Dynamics of Innate Spatial-Temporal Learning Process: Data Driven Education Results Identify Universal Barriers to Learning

Wenjie Hu, Mark Bodner, Edward G. Jones, Matthew R. Peterson, Gordon L. Shaw
M.I.N.D. Institute, Costa Mesa CA 92626

Abstract
Spatial-temporal (ST) reasoning - thinking in patterns - data from computerized STAR (ST Animation Reasoning) video games designed to dynamically enhance students learning mathematical concepts (www.MindInstitute.net) are gathered over the internet. ST reasoning has been shown to be innate to the structured columnar cortex and to be highly trainable. The data containing fundamental ST information (learning curves) are analyzed and then sent back to teachers so that students can be trained efficiently in an interactive manner. Here we report the use of data mining techniques to examine the dynamics of the learning process - Data Driven Education (DDE). The learning curves for each STAR game, played a number of times on several days, are grouped into different categories according to contours, identifying the different phases of learning. We present our first DDE results from > 2,200 2nd graders on one STAR game showing plateaus in the learning curves. These plateaus are then identified with universal sharp barriers to learning related to specifics in the game design common to many computer games. Simple changes in the design of this game will be tested to see if these sharp barriers to rapid learning are removed. Further DDE studies will not only provide fundamental information on how learning occurs, but may also form the basis for a revolution in education.

1. Introduction

ST reasoning is innate to our structured columnar cortex and is highly trainable [1-3]. The systematic development of ST reasoning can significantly improve learning to think and reason. We will focus here on math. Mastering math involves understanding difficult concepts (as well as performing well on standardized tests) which are usually taught and assessed using language based approaches (equations, word problems, symbols). Although ST learning is crucial for the understanding of math and science at all educational/grade levels, it is essentially ignored in schools.

Previous studies have demonstrated that piano keyboard training for 3-year-olds causally gave long-term enhanced ST reasoning [4] (complementing the short-term causal Mozart listening studies [5] with college students). Combining piano keyboard training with STAR training was found to greatly enhance learning of fractions and proportional math by second graders [6]. This led to the ST Math+Music (M+M) Program (www.MindInstitute.net) now used by over 8,000 2nd - 4th graders in 40 schools [2]. The M+M program bridges the ST approach to the usual language based math training. STAR video games are designed so that a child has a number of plays during the 45 minute period. The scores arrive over the internet, and we can plot and analyze each child's learning curve, Fig. 1, in real time. Instead of a snapshot of the child's performance from a quiz, we are seeing the learning process as it happens.

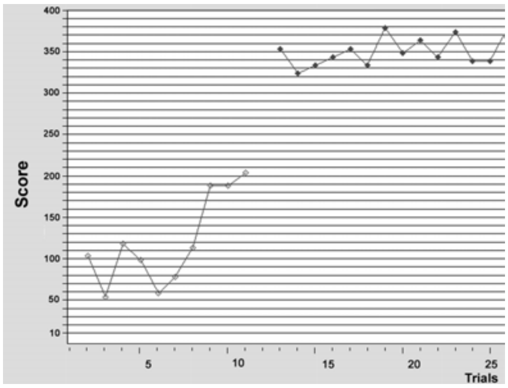

Figure. 1. Observation of ST learning process. An example of the learning curve for one of the STAR math video games, Bricks (see Fig. 2). Points on the graph indicate the score obtained on each play or trial of the game. The break in the curve indicates different day of play. A score of 300 is passing and 400 is maximum. Note the huge (not typical) jump (consolidation) in this 2nd grader's performance from day 1 to day 2.

We have constructed, from analysis of learning curves for each game, diagnostic feedback to the teacher: a) Having difficulties -help, b) good progress – leave alone, c) mastered game – move on (to next game or to a challenge game). If you observed one or two plays of the child on day 1, Fig. 1, you might think that the child needed help. Our analysis software tells us, and the teacher that the day 1 data are not diagnostic for a), but b). On day 2, the diagnosis is c).

We report here the use of data mining analysis on the large and growing M+M database. This is the beginning of data driven education – DDE – as contrasted to theory driven education derived from small sets of data. Our first DDE results presented here provide striking evidence against some common usage in computer games that add specific features designed to capture and maintain children's attention during learning process. Not only are these not necessary, but they appear to greatly inhibit the learning process. Simple changes in the design of this game will soon be tested to see if these sharp barriers to rapid learning are removed.

2. Methods

2.1 ST Data

The data analyzed here consists of sequences of consecutive scores obtained from over 2200 2nd graders on the Bricks STAR video game. Each stage or screen consists of a ST reasoning problem(s), Fig. 2. A problem consists of the presentation of a shape to match. The child selects 1 of 3 sets of shapes after performing a mental ST sequence of operations: i) unfolding or folding along a symmetry axis, ii) assembling a set of two or more individual shapes, iii) performing a rotation. If the correct matching shape(s) is selected, the game moves on to the next problem, and 10 points are assigned. (-5 points for an incorrect answer). Two subsequent incorrect responses results in termination of the particular trial, and a new trial is begun from the beginning (with the score reset to 0). The Bricks game is language free. Completion of the game consists of correctly answering a sequence of 40 problems. The game starts with an introductory sequence of 8 problems without extensive game play action. Problems initially consist of simple mental operations and then build into more complex concepts. After the Introduction a number of game-play components unrelated to ST reasoning are introduced consisting of movements of the game character and surroundings, and timing components at specific points.

On average, 10 trials on Bricks are performed by each child in a given 45 minute class period. Scores obtained on consecutive trials are recorded, along with the time duration for each individual trial.

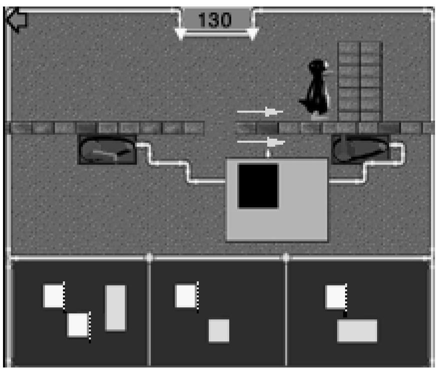

Figure. 2. Screen shot of the Bricks STAR game showing one of four problems with a time component. The correct response (bottom right) requires both unfolding along a symmetry axis (dotted lines at the edge of the shape) and assembling the separate shapes. The timing element consists of the floor being slowly removed. The correct response must be given before the floor disappears from beneath the character (~ 5 seconds) ending the trial. Problems and possible wrong solutions are chosen from a data set in each trial, but the positions of the four timing problems in the 40 problems are fixed at 13, 19, 26 and 33.

Our Bricks learning data were from > 2200 2nd grade children in 32 public and private elementary schools in our M+M Program. These schools ranged from low to high socio-economic demographics..

2.2. Learning Curve Categorization

The learning curves were screened by time windows from one day up to three days. The learning curve data for each child were preprocessed for subsequent categorization analysis. Preprocessing was carried out using scores and timing factors to normalize the curves to take into account varying numbers of trials for each child, and to remove "spurious noisy" trials not associated with learning.

Each subset (day) of the learning curves was grouped into homogeneous classes by a clustering algorithm. Considering the playing time of each child and the observations (scores), we converted each child's learning curve into the following normalized *feature vector* as the input to the clustering algorithm.

<Attribute 1, Attribute 2, …, Attribute n>

where attribute 1 is the average playing time; attribute 2 to attribute n are sampled observations (scores) of the learning curve. The value of number n is dependent on how many days' points are included. We sampled 3 valid (noise removed) points each day.

To classify the learning curves into C clusters, where C is a given constant, we applied the unsupervised clustering method, Fuzzy C-Means (FCM), to the subsets obtained via time screening. The FCM method [7, 8] can be seen as the generalized K-Means method using Fuzzy Theory. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, \qquad 1 \le m < \infty \tag{1}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and $\| \ \|$ is any norm expressing the similarity between any measured data and the center. Fuzzy partition is carried out through iterative optimization of the object function (1), with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|^2}{\left\| x_i - c_k \right\|^2} \right)^{\frac{-2}{m-1}}, \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \qquad (2)$$

The iteration will stop when $\max\{| u_{ij}^{(k+1)} - u_{ij}^{(k)} |\} < \varepsilon$, where ε is a termination criterion between 0 and 1, and k denotes iteration step. This procedure converges to a local minimum or a saddle point of J_m.

3. Results

The learning curves obtained on the first day of play (day 1) were partitioned into four classes (class 1-I, 1-II, 1-III and 1-IV) according to the contours of the learning curves. The children in classes 1-III and 1-IV, who did not pass the game on day 1, were further partitioned into three classes (2-I, 2-II and 2-III) on day 2 in order to show more detailed information. However the clustering results are based on sampled points only. Our purpose was to estimate the real-valued learning models defined by all observations. Therefore we fit the polynomial regression model to all data in each class on day 1 and day 2. Fig. 3 represents the estimated learning curves with all data using the third order polynomial from day 1 and day 2. It can be seen that students all begin with a rapid acceleration of learning, after which plateaus in the learning process occur. These identify specific information on how learning occurs.

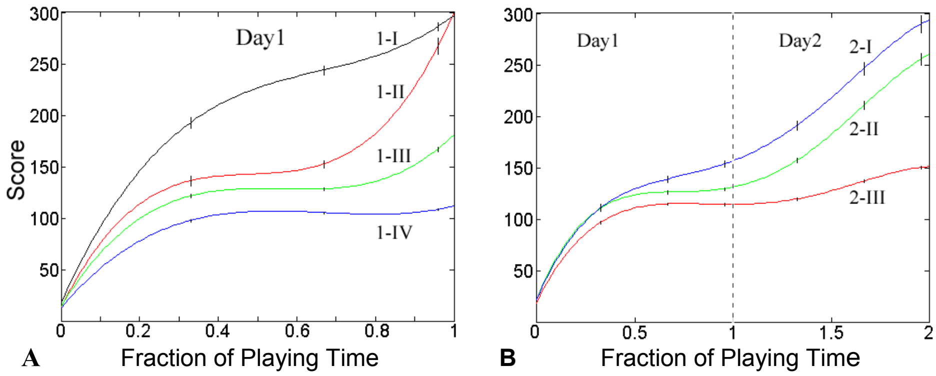

Figure. 3. Learning curves of students obtained after clustering and polynomial regression. **A:** Learning curves from data obtained from students on their first day of play. Learning curves are partitioned into 4 significantly different categories (error bars on curves indicate standard errors). Categories I and II obtain a passing score (corresponding to a score of 300 or higher) while categories III and IV plateau

and do not pass on day 1. Note the early stages exhibit rapid learning for all categories, and then separate into distinct plateaus indicating specific learning barriers for large groups of the 2nd graders. For category 1-I, there are 407 children (18%), 1-II 203 children (9%), 1-III 601 children (27%) and 1-IV 1021 children (46%). **B:** Learning curves for data from students who did not pass on day 1 (data from curves III and IV in **A** that had an additional day of play). Learning curves are partitioned into 3 significantly different categories which separate similarly to 1-II to 1-IV in **A**. For category 2-I, there are 255 children (17%), 2-II 462 children (31%), 2-III 765 children (52%).

To gain insight into the nature of the plateaus in Fig. 3, we plot in Fig. 4, histograms of the last trails on day 1 of the children in each of the 4 categories 1-I to 1-IV. The results show 5 distinct peaks which we identify with features of the Bricks game, the 1st peak with the end of the Introduction where somewhat more sophisticated (possibly distracting) graphics occur and the next 4 peaks where timing factors are present (Fig. 2).

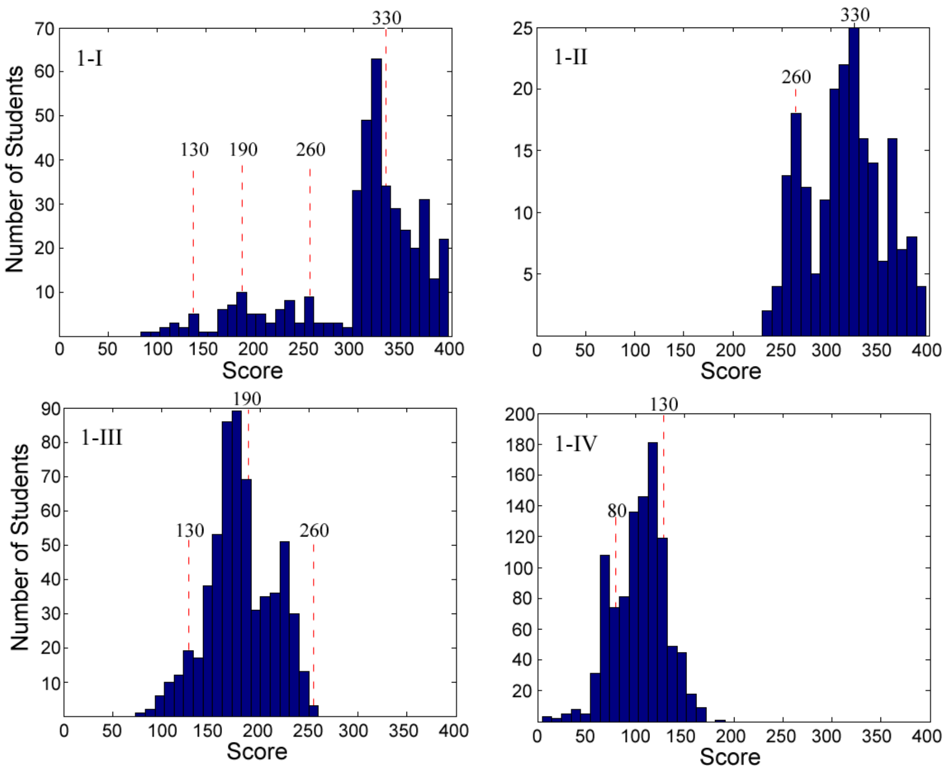

Figure. 4. Histograms of the last scores of the children categories 1-I to 1-IV on day 1 (see Fig. 3). It is clear that the distributions are multi-modal, exhibiting five peaks or specific "barriers" beyond which students had difficulties advancing.

Examination of the Bricks game identifies the source of those barriers. The first barrier appears to occur at the end of the Introduction. The other four barriers correspond to the four timing component problems, Fig. 2. The 5 dotted vertical lines correspond to scores if no mistakes were made before the barriers. Note that children's last scores are sometimes considerably below their highest score, presumably due to various attention factors especially (see 1-I) if they have quickly mastered the game.

4. Discussion

ST learning curves, Fig. 1, allow the examination of the dynamics of the learning process in contrast to snapshots given by quizzes. *ST reasoning has been shown to be innate to the structured columnar cortex and to be highly trainable*. ST learning is crucial for understanding math and science, and should precede and complement language based learning as in the M+M Program.

We analyzed ST learning curve data from > 2,200 2nd graders in 32 schools gathered from their training on the STAR math video game Bricks (Fig. 2). We used data mining techniques to examine the dynamics of the learning process - DDE. The learning curves for Bricks, played a number of times on several days, are grouped into different categories according to contours, identifying the different phases of learning (Fig. 3). These first DDE results show plateaus in the learning curves. These plateaus are then identified with universal barriers to learning related to specifics in the game design common to many educational computer games (Fig. 4). We use the term universal in the sense that the barriers were present in the 2nd graders regardless of the diverse demographics in the schools participating in the M+M Program.

Straightforward changes in the design of the Bricks game identified by our analysis will be tested to see if these sharp barriers to rapid learning are removed. The most obvious, relevant to the most children and easiest to change, is to remove the 4 timing problems and test a new group of children (from the same demographics) in one training session and compare with the present results in Figs. 3-4. In order to proceed with our goal[2] of having all children use their large innate ST abilities [3] in reaching their potential in mastering math and science, we must optimize the design of the ST computer games to reduce barriers to learning that are due to ST computer game design. The DDE program presented here allows this to happen.

Another large goal of future DDE studies is to closely examine the causal relation between music training enhancing learning math concepts [3, 6] using the new STAR piano keyboard game. Our new STAR math and music training games record all keystrokes in addition to scores. We continue to add grades, schools and students to our M+M Program. Science games will be added. Future DDE studies of the growing M+M database following children over years will provide fundamental insight on higher brain function [2, 9] and how learning occurs, as well as forms the basis for a revolution in education.

We use this forum to invite potential collaborations with experts in other areas of data mining, and other researchers to explore additional ways to examine our unique (encrypted) M+M database as well as pose additional crucial questions on how children learn to think and reason in math, music and science. Such collaborations are crucial in helping make the potential revolution in education a reality.

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