Visualizing Adaptive Learning Effects on Clinical Skill Acquisition and Decay

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Abstract. The purpose of this paper is to present a visualization tool, grounded in modern psychometric theory, for optimizing the parameters of adaptive training systems. The tool can be used in a research capacity to rapidly visualize the course, trajectory, and shape of one's learning curves resulting from different adaptive training conditions and how these are affected by conditions intrinsic to both the task domain and the learner.

Keywords: Adaptive training, skill acquisition, data visualization, medical simulation.

1 Introduction

Adaptive training technologies have emerged as a dominant instructional methodology within instructional designers' and developers' toolkits. The ability to adapt the instructional environment to the unique skill configuration of the individual learner introduces a host of possibilities for improving the rate of skill acquisition and promoting long-term skill retention. The instructional potency of training adaptations relies on the underlying concept of tailored instruction: by administering only content that is relevant to an individual given his or her current skill profile, the training process can maximize the amount of time spent isolating and correcting deficient skills, thereby accelerate learning outcomes.

Adaptive training and intelligent tutoring technologies has a long history in the fields of educational psychology, instructional design, and computer science. Recent developments in computational power and storage capacity have enabled the mass transmission of these technologies to wider audiences of learners in industrial environments, most notably in the military, clinical settings, manufacturing, and high risk occupations. The widespread availability of methods and underlying technologies for adaptive training has reframed the basic questions regarding their efficacy in promoting immediate and long-term skill development. Not only are researchers and instructional designers interested in whether adaptive training technologies affect skill learning, but in what specific methodological details and learning theory concepts maximize their utility in real-world learning environments.

The purpose of this paper is to present a visualization tool for optimizing the parameters of adaptive training systems. The tool can be used in a research capacity to

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rapidly visualize the course, trajectory, and shape of one's learning curves that are likely to result under different adaptive training conditions (e.g. magnitude and variability of between-scenario difficulty increments), and how these are affected by conditions intrinsic to both the task domain (e.g. initial scenario difficulty, susceptibility to skill decay) and the learner (e.g. initial skill level, learning rate). The tool is grounded in modern psychometric theory to enable an apples-to-apples comparison between the skill demands of specific tasks and the skill resources of the learners performing those tasks. Although the tool can be applied to any domain as a planning tool for the development of adaptive training schedules, we use simulated data to demonstrate its efficacy in the context of adaptive training for clinical skill learning.

1.1 Adaptive Training

An imposing challenge in simulation and game-based training is the ability to replicate, with high verisimilitude, the psychological stress of high stakes tasks. Simulation-based training affords a means for trainees to perform difficult procedures (e.g., emergency trauma care) in an immersive environment that eliminates the consequences of performance errors (e.g., fratricide, patient disability or death). Although this is the very purpose of simulation, eliminating consequences of errors makes for a comparatively less stressful experience than the analogous real-world task. If effective performance under stress is itself a training objective, a critical question arises: How do we create simulations that have the same effect on the trainee's stress experience as real-world practice, while still maintaining a safe practice environment?

Adaptive training and intelligent tutoring technologies offer an important mechanism for enhancing the long-term learning and performance benefits of instructional interventions in complex domains (Mangos, Campbell, Lineberry, & Bolton, 2012). These technologies provide a mechanism for achieving a state of constant readiness, where routine, challenging, and "worst case" scenarios are practiced with high frequency, and trainees only experience content that challenges their unique set of deficiencies. The concept of tailored training stems from on aptitude-treatment interactions, which suggests that the effectiveness of instruction is influenced by specific individual differences and endorses an idealized model for instruction in which instructional events are customized to challenge a given learner's unique skills (Kanfer & Ackerman, 1989; Snow & Lohman, 1984).

A critical challenge in developing and delivering adaptive training has to do with accurate assessment of trainees' skill and knowledge constructs as they interact with a dynamic training environment. How does one adapt the training environment to a trainee's skill level if the skill is (hopefully) improving over the course of training, and the training environment is changing in response to his or her actions? A number of modeling strategies to address or both task analysis and assessment of trainee skill and knowledge domains have been used to address this concern. Modern psychometric theory, a family of models for independently and invariantly estimating parameters of test items and latent skills, provides one solution (Embretson & Reise, 2000). These benefits are made possible as trainees engage with accurately calibrated training content and are assessed using a psychometric framework that allows apples-to-apples comparison between multiple trainee skills and the skill demands of a dynamic scenario.

Knowing how well a trainee is performing with respect to a training scenario with a known difficulty level, however, is only one piece of the adaptive training optimization challenge. The remaining challenge is knowing how to adapt the training environment: how much more difficult a given scenario should be with respect to the individual's measured skill level, the distribution of easy versus difficult scenarios, the optimal skill mix inherent in each scenario, and the optimal time duration between the introduction of new skill components. These are but a small portion of the different aspects of the training environment that must be considered when engineering an adaptive training system. Such decisions should be determined jointly by cognitive science theories of skill acquisition and psychometric data specific to the training environment. However, there remains a need to be able to rapidly simulate and visualize how adaptive training modifications will affect skill acquisition.

1.2 Objective

The objective of the current effort is to create a modeling, simulation, and visualization tool capable of enabling instructional designers to visualize the effects of adaptive training manipulations under different task and person conditions. The tool can be used within an optimization framework, allowing instructional designers to model and simulate the effects of different adaptation algorithms. This can help users decide which specific manipulations are most useful under what conditions, and considering the objectives of the specific training situation (e.g. immediate learning, long-term skill retention, overall skill learning over time as indexed by the total area under the skill learning curve).

2 Methods

To demonstrate the utility of the tool, we performed an extensive Monte Carlo data simulation study in which we generated a large number of algorithms for producing simulated skill learning curves under various conditions. The purpose of this data simulation exercise was to demonstrate how different adaptive training manipulations could affect skill learning over 100 simulated clinical scenarios, given predetermined parameters of the task in the trainee. This would produce simulated training data that closely resembles actual data that could be modeled and analyzed with the tool. The various factors simulated to affect the shape and trajectory of the learning curves include:

1. Person factors:

- Initial skill level estimate (theta)
- Learning rate

2. Task factors:

- Initial scenario difficulty level
- Scenario psychometric properties:

  - Average scenario difficulty
  - Average scenario discrimination

- Skill decay parameter

3. Instructional design features:

- Incremental (between-scenario) scenario difficulty level
- Practice down time (i.e., time between scenarios)

2.1 Data Simulation

Simulated (Monte Carlo) data were generated using the Mplus program (Muthén & Muthén, 2010). The primary data set contains data emulating the performance of simulated trainees, translated into estimates of latent, underlying skills using the two parameter logistic item response theory model (2-PL) (Embretson & Riese, 2000).

We generated 5000 individual experimental conditions. The conditions are defined by unique combinations of values for the manipulated task, person, and instructional design variables. Many of the variables had a continuous range of possible values. Therefore, the individual values for each variable that represented a single experimental condition were generated via random sampling of the normal distribution. Specifically, the initial scenario difficulty, initial scenario discrimination, difficulty increase parameter, initial trade estimate, skill decay parameter, and learning rate parameter were all generated via random sampling from a normal distribution. Inspection of histograms and bivariate scatterplots for each combination of these randomized variables shows that all meaningful combinations of variable levels were well represented in the resulting data set.

For each experimental condition, we generated 100 individual simulated practice sessions with corresponding estimates of scenario difficulty, discrimination, and latent trait estimates. The task domain arbitrarily selected for contextualizing the study results was clinical performance in emergence response/patient stabilization scenarios. However, as IRT produces standardized estimates of task/test difficulty and skill levels that are invariant to any domain, the visualization results and underlying data can reflect any domain in which adaptive training is used. Latent trait estimates, arbitrarily reflecting clinical diagnostic acumen, were computed for each of these individual practice sessions. Next, we used latent growth curve analysis to estimate the initial latent trait level, the level of growth in the latent trait level across the 100 practice sessions, and the pattern or shape of the growth pattern over time. Specifically, we estimated linear, quadratic, logarithmic, and exponential models to characterize patterns of growth change over time. Finally for each of the resulting growth curves, we estimated the area under the curve, reflecting cumulative change in the latent skill being trained over the course of the training.

3 Results

The values of the simulated data points are completely arbitrary. Although different combinations of the experimental variables may result in higher cumulative levels of the latent skill estimates, higher initial learning, or better overall resistance to skill decay, it is difficult to make unequivocal inferences about the use of specific instructional manipulations (e.g. moderate initial skill difficulty, moderate average increases in difficulty, high overall discrimination) without the task and person specific variables being tied to actual tasks and learners with quantifiable properties (e.g., a specific task with a quantified skill decay parameter, a learner with a quantified learning rate). Therefore, our results focus solely on the visualization capabilities of the tool for showing how hypothetical combinations of learner and task characteristics, combined with strategic instructional interventions can result in different patterns of learning and long-term skill retention.

For the sake of demonstrating how these different combinations can affect learning curves, we selected various levels of the task and person variables that had statistically and practically significant effects on the parameters of the simulated learning curves. These were modeled within a multiple regression framework, with a single model estimated for each of multiple dependent variables reflecting initial learning, change in learning, and cumulative skill growth.

For illustration purposes, we estimated a regression model using the area under the first order (linear) growth curve as the dependent variable. After several iterations of model testing and variable selection, the final retained set of predictors including the difficulty increase parameter, skill decay parameter, learning rate parameter, initial scenario difficulty, and initial trait estimate collectively accounted for 87% of the variance in the dependent variable. Although invariant task and person variables that cannot be manipulated by instructional designers (e.g. decay parameter, learning rate parameter) where the dominant predictors, the instructional variables such as initial scenario difficulty and the difficulty increase parameter had statistically and practically significant effects.

The visualization tool allows one to graphically display the learning curves associated with different combinations of the task, person, and instructional variables, while manipulating these variables in real time. Additionally, it allows one to overlay different growth trends corresponding to linear, polynomial, logarithmic, and exponential growth models. One can also simultaneously show the patterns of change for scenario difficulty and for the latent trait estimate. Because the underlying psychometric framework – item response theory – enables apples-to-apples comparison of task and person characteristics using a common metric, the simultaneous display of these two growth curves and the divergence between them are directly interpretable. For example, for a specific task (with known average difficulty, skill decay parameter, etc.) and person (with known available practice time and learning rate) the ideal pattern of scenario difficulty manipulations may be one in which the scenario difficulty is consistently a small degree higher than the estimated trait level. The visualization tool would reveal this pattern as an accelerating, increasing trend in the trait estimate curve with a closely conforming difficulty curve, perhaps separated by a fixed number of units on the Y axis.

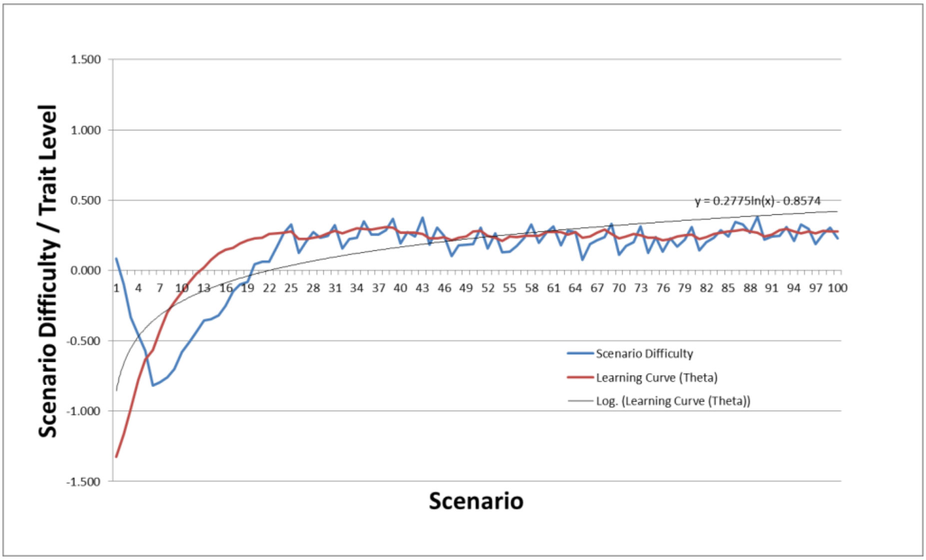

Fig. 1. Difficulty Increment = 13%, Learning Parameter = 6%, Decay parameter = -.3%

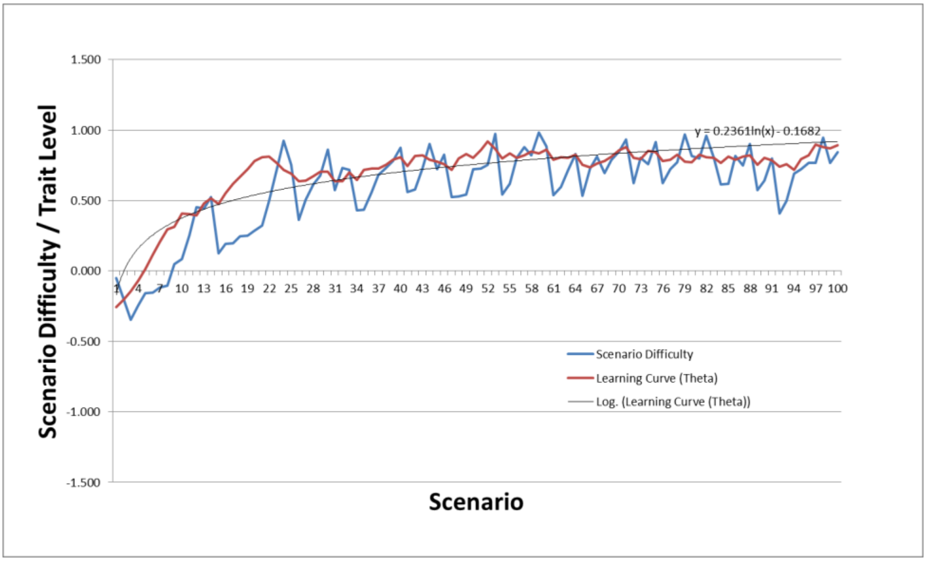

Fig. 2. Difficulty Increment = 22%, Learning Parameter = 11%, Decay parameter = -.5%

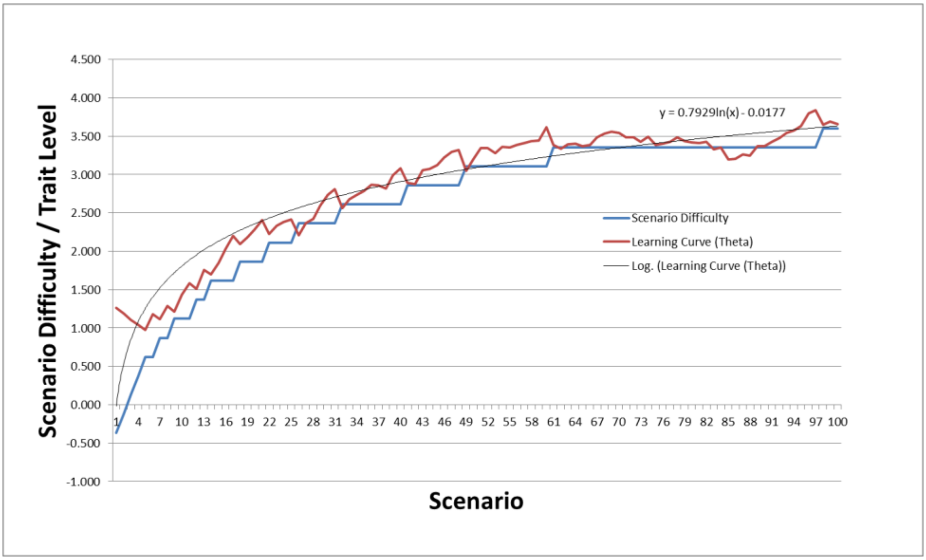

Fig. 3. Difficulty Increment = 25%, Learning Parameter = 31%, Decay parameter = -.1%

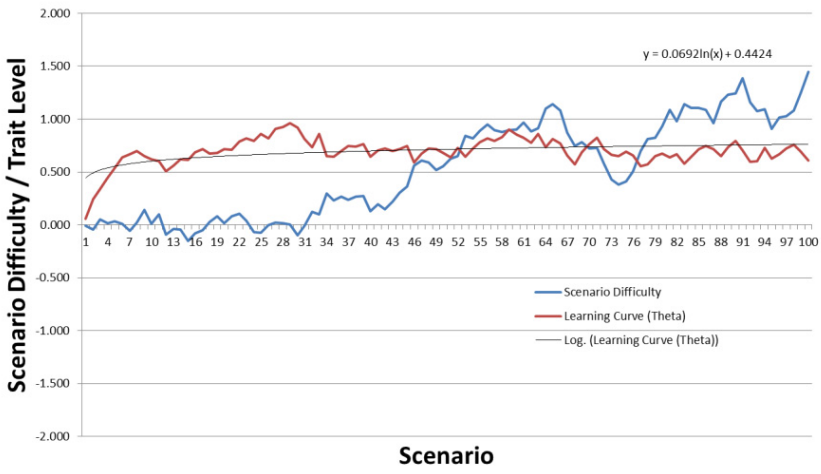

Fig. 4. Difficulty Increment = 2%, Learning Parameter = 23%, Decay parameter = -1%

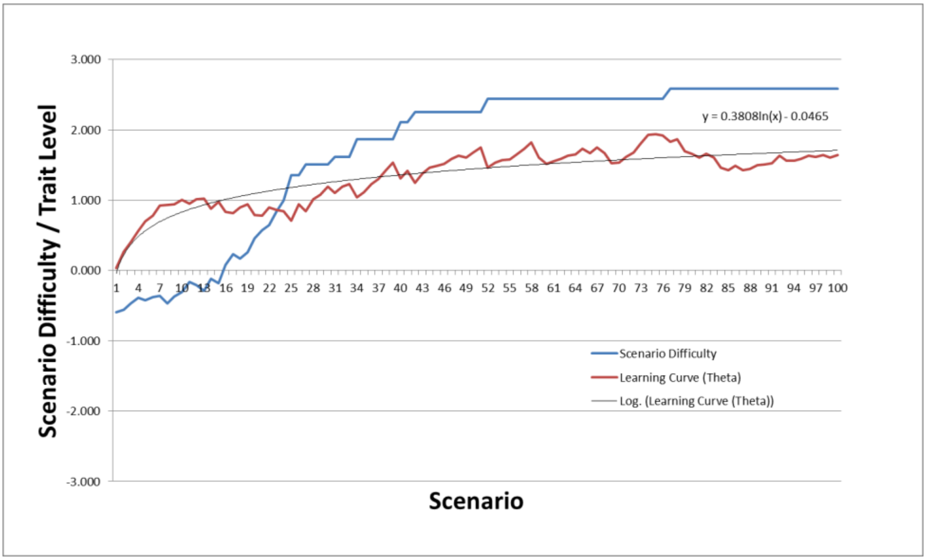

Fig. 5. Difficulty Increment = 7%, Learning Parameter = 28%, Decay parameter = -1%

4 Conclusion

The objective of the current research was to provide a framework for modeling, simulation, and visualization of the effects of adaptive instruction manipulations on patterns of immediate and long-term skill acquisition. Adaptive training methodologies have proven useful as a means for tailoring instruction to the unique skill profile of the individual learner. The visualization tool permits finer grained analysis of the potential effects of various adaptation manipulations on the level, rate, and pattern of skill acquisition. This provides a foundation for a superordinate level of training customization: tailoring of the pattern of training adaptations to maximize skill learning for an individual learner.

There are a multitude of ways in which instructional designers can adapt training content. The current research focused solely on between-scenario adaptations of difficulty, including the average between-scenario difficulty increment, average scenario difficulty, and average scenario discrimination. As these were selected for illustrative purposes to demonstrate the potential utility of the visualization tool, they represent an oversimplification of the multidimensional nature of clinical skill acquisition. Even relatively simple clinical tasks require the successful convergence of multiple knowledge and skill domains. For example, an emergency response team performing a basic resuscitation scenario must have knowledge of the basic steps of CPR, the requisite perceptual skills to detect vital signs without equipment, and teamwork skills to orchestrate the performance of individual team member tasks. A simulated training scenario would benefit from a measurement framework capable of independent assessment of each of these multiple knowledge and skill domains, and therefore, independent manipulation of scenario elements targeting each domain. This introduces additional dimensions for constructing an adaptive training algorithm. In addition to manipulating scenario difficulty, difficulty variability, and discrimination, instructional designers can tailor the skill mix of the scenarios, that is, the relative emphasis each scenario places on each of the knowledge and skill domains required for effective task performance.

The application of psychometric theory provides an overarching framework for meaningful, simultaneous measurement of task demands and trainee skills. The parameters produced by Adam response theory models, for example, difficulty, discrimination, and skill dimensionality provide a foundation for organizing, planning, and instantiating training adaptations. However, adaptive training algorithms can incorporate parameters for any aspect of the training environment that can be manipulated:

- The duration of overall scenarios or discrete scenario events
- The number, difficulty, and combinations of scenario events
- Quality, quantity, and timing of performance feedback,
- Timing of complementary, mixed format training events (e.g., textbook or instructor led training)
- Practice schedules for coordinating massed versus distributed practice
- Content variability
- Incorporation of online perform support tools (e.g. hinting)

These variables, among many others, can be easily quantified and used within the visualization tool to model and predict training outcomes given known parameters of the person and the environment. This provides a robust mechanism for instructional designers to thoroughly plan the specific details of how training adaptations will be carried out in the context of adaptive, simulation-based training.

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