nodes relating to one sub-concept in the assessment. Each rectangle corresponds to a node in the lattice described earlier, and connectivity between nodes (though not explicitly shown in this diagram) are also in the form of directed links. The content of the rectangles includes a representative portion of the screen (or animation) that appears when the student is being assessed on the concepts in that particular node. In order to overcome the problem of how to represent multiple students progressing through the assessment at the same time, the right half of each rectangle contains a schematic of boxes, where each box represents a student. A color scheme highlights how well the students have performed on each question asked. A focus group is planned in the near future in order to evaluate this new interface design.

4. SUMMARY

We have presented the motivation, design and implementation of a methodology and system for agent-based analysis and visualization of a large, human interaction data set. The ultimate goal of the integration of agent-based modeling techniques into the CPAA tool is to be able to track dynamically and more effectively the behavior of the human learners and be able to predict their actions, tailoring the assessment by effectively pre-loading questions according to the students’ prior interactions. Over time, a probabilistic model of the student’s interactions with the system is accumulated; the more data contributing to the model, the more accurate it will be in terms of emulating the student. This will give us the means to customize interventions based on students’ immediate needs, resulting, over time, in improved learning.

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