charles river analytics

+ Charles River Analytics Inc.
625 Mount Auburn St.
Cambridge, MA 02138

www.cra.com

+ p: 617.491.3474
f: 617.868.0780

15 JUN 2010

Reference: Government Contract No. N00014-09-C-0050, “Enhancing Simulation-based Training Adversary Tactics via Evolution (ESTATE)”
Charles River Analytics Contract No. C08098

Subject: Contractor’s Status Report: Quarterly Status Report #6
Reporting Dates: 3/15/2009 – 6/15/2010

Dear Dr. Hawkins,

The following is the Contractor’s Quarterly Status Report for the subject contract for the indicated period. During this reporting period we have concentrated on Task 4: Develop Trainee Model Processing and Task 6: Sim-based Training System Integration.

1. Summary of Progress

During this reporting period, we have leveraged prior analysis of the MoneyBee dataset with our academic partner to further analyze the student learning of the task. We have also begun the design of a simulated training context and ESTATE architecture implementation to address this context.

1.1 Analysis of Learning in the MoneyBee Dataset

The goal of this task is to discover a method to measure student learning and to determine if students are gaining proficiency in this pre-algebra activity. This method will augment our student assessment and challenge adaptation techniques by providing a better estimate of student ability and Zone of Proximal Development (ZPD). Earlier exploration of the MoneyBee Dataset indicated that the students score better as they attempt more problems, but because of student selection of problems, it was unclear whether the students were improving or simply choosing easier problems to attempt (Rosenberg, 2009). Also, we discovered that our heuristic estimate of problem difficulty correlates with the time to complete a problem (Rosenberg, 2010). The results of the current analysis below show that as the number of problems attempted by a student increases, 1) the mean and median difficulty increases and 2) the mean and median time to complete decreases. This provides strong evidence for learning on the MoneyBee task.

MoneyBee is a coin algebra activity. The student is given a sum and a number of coins and has to pick out which coins add up to the sum. A session consists of paired exercises until a student completes five problems. In each exercise, students create problems for the other to solve, followed by the reception of a student-created problem and a graphical workbench for solving

Report Documentation Page

Form Approved
OMB No. 0704-0188

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE **15 JUN 2010**	2. REPORT TYPE	3. DATES COVERED **00-00-2010 to 00-00-2010**

4. TITLE AND SUBTITLE **Enhancing Simulation-based Training Adversary Tactics via Evolution (ESTATE)**	5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Charles River Analytics, Inc.,625 Mount Auburn St,Cambridge,MA,02138**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR’S ACRONYM(S) 11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**7**	

the problem. The record of each exercise collects a detailed timeline, down to a tenth of a second, recording when players add and subtract coins towards solving the problem they are presented. When a student solves a problem, both the student and his or her partner receive points equal to the estimated problem difficulty. Thus, students are incentivized to choose the most difficult problems they believe their partner can solve.

Our difficulty heuristic performs the following calculation to estimate difficulty. Beginning with the initial amount of cents:

1. Remove the odd pennies (modulo five)

2. Search for the solution adding a single coin in a breadth first search (first quarters, then, dimes, then nickels, then pennies), until the problem has only one coin type remaining.

This heuristic makes the assumption that players will attempt larger valued coins first, and that players mentally search for a solution by considering all alternatives in sequence. Because breadth first search is exponential in the number of nodes explored, we take the logarithm of the heuristic as the estimate.

Figure 1-1 shows a graph of the estimated problem difficulty per session. As students play more sessions they are given problems with higher estimated difficulty. Thus, as students play more sessions their partners estimate that they will be able to solve more difficult problems. Figure 1-2 and Figure 1-3 show the relation between number of sessions played and mean and median time to completion. As students play more sessions their time to complete each game decreases, indicating that they are able to solve these problems with more proficiency. Together, these analyses indicate that students are learning through challenges, solving more difficult problems in less time as they gain experience.

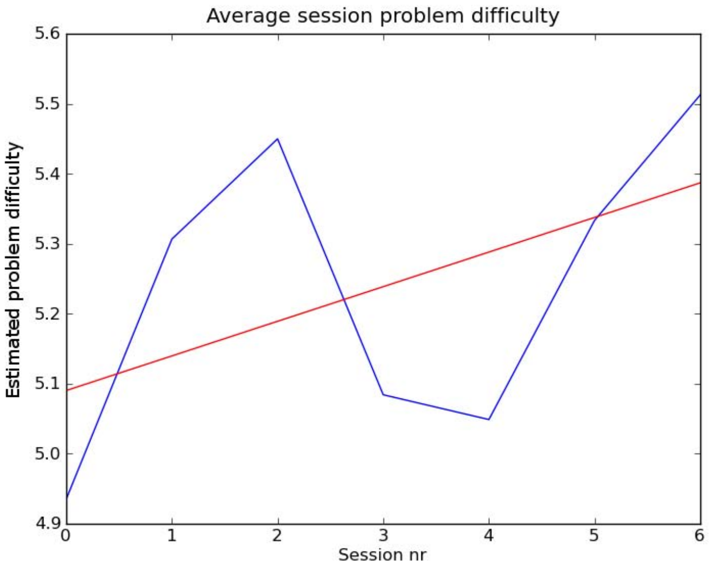

Figure 1-1: Estimated problem difficulty per session.

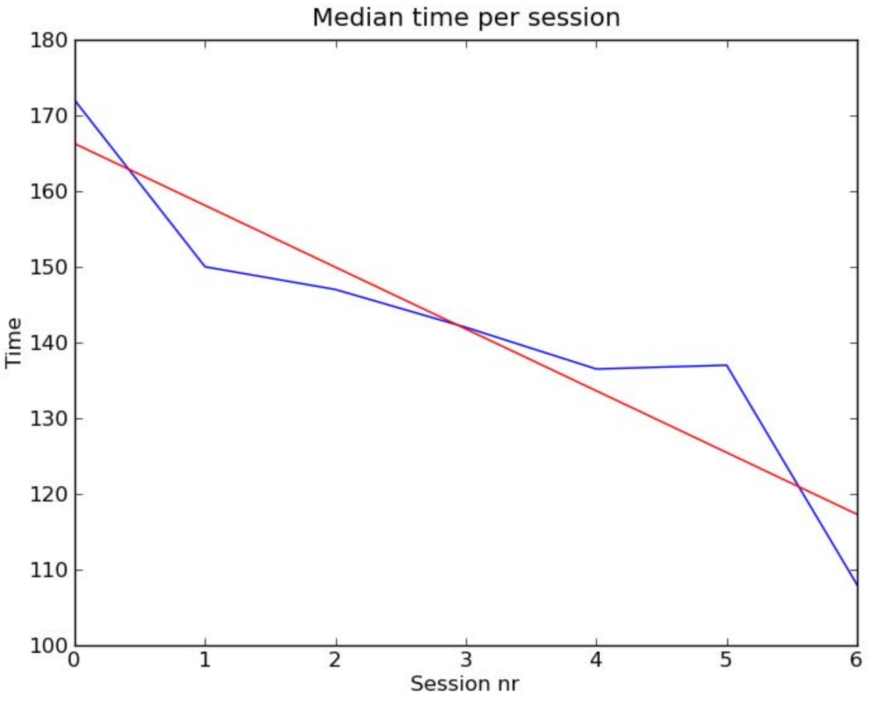

Figure 1-2: Median average game time per session

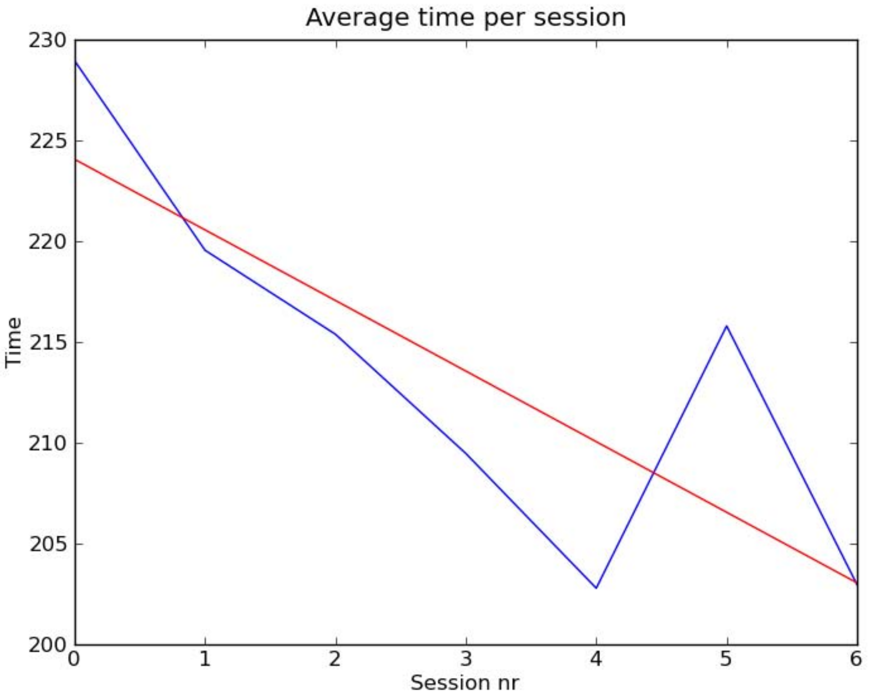

Figure 1-3: Mean average game time per session

DISTRUBITION A. Approved for public release; distribution is unlimited

Our next steps with the MoneyBee dataset will be to improve our visualizations of the strategy choices, developing a strategy "heat map" to provide an observable visual overview of how the students move between states in the problem space. For instance, choices that are mode more often may be drawn with thicker arrows, making the most common paths more apparent. Comparing these visualizations between inexperienced and experienced players may provide information as to how strategies evolve due to experience. We can then use this analysis to create models of different players for future experiments.

1.2 Development of Simulated Training Context and Corresponding ESTATE Architecture Implementation

Previously, we have demonstrated the use of the MaxSolve monotonic solution concept (De Jong, 2005) for coevolution. Ficici (2004) identifies *solution concepts* as a method to analyze the relationship between the selection of individuals in coevolution and the meeting of the overall goals of the coevolutionary process. It indicates which individuals to keep for future populations; thus, a solution concept is a type of memory mechanism. A well functioning solution concept will drive the population towards the goals (e.g. being a better game player), while a poorly functioning solution concept will cause the population to flounder due to one or more coevolutionary pathologies.

Our criteria for selecting a solution concept was that 1) the solution concept performed well in practice and 2) the solution concept did not further constrain on the problem. Performance comparisons between these algorithms (De Jong, 2005; De Jong & Bucci, 2006), communications with authors (Bucci, 2010), and consultation with our academic partner, an expert in this area, led us to choose the MaxSolve solution concept as the best candidate for implementation and testing. MaxSolve has exhibited high performance on a number of different challenges, and it does not place any additional constraints on our problem space. We previously implemented MaxSolve and tested the technique on the COMPARE-ON-ONE, Challenge tree, and Nim games, showing that MaxSolve performed well in these domains (Rosenberg, 2010).

Our next step is to design and implement a simulated training context to test the performance of the ESTATE approach with MaxSolve coevolution. As an initial implementation, the challenge tree approach, shown in Figure 1-4, offers a number of advantages. First, the challenge structure is simple, and will ease the diagnosis and debugging of implementation issues. Second, our coevolutionary technique has been tested on this structure and it performs well. Third, this type of challenge can be readily adapted to a number of challenge domains.

We plan to first implement a maze challenge: trainees are dropped inside a room in a virtual maze and traverse the challenge tree by selecting doors to walk through, without backtracking. Each room is decorated with clues that indicate to the trainee which door to choose to stay on a path to an exit. For instance, a house plant and a picture of a sailboat could indicate choosing the leftmost door. By repeatedly attempting the challenges, trainees are taught how the clues combine to indicate a door choice. Following this initial implementation, we plan to implement a cultural training application. Here, the trainee is presented with a conversational goal and a current conversational state in a dialog tree. Based on the current state, the trainee must repeatedly choose actions or lines of dialog until the interaction is completed, either with success or failure. We map the nodes of the challenge tree to conversation states, and the edges of the tree to trainee dialog or action choices. By repeatedly attempting new challenges, trainee learns how indicators about the current conversational state can be used to choose actions.

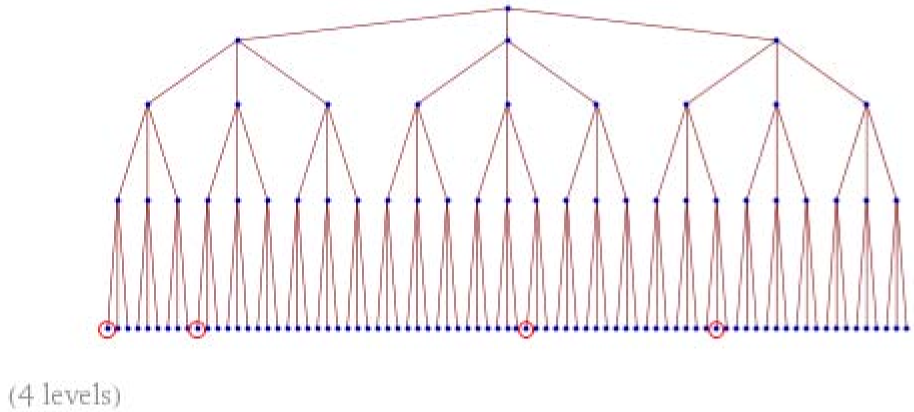

Figure 1-4: An example challenge tree game. The trainee begins at a node and chooses edges to move down the tree until a leaf node is reached. The leaf nodes are either marked as successes (circled) or failures (not circled).

To implement this simulated training context and gather performance data, we must provide initial, prototype implementations of the entire ESTATE architecture, shown in Figure 1-5. Our implementation of the **Training System** must include a **Simulated Environment**. For the maze challenges this environment will be a definition of the maze structure and of the protocol for decorating rooms, and, for the cultural trainer, this environment will be a definition of the conversation tree and the method for creating dialog and action options. The **Training System** will also simulate **Trainee Models**, which may include trainees that exhibit a number of learning bugs (e.g., failure to recognize the decoration mechanism, ignoring one or more features, slow learning, or general forgetfulness). The **Trainee Model Extractor** will use a diagnosis routine to generate a number of trainee models. This routine will use the known trainee moves to sample from the possible strategy space of the trainee, producing a number of simulated individuals as the initial population of coevolution. These individuals will be sent to the problem generator to run the MaxSolve coevolution with these individuals and an archive of challenges as the **Adaptation** technique. The problem generator will use an estimate of the ZPD to stop the coevolution at a specified point and send the next top challenge to the trainee to repeat the cycle. The estimation of the ZPD may be the number of generations in coevolution, the number of new tests discovered, or some distance calculation between individuals or tests in the population.

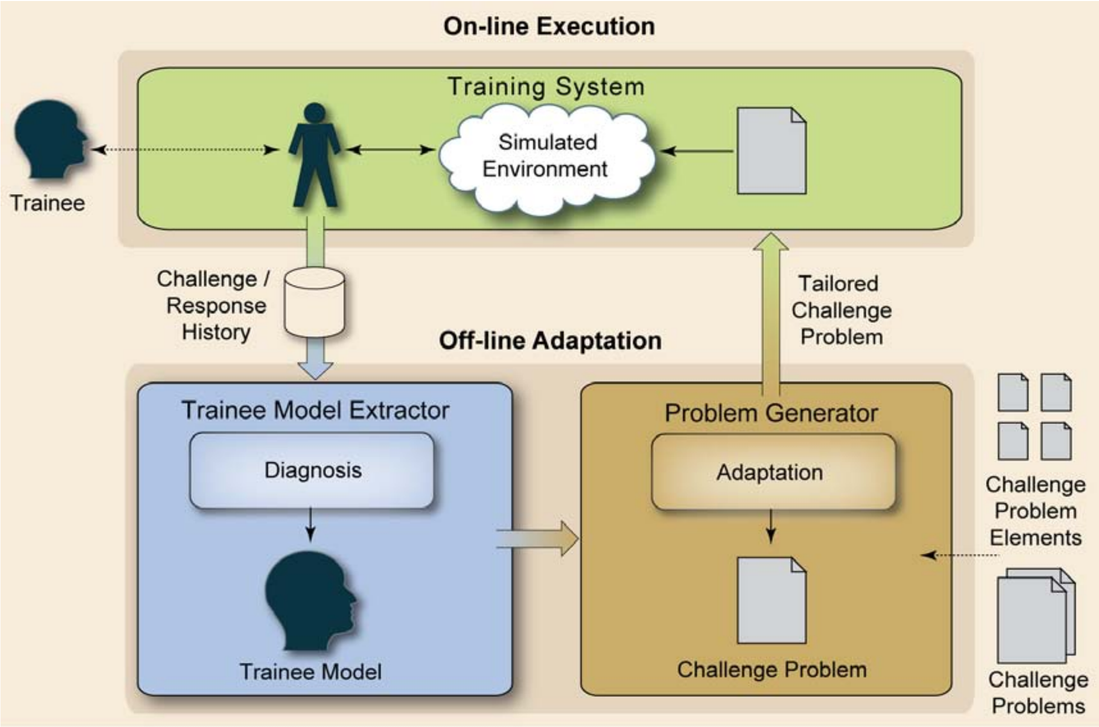

Figure 1-5: ESTATE Challenge-Response System Architecture

Our next steps are to complete the design of the simulated training context and begin implementation of the maze and cultural training applications. We aim to have both a set of simulated trainee models and a simple user interface for human users to test the system.

2. Reference List

Bucci, A. (2010).
Ref Type: Personal Communication

De Jong, E. (2005). The MaxSolve Algorithm for Coevolution. In Washington, DC.

De Jong, E. & Bucci, A. (2006). DECA: Dimension Extracting Coevolutionary Algorithm. In.

Ficici, S. G. (2004). *Solution concepts in coevolutionary algorithms.* Brandeis University.

Rosenberg, B. (2009). *ESTATE, Fourth Quarterly Status Report* Cambridge, MA: Charles River Analytics.

Rosenberg, B. (2010). *ESTATE, Fifth Quarterly Status Report* Cambridge, MA: Charles River Analytics.

3. Scheduled Items

In the next reporting period we plan to address the following items:

- Further investigate trainee strategy modeling.

- Design and begin implementation of a simulation of 1) trainees attempting challenges, 2) assess trainee skill and strategy, and 3) challenges evolving.

- Continue MoneyBee strategy data analysis and visualization.

Sincerely,

Brad Rosenberg
Principal Investigator