Gunzelmann, G., & Gluck, K. A. (2004). Knowledge tracing for complex training applications: Beyond Bayesian mastery estimates. In *Proceedings of the Thirteenth Conference on Behavior Representation in Modeling and Simulation* (pp. 383-384). Simulation Interoperability Standards Organization.

Knowledge Tracing for Complex Training Applications: Beyond Bayesian Mastery Estimates

Glenn Gunzelmann
Kevin A. Gluck
Air Force Research Laboratory
6030 South Kent Street
Mesa, AZ 85212-6061
480-988-6561
glenn.gunzelmann@mesa.afmc.af.mil, kevin.gluck@mesa.afmc.af.mil

Keywords:
Learning, Forgetting, Power Law, Distributed Practice, Training, Knowledge Tracing

1. Introduction

Effective training for military personnel is a top priority to ensure preparedness for mission operations. Increasingly, there is a desire to provide training in a manner that takes advantage of advances in cognitive science. The goal is to provide simulation-based training that leverages cognitive agents in several ways both to increase training effectiveness and also to reduce the costs of providing such training. One application of cognitive agents is that they can be used to help assess and track the acquisition of mission-relevant skills through a process called knowledge tracing [1].

As used in academic tutoring, knowledge tracing involves the modular representation of cognitive skills in a computational process model capable of performing those skills. As students perform the task, the expert model is able to compare their actions against the optimal actions in the task situation. Importantly, this cognitive model also has knowledge of errors that may be made in the task and how those errors are produced. As a result, when students make errors, the model is able to both identify them and provide specific feedback about why the action was incorrect, what the correct action was, and what the students should do to correct their mistake. This approach to skill training has had a history of success, particularly in terms of academic tutoring in areas like Lisp programming [2] and algebra [3].

While the knowledge tracing approach has been shown to be effective in helping students learn, it suffers from at least one important limitation. Specifically, the approach uses Bayes' theorem to assess mastery learning based upon the history of success and failure on particular units of skill within the task. In the Bayesian knowledge tracing approach, once a skill has been mastered, it is assumed to be mastered forever. This approach does not account for forgetting, and thus cannot provide predictions about skill retention.

For military personnel, training opportunities may be distributed at irregular intervals across days, weeks, or months. In the intervals between training opportunities, particular skills may be left unpracticed. In these circumstances, decay in skilled performance is inevitable. The goal of this research is to move beyond the traditional approach of Bayesian mastery estimates and investigate the use of mathematical models of learning and forgetting that more accurately reflect our understanding of the dynamics of cognition and allow for a more realistic estimate of competence.

2. Current Research Approach

Our research is currently focused on validating a mathematical approach to describing the rates of learning and forgetting of knowledge and skills. The fundamental equation is taken from Anderson and Schunn [4]:

$$Performance = A * N^{c} * T^{(-d)}$$

This equation is able to capture both the Power Law of Practice [5] and the Power Law of Forgetting [5,6]. In the equation, N is the amount of practice and T is time. The learning rate is controlled by the parameter c, and the decay rate is d. The variable A is simply a scaling parameter. With this simple equation, it is possible to capture the trends in the data across the continuum of psychological research, from simple list learning, to complex skill acquisition, to long-term knowledge retention. Our current efforts are directed toward testing the capabilities and limitations of this equation for predicting current performance and for generating training requirements to achieve a desired level of performance.

There are two steps involved in using this modified knowledge tracing approach. First, by knowing the history of training opportunities and current performance level for an individual on a particular set of skills, it will be possible to fit learning and decay parameters for individual trainees. Step two is to use those parameters in predictive and prescriptive models of future performance. Given specific assumptions about the frequency and schedule of future training and rehearsal, one can predict competence level at any particular time in the future. Given knowledge of the current and desired levels of competence, one can perform analyses of alternatives in the training design space and prescribe training and rehearsal schedules that achieve competence requirements most efficiently.

Although the equation above is powerful for predicting current performance as a function of practice, it does suffer from one significant limitation. It is not able to account for the effect of distributed practice on performance, or the spacing effect. The spacing effect is a cognitive phenomenon where the distribution of practice on a particular skill impacts the final performance. In general, massed practice, or practice that is confined to a relatively short period of time, results in poorer long-term learning than if the same amount of practice was distributed, or spaced, over a longer time interval.

The equation above assumes that all practice occurred at T=0, thereby embodying a strong assumption of massed practice. The ability for this research to progress to the point of being able to make predictions on the basis of individualized training histories will require the ability to account for the distribution of practice opportunities. Some research on detailed modeling of spacing effects been done [7], and we suspect it will be important to incorporate those or similar mechanisms into this work, as we take knowledge tracing the next step beyond Bayesian mastery estimates.

3. References

[1] Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction, 4*, 253-278.

[2] Corbett, A. T., Anderson, J. R., & O'Brien, A. T. (1995). Student modeling in the ACT Programming Tutor. In P. Nichols, S. Chipman, and B. Brennan (Eds.), *Cognitively diagnostic assessment* (pp. 19-41). Hillsdale, NJ: Lawrence Erlbaum Associates.

[3] Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. *The Journal of the Learning Sciences*, *4*(2), 167-207.

[4] Anderson, J. R. & Schunn, C. D. (2000). Implications of the ACT-R learning theory: No magic bullets. In R. Glaser, (Ed.), *Advances in instructional psychology: Educational design and cognitive science (Volume 5)* (pp. 1-34). Mahwah, NJ: Lawrence Erlbaum Associates.

[5] Newell, A., & Rosenbloom, P. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 1-55). Hillsdale, NJ: Lawrence Erlbaum Associates.

[6] Rubin, D., & Wenzel, A. (1997). One hundred years of forgetting: A quantitative description of retention. *Psychological Review, 103*(4), 734-760.

[7] Pavlik, P., & Anderson, J. R. (2003). An ACT-R model of the spacing effect. In F. Detje, D. Dorner & H. Schaub (Eds.), *Proceedings of the Fifth International Conference of Cognitive Modeling* (pp. 177-182).

Author Biographies

GLENN GUNZELMANN is a National Research Council Research Associate at the Air Force Research Laboratory's Warfighter Training Research Division in Mesa, AZ. His research interests include all aspects of higher-level cognition, particularly spatial cognition, with a strong interest in computational models of complex cognitive processes. He earned his PhD in Cognitive Psychology from Carnegie Mellon University in 2003.

KEVIN A. GLUCK is a Research Psychologist at the Air Force Research Laboratory's Warfighter Training Research Division in Mesa, AZ. He is the Director of the Performance and Learning Models Research Program and his research is in the area of basic and applied cognitive modeling. He earned his PhD in Cognitive Psychology from Carnegie Mellon University in 1999.