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Investigation of Procedural Skills Degradation from Different Modalities

Jong W. Kim (jongkim@psu.edu)
Richard J. Koubek (rkoubek@psu.edu)
Department of Industrial and Manufacturing Engineering

Frank E. Ritter (frank.ritter@psu.edu)
College of Information Sciences and Technology
The Pennsylvania State University, University Park, PA 16802 USA

Abstract

Can we help people forget less by knowing how they learn? Can we decrease forgetting by modifying what they learn? These have been long-standing questions in applied cognitive psychology. This paper reports a study designed to investigate procedural skills degradation in a set of spreadsheet tasks. The task can be taught and performed as knowledge and skills that are declarative or procedural, and perceptual-motor or cognitive. To examine the effect of these characteristics on learning and forgetting, one group of participants used key-based commands to complete the task, and the other group used a novel mouse and menus to do the task. Participants were able to learn the task well in four learning sessions. Retention intervals (6-day or 18-day) showed clear effects on the amount of forgetting. This paradigm can measure forgetting in terms of modalities and skill types. We found evidence that the menu mode was not better than keystrokes. Furthermore, the modalities showed different effects on forgetting in terms of retention intervals.

Keywords: forgetting; procedural skills; modalities

Introduction

Disuse or infrequent use of knowledge and skills can produce poor human performance. A generally observed human characteristic is that learning is often forgotten. Knowing how people forget in various tasks can help to produce better performance.

Previous forgetting studies have measured degradation of declarative knowledge. For example, Pavlik and Anderson (2005) investigated forgetting of a paired-associates of declarative knowledge.

To help learning by decreasing forgetting, there are several approaches already proposed and studied such as maximizing the amount of original learning, using refresher training, or optimizing retention intervals (e.g., Farr, 1987; Healy, 1995; Sabol & Wisher, 2001; Wisher, Sabol, & Ellis, 1999).

In this study of procedural tasks, we investigated an approach to decrease forgetting by modifying the modality, knowledge, and skills in that task, based on a theory based on the learning and forgetting equations in ACT-R (Anderson & Lebiere, 1998).

Types of Knowledge and Skills

Surveys have shown that personnel in technical jobs perform mostly procedural tasks (Tarr, 1986). For example, in an emergency situation, the most important knowledge and skills would be procedural, such as cardiopulmonary resuscitation (CPR) or a decontamination task of biological/chemical agents. A procedural task includes several decision-making points as cognitive tasks. Konoske and Ellis (1991) noted that many procedural tasks can be viewed as an ordered sequence of steps or operations performed on a single object or in a specific situation to accomplish a goal.

Several theoretical views support this view of procedural and declarative knowledge. Anderson and his colleagues have proposed representations of declarative and procedural knowledge and their corresponding memories (Anderson & Lebiere, 1998). They note that declarative knowledge indicates factual information and procedural knowledge indicates knowledge representing our behavior.

Another terminology, "how-to-do-it" knowledge, has been recognized in the literature (Kieras, 1997). A user performing a task uses "how-to-do-it" knowledge that can be typically modeled using production rules. This "how-to-do-it" knowledge is also viewed as procedural knowledge because it also describes our behavioral aspects of performance with goals, operators, methods, and selection rules.

Forgetting Procedural Skills

Humans acquire knowledge and skills from training. The acquired knowledge and skills can be forgotten with the passage of time. Forgetting can cause decreased performance.

Particularly, procedural skills may not be always well retained over time and they need to be. For example, non-medical trainees on a space flight may need to rapidly perform an advanced cardiac life support task during space flight missions (Ramos & Chen, 1994). Cardiopulmonary resuscitation (CPR) is an emergency medical procedure for restoring normal heartbeat and breathing to victims of heart failure. McKenna and Glendon (1985) studied skill retention of CPR. They had 120 occupational first responders as experimental subjects. They reported that less than a quarter of their trained personnel were skillful at performing the CPR task six months after training.

Interestingly, as shown in the study, procedural skills are not always well retained. The CPR task is a procedural task that includes several decision-making points as cognitive tasks. Therefore, it is presumed that there may exist different relationships of forgetting between different types of knowledge and skills.

Hagman and Rose (1983) mentioned that the best predictor of forgetting is the number of steps required in the procedural tasks. There is a supporting study of skill retention by the US Army Research Institute during the mobilization of the Individual Ready Reserve (Sabol & Wisher, 2001; Wisher, Sabol, Sukenik, & Kern, 1991). However, it seems that we rarely forget how to ride a bicycle or how to swim after learning these skills. These are perceptual-motor control skills. This aphorism and their investigations suggest that procedural (discrete) skills might be forgotten much more rapidly than perceptual-motor (continuous) skills.

A Way to Test Forgetting

Research of text editing skills has provided important findings on human performance and information processing. For example, Card, Moran, and Newell (1983) studied how a user's skills would interact with computer-based systems focusing on text editing tasks. Singley and Anderson (1989) investigated the transfer of cognitive skills in text editing tasks by providing an in-depth theory of learning through the ACT* architecture.

In our study, as an extension of text editing tasks, a set of spreadsheet tasks were examined to measure degradation of procedural knowledge and skills. A spreadsheet task provides cognition-demanding task characteristics for the experimental study, and it can be modified to support different types of inputs. It also provides a task with some ecological validity. Our spreadsheet task is done with a tool that allows us to examine two sets of knowledge and skills, that is, procedural or declarative, and cognitive or perceptual-motor skills.

Can a Cognitive Model Predict a Forgetting Curve?

Cognitive architectures provide a framework to build a model. The architectures not only support but also confine modeling capabilities to provide models that match possible human behavior (Taatgen, Lebiere, & Anderson, 2006).

These architectures have started to be used to examine forgetting. Pavlik and Anderson (2005) investigated the spacing effects of a paired-associates memory and optimization of learning based on the ACT-R architecture (see Anderson & Lebiere, 1998). ACT-R is a cognitive architecture and has been validated to model human behavior and learning in a variety of tasks (Anderson & Lebiere, 1998).

Chong (2004) stated that the existing set of mechanisms from several architectures could not model forgetting procedural skill. For example, EPIC does not provide a rule learning mechanism. In Soar, as a rule learning mechanism, chunking is used to model learning but not skill degradation. ACT-R is limited to learning and forgetting of declarative knowledge. Thus, it is worth exploring and extending the existing architectural mechanisms to model procedural skill degradation.

We are using ACT-R for this project. For the first step of our investigation, we delved into the utility theory in ACT-R 5 and report findings in this paper. In the meanwhile, the current version of ACT-R 6 introduced a new utility learning mechanism. The utilities of productions change in terms of the rewards they receive based on the difference learning equation. It is necessary to note that the current version of ACT-R 6 no longer uses the PG-C formulation.

ACT-R 5 selects one production to fire among competing productions, to achieve the model's goal. The mechanism allows a model to learn problem-solving strategies from experience based on the probability of success and the relative cost of different strategies in a production. Each production rule is associated with a utility value indicating how much the production is able to achieve the model's current goal ($U_i = P_i G - C_i + \varepsilon$). P_i is the expected probability to successfully achieve the model's current goal. The probability is decomposed to q and r ($P = qr$, where q is the probability that a production will achieve its intended next state, and r is the probability that the production achieves its goal when it arrives at the intended next state). C_i is the expected cost to achieve the model's objective. G is the value of the goal. ε is noise.

The probability of success is calculated by the number of successes divided by the number of successes and failures, as shown in equation 1.

$$P = r(t) = \frac{Successes(t)}{Successes(t) + Failures(t)},\ q = 1 \qquad (1)$$

This is the probability learning equation in ACT-R 5. Lovett (1998, p. 265) proposed time-based decay in ACT-R's production parameter learning. This mechanism discounts past experience and adjusts the timing of successes and failures. Similar to the ACT-R's base level activation, each success and failure experience in a production is decayed in terms of a power function.

$$Successes(t) = \sum t^{-d} \qquad (2)$$

$$Failures(t) = \sum t^{-d} \qquad (3)$$

We simply applied the time-based decay mechanism of ACT-R's production parameter learning to modeling of skill degradation. Successes can be considered as learning sessions and failures can be knowledge retention without learning. Figure 1 shows the probabilities ($r(t)$) of achieving a goal over time using equations from Lovett (1998). From Day 1 to 4, the probabilities increase indicating learning. Then, without learning, the values of $r(t)$ decrease, and increase again with learning.

To test the general results of this theory (that knowledge is learned and forgotten) and how a different interaction modality may help decrease forgetting we trained and tested learning and forgetting on a set of spreadsheet task with new input modality, which we present next. We also found an interesting effect in this aspect of ACT-R, which we will need to take up in later work why the model predicts poorer performance at day 22 than when it started.

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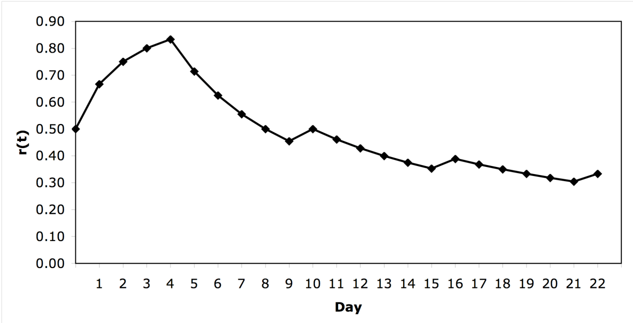

Figure 1: Time-based decay of ACT-R's production parameter learning.

Method

Participants

Nineteen undergraduate and graduate students at Penn State were recruited and completed the task. None had prior experience with the Dismal spreadsheet or using a vertical mouse. They were randomly assigned to conditions.

Materials

The Dismal[1] spreadsheet was implemented to gather and analyze behavioral data (Ritter & Wood, 2005). Dismal extends the GNU Emacs editor using its extension language, Emacs Lisp. Dismal is useful here because it is novel to the participants. Figure 3 shows an example Dismal spreadsheet. We have used a vertical mouse, shown in Figure 2, because it provides new motor skills to learn (and to forget). The vertical mouse is ergonomically designed to reduce stress on a user's wrist. Instead of a palm-down position of a regular mouse, this vertical mouse requires different hand and forearm postures. None of the participants had used a vertical mouse so we could minimize participants' previous knowledge and skills. Keystrokes, mouse clicks, mouse movements, and task completion time were recorded by the Recording User Input (RUI) system (Kukreja, Stevenson, & Ritter, 2006).

Design

The experiment was constructed by two independent variables, modality and retention interval. Modality consists of two levels including menu-based command users with a vertical mouse (M) and key-based command users with a keyboard (K), representing two different types of skills in the task.

For the key-based command users, ten participants performed the procedural spreadsheet task using only a keyboard (K). For instance, the key-based command for "Open (or find) a file" is `C-x C-f`. (`C` indicates holding down the control key while pressing `x`).

For the menu-based command users, nine participants performed the same task using a vertical mouse (M). For instance, to open a file, they moved the mouse pointer to `File` on the menu bar, then clicked `Open File`.

Figure 2: A vertical mouse from the Evoluent company.

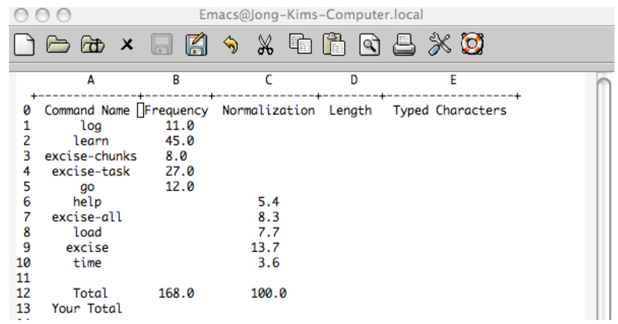

Figure 3: A screenshot of the spreadsheet task in Dismal.

Procedure

The experiment consisted of 115 sessions (76 for learning and 39 to measure forgetting) with nineteen participants. A learning session was constructed from a study and a test task. A forgetting session was constructed only by a test. A study task is when a participant uses the study booklet (Users Guide for the Dismal Spreadsheet) to learn. Each study task was limited to 30 minutes of study. A test task is when participants perform the given tasks with the booklet during learning sessions and without the booklet during forgetting sessions.

In the first week, four consecutive learning sessions were held. On Day 1, participants had a maximum of 30 minutes to study the given spreadsheet task, and then performed the task. On Days 2 to 4, participants were allowed to refresh their acquired knowledge and skills from Day 1, using the study booklet, and then performed the tasks.

After the four learning sessions in the first week, participants returned for forgetting sessions as part of one of two types of retention interval. Retention interval (R) indicates a time period of skill disuse.

Participants had a 6- or 18-day retention interval. For the group with 6-day retention intervals (R6), participants returned back to be measured every 6-days for three times on Day 10, 16, and 22. For the group with an 18-day retention interval (R18), participants returned back to be measured 18 days after the learning session on Day 22.

Participants performed a set of two novel spreadsheet tasks. The spreadsheet (Figure 3) consists of five columns

[1] http://acs.ist.psu.edu/dismal/dismal.html

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(A to E). Column A had ten different names of computer commands. Column B had frequencies of each command listed from row 1 to 5. Column C had normalized frequencies listed in rows 6 to 10. There are five blank cells in B and C columns (e.g., B6 to B10, and C1 to C5). Column D and E had ten blank cells.

The set had 14 steps. First, they opened a Dismal spreadsheet, saved the file as another name, and completed the complex spreadsheet manipulation by calculating and filling in the blank cells, basically using these two equations with commands (e.g., summation or multiplication).

$$\text{Normalization} = \frac{(\text{Frequency} \times 100.0)}{\text{Total frequency}} \quad (4)$$

$$\text{Frequency} = \frac{(\text{Normalization} \times \text{Total freqeuency})}{100.0} \quad (5)$$

The steps had multiple sub-steps, including five data normalization calculations, five data frequency calculations, ten calculations of length, ten calculations of total typed characters, four summations of each column, and an insertion of the current date using a Dismal command, (*dis-current-date*).

Results

All nineteen participants that completed learning sessions were able to complete forgetting sessions—one participant could not complete the series due to a scheduling conflict (i.e., job interview) that arose in the course of the experiment. This resulted in a cell distribution of 5, 5, 4, and 5 participants. We report all these participants here. In the R6 group, there were ten participants, five mouse users and five keyboard users. In the R18 group, there were nine participants, four mouse users and five keyboard users.

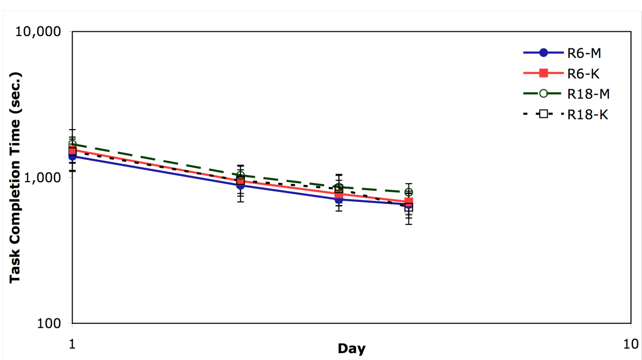

Figure 4: The log-log plot of learning curves for the four groups in the learning sessions.

Learning Procedural Skills

Figure 4 shows the log-log plot of learning curves of the four study sessions. This figure shows that the groups all learned over the four learning sessions. They all performed at pretty much the same level. Their average time to perform the set of tasks decreased from an average of 1,396 to 654 s for R6-Mouse, 1,549 to 680 s for R6-Keyboard, 1,690 to 791 s for R18-Mouse, and 1,504 to 625 s for R18-Keyboard. Independent samples t-tests were conducted for mouse (M) and keyboard (K) users for each study session. There were no significant differences, for all comparisons, $t(17) < 1.1$, $p \geq .33$. These results suggest that the input/manipulation style factor, keystroke or mouse driven, did not lead to significant differences in learning on this task over this time range and for this population.

Power Law of Learning: Mouse vs. Keyboard

Figure 5 shows the average time for the two modalities (M or K) over the four consecutive days of learning. The averages of the task completion time of the mouse (M) group were $1{,}527 \pm 374$ s on Day 1, 950 ± 160 s on Day 2, 775 ± 149 s on Day 3, and 714 ± 135 s on Day 4. The averages of the task completion time of the keyboard (K) group were $1{,}527 \pm 321$ s on Day 1, 949 ± 212 s on Day 2, 803 ± 182 s on Day 3, and 653 ± 132 s on Day 4. The learning curves of the mouse (M) and keyboard (K) groups follow the Power law of learning:

$$y = 1477x^{-0.56},\ R^2 = 0.98 \text{ for the Mouse group}$$
$$y = 1503x^{-0.59},\ R^2 = 0.99 \text{ for the Keyboard group}$$

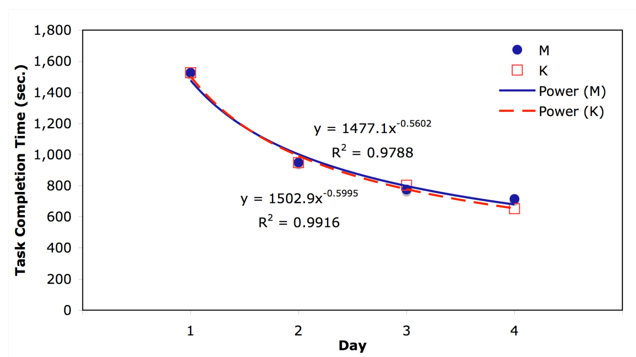

Figure 5: The Power curves of learning: M vs. K.

Forgetting Procedural Skills

Figure 6 shows overall performance on the spreadsheet task over the learning and forgetting sessions. There are four groups in terms of two retention intervals (R6 and R18) and two modalities (M and K). All of four groups similarly learned the spreadsheet task. However, participants in each group forgot in a different manner.

Forgetting: 6-Day Retention Interval

Participants (n=5) using menu-based commands with 6-day retention intervals (R6-M) showed a 42% increase in task completion time at the first forgetting measure on Day 10. The task completion time on Day 4 is 654±127 s. The task completion time at the first return on Day 10 is 930±252 s. However, paired samples t-test revealed that there is no significant difference between Day 4 and Day 10 performance, $t(4) = -1.77$, $p > 0.05$.

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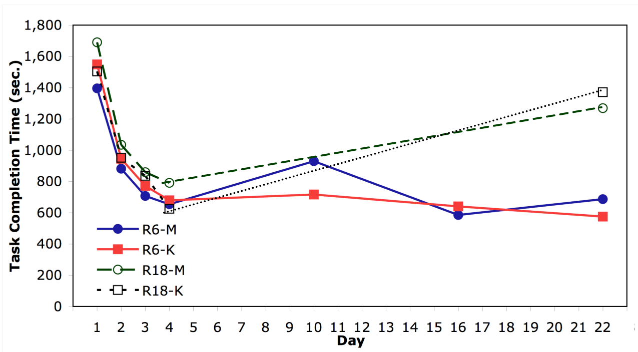

Figure 6: Learning and forgetting curves of four different groups, R6-M, R6-K, R18-M, and R18-K.

Participants (n=5) using key-based commands with 6-day retention intervals (R6-K) showed a 5% increase in task completion time at the first forgetting measure on Day 10. The task completion time on Day 4 is 680±124 s. The task completion time at the first return on Day 10 is 716±169 s. Paired samples t-test revealed no significant performance difference between on Days 4 and 10, t(4) = -.66, $p > 0.05$.

Forgetting: 18-Day Retention Interval

Participants (n=4) using menu-based commands with an 18-day retention interval (R18-M) showed a 60% increase in the task completion time at the first forgetting measure on Day 22. The task completion time is 791±116 s on Day 4 and 1268±177 s on Day 22. Paired samples t-test revealed that there is significant difference between Day 4 and Day 22 performance, t(3) = -3.60, $p < 0.05$.

Participants (n=5) using key-based commands with an 18-day retention interval (R18-K) showed a 119% increase in the task completion time at the first forgetting measure on Day 22. The task completion time is 625±149 s on Day 4 and 1371±329 s on Day 22. Paired samples t-test revealed that there is significant difference between Day 4 and Day 22 performance, t(3) = -4.30, $p < 0.05$.

Forgetting: Retention Interval and Modalities

It is of interest how much knowledge and skills can be retained with respect to retention intervals (R6 and R18) and modalities (M and K). We compared the two data points, which are based on the last day of learning sessions and the first return day after any given retention intervals. Table 1 provides the task completion time of those two data points.

Under a 6-day retention interval, participants in the menu-based modality, M, took 276 s more to complete the task after the retention interval. Participants in the key-based modality, K, took 37 s more to complete the task after a 6-day retention.

On the contrary, under an 18-day retention interval, participants in the key-based modality, K, took 746 s more to complete the task after the retention interval. Participants in the menu-based modality, M, took 478 s more to complete the task.

Table 1: Increase in task completion time

		Time		Difference	% Increase
		Day 4	Day 10		
R6	M	654 s	930 s	276 s	42 %
	K	680 s	716 s	37 s	5 %
		Day 4	Day 22		
R18	M	791 s	1268 s	478 s	60 %
	K	625 s	1371 s	746 s	119 %

In this spreadsheet task, knowledge and skills in the menu-based modality (M) are more susceptible to decay than those of the key-based modality for a 6-day retention interval. However, for longer retention interval (18-day), knowledge and skills in the key-based modality (K) are more susceptible to forgetting that those of the menu-based modality (M), although these results are not yet statistically reliable.

Discussion and Conclusions

We showed that the approach of using Dismal and RUI supports exploring learning and forgetting in a procedural task, an office work task that has some external validity. Participants were able to learn it well in four learning sessions of less then an hour each.

The results suggest that the learning curve applies to this relatively large cognitive task (cf. Newell & Rosenbloom, 1981). The data in this study are very similar in how fast each interaction style group learns and in how fast they perform the task during learning.

Two different retention intervals (R6 and R18) showed clear effects. The 18-day retention interval was much worse than the 6-day retention interval, and performance on Day 22 after an 18-day forgetting period is still better than Day 1 (cf. Figure 6).

This forgetting rate needs to be compared to the ACT-R theory that has been started. In Figure 1, the probability that a production achieves its goal increases and decreases in terms of time and experience. For further work, this mechanism is to be fixed to model forgetting over time. Also, it is necessary to consider a new utility learning in ACT-R 6 to study how it plays a role in modeling forgetting. It appears that like many others we have found that forgetting is not a linear function.

The effect of modifying the interface modality has produced some interesting effects. During learning the keystroke and mouse driven interfaces were equally easy to learn and equally fast. This is slightly surprising, as many interface designers have argued for the superiority of menu driven interfaces over keyboard driven interfaces (e.g., Shneiderman, 1983). However, in this study, the two interfaces to the same task, one driven by keystrokes and one driven by mouse movements, basically took the same time to learn and the same time to perform. We are running further participants to clarify this effect (or lack of it).

More interestingly, we see that there may be some differences between retention intervals and these skills. The data in Figure 6 suggest that there may be a difference in the forgetting curves of these two types of skills. More participants will have to be run before we can say more about this, but it looks promising that there may be an interaction between modalities on forgetting.

Further work remains. The number of participants in this study is somewhat small, and some differences are perhaps not emerging because of the small sample size. We will be running more participants as time goes on. We will also examine the missing retention interval of 12 days. This will help explain how fast forgetting occurs and when it occurs. On Day 10 we saw very little forgetting, and on Day 22 we saw a lot of forgetting. The middle ground of Day 16 will help fill in the curve.

In addition, we will investigate the knowledge attributes of various subtasks in the set of tasks here to provide implications on forgetting. For example, there could be differences of learning and forgetting between the subtask of calculations using a normalization equation and opening a file. The former is more a cognition-demanding task than the latter that is simple declarative knowledge retrieval.

Also, we will need to investigate how the keystroke and mouse move times changed with forgetting. Did, for example, the Fitts' law constant change with forgetting? Did the simple keystroke level times that can be derived from an ACT-R model on this task increase with the forgetting interval?

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