Introduction

Combining principles of learning with computer technology offers powerful but largely unrealized potential to improve instruction. In our research, we focus on realizing this potential for a wide variety of learning tasks, including perceptual learning and pattern recognition, learning facts, categories, and procedures.

Here we describe research on novel adaptive algorithms that sequence learning items based on the learner’s accuracy and speed of responding on earlier trials. These algorithms allow implementation of a number of laws of learning, potentially allowing improved efficiency for factual learning as well as perceptual learning and pattern recognition.

Dynamic Sequencing

Consider a set of n items to be learned. These could be factual items, patterns, concepts, or procedures. How can we optimize the learning of the set of items? We describe a patented sequencing algorithm that assigns to each item in the set a priority score (Pi), such that:

- The highest priority item is selected for presentation on each trial.
- Initial priority scores may be equal, or some items may be given higher priority (scaffolding).
- Priority scores for each item are updated after each trial, based on:
  - Accuracy of last response(s) for that item
  - Response time on last response(s) for that item
  - Time since last presentation
  - Parameters indicating relative importance of speed, accuracy, and elapsed trials
- Score updating is based on a Sequencing Equation. A typical form is:

\[ P_i = a (N_i - D) \left[ b (1 - \alpha_i) \log \left( \frac{RT_i}{r} \right) + \alpha_i W \right] \]

\( P_i \): priority score for item i
\( N_i \): number of trials since item i was presented
\( D \): enforced delay constant
\( a \): priority increment constant
\( \alpha_i \): 0, if learning item was answered correctly on previous presentation
\( 1 \), if learning item was answered wrongly on previous presentation
\( W \): incorrect answer priority increment
\( RT_i \): response time on most recent presentation of item i
\( b, r \): response time weighting constants

Retirement

To ensure mastery and also to remove well-learned items from the learning set, learning criteria based on accuracy and speed are used. Combining sequencing with retirement of mastered items may provide an especially powerful method for producing effective and efficient learning.

Implementing Laws of Learning

This learning framework allows easy implementation of laws relating to learning and memory; and it provides adjustable parameters to accommodate content of different difficulty or learners at different levels. In the studies reported here, we have incorporated several key principles:

- Combined speed and accuracy measures: Allows more comprehensive assessment of learning strength and fluency to determine sequencing and retirement.
- Tracking and learning-to-criterion for each item ensures mastery (Bloom, 1984; Keller, 1968).
- Enforced delay: Even high-priority items are subject to a delay between presentations, ensuring exercise of retrieval from long term, not working, memory.
- Stretching the retention interval: As items become better learned, their priority scores change to produce longer delays, maximizing the benefits of learning trials (Landauer & Bjork, 1978).
- Issues of optimal scheduling are addressed by basing delay on item learning strength as indexed by the learner’s RT, potentially avoiding some issues of fixed schedules (e.g., Karpicke & Roediger, 2007).

Dynamic Sequencing in ITEM LEARNING

**EXPERIMENT 1. “BIGH SQUARES” Task:** Participants learned 14 multiplication problems, all squares between 1 and 99.

- Example: \( 37 \times 37 = 1369 \)
- This task was chosen because it is difficult and because it bears some resemblance to the child’s task in learning basic multiplication facts.
- Participants: 48 college students, instructed to memorize, not calculate. Feedback given after each trial.
- All 14 items tested in immediate posttest and after one week. As the material was highly difficult, delayed posttest consisted of three consecutive blocks with feedback (modified savings method).

**RESULTS**

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Trials to Criterion</th>
<th>Mean Posttest Score</th>
<th>Mean 1st Delayed Posttest Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sequenced with Retirement</td>
<td>137</td>
<td>.74</td>
<td>.36</td>
</tr>
<tr>
<td>Random with Retirement</td>
<td>160</td>
<td>.61</td>
<td>.28</td>
</tr>
<tr>
<td>Random, No Retirement</td>
<td>245</td>
<td>.77</td>
<td>.35</td>
</tr>
</tbody>
</table>

Trials to Criterion and Posttest Performance were combined into a single measure of EFFICIENCY:

\[ \text{EFFICIENCY} = \frac{\text{# of items correct on posttest}}{\text{# of learning trials invested}} \]

**CONCLUSIONS**

- Both Dynamic Sequencing and Retirement improved learning efficiency.
- In combination, Sequencing with Retirement improved efficiency by more than 100% compared to random presentation.

Department of Education.