THE SCIENCE OF MARI'S JUST-IN-TIME MASTERY ESTIMATION AND RECOMMENDATIONS

SKILL DECAY CURVES

Acquiring new skills is only the beginning of demonstrating proficiency in a subject area and maintaining that proficiency over time. Numerous studies dating all the way back to Hermann Ebbinghaus' foundational work in memory retention in 1885 have documented the effects of time on human memories and skill retention. While it is quite clear that memories fade over time, the specific rates at which memories and skills fade seem to be dependent on a number of factors, including topic difficulty, frequency of recall, individual learner differences in long-term memory retention, and even the level of importance that the learner places on the material being learned. Modern technologies are making it possible to isolate some of these variables, among others, in an attempt to provide adaptive, analytical tools to help determine the optimum refresh cycle for each individual learner and topic domain. This allows learners to more easily anticipate when they need to refresh their skills to maintain peak performance in their professional and personal lives. This paper briefly discusses one approach to managing the effects of time on human memory and anticipating the need for additional practice or training to meet those goals.

INFORMATION RETENTION AND GRADUAL DECAY

Humans are capable of learning large quantities of information and perfecting many different skills over their life time, but much of that learned information is just as quickly forgotten and replaced by other new information. In fact, retention of any fact committed to memory will diminish over time if there is no attempt to retain it [1, 4, 5]. Consequently, learned skills will diminish if those skills are not practiced and re-evaluated to ensure the skills are kept fresh (Figure 1). Hermann Ebbinghaus originally developed a relatively simple model of memory retention [1] that shows the exponential nature of forgetting. The model adheres to the following simple formula:

$$R = e^{-\frac{t}{p}}$$

Where:
- R = memory retention
- p = relative persistence
- t = time.

Skill retention is reduced exponentially with regard to increasing time since the material was originally learned, but that reduction can be somewhat retarded (or accelerated) based on how easy the material persists in the learner's mind over time. The actual retention rate differs for each skill or fact [5]. For instance, most people learn how to swim once and then remember it for their entire life without the need to relearn the skill later, while retaining the details of a foreign language without additional practice and re-learning is fairly rare.

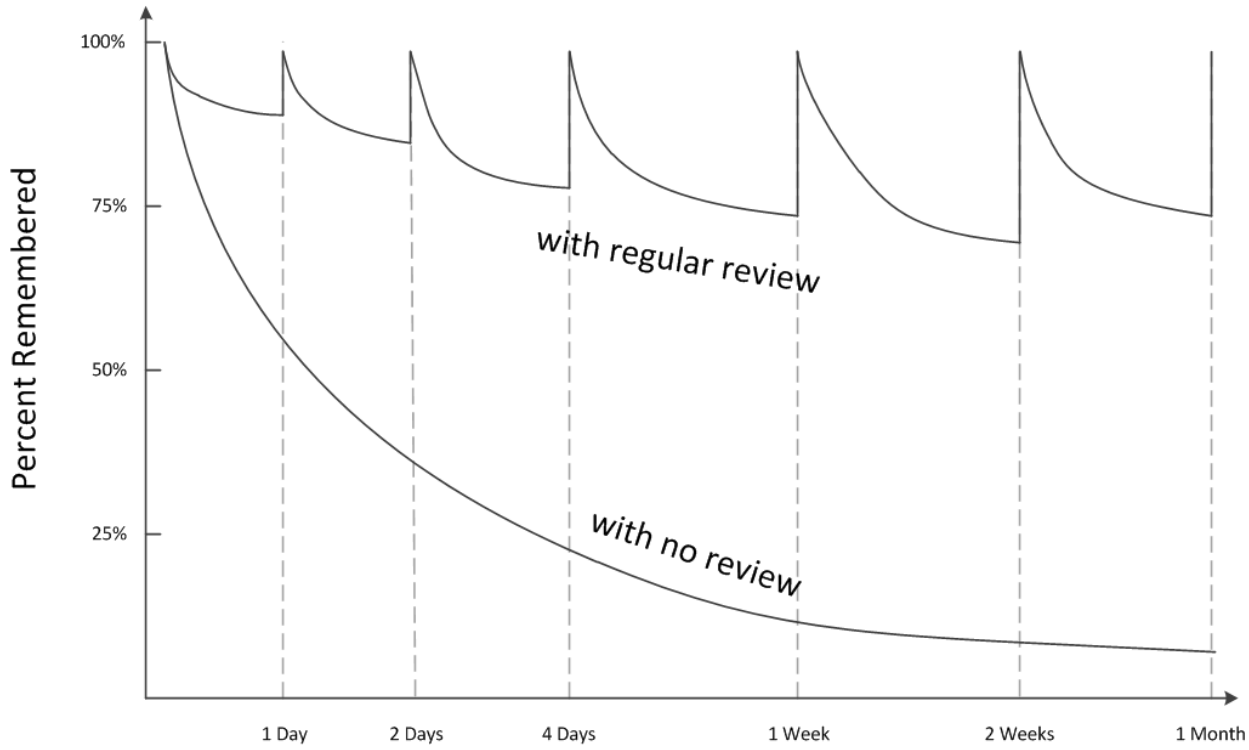

Figure 1: Effects of Periodic Review on the Skill Decay Curves

Consequently, swimming would have a high relative persistence score (*p* value), while mastering a foreign language would have a fairly low *p* value. Furthermore, the retention rate may also be influenced by an individual's personal strength of memory within a topic domain and the relative importance that an individual assigns to any given fact.

Learning *p* values from empirical data about how difficult it is to retain information related to specific skills [1, 4] allows MARi to more accurately estimate an individual's true retention of a particular skill at any point in time.

Experience is Demonstrated Over Time

The decay process discussed thus far in this document pertains to instantaneous estimation of how confident we can be about an individual's skills and knowledge based on how long it has been since the last directly observed assessment. A related, and perhaps more interesting, question is "what can we tell

about an individual's experience with a particular skill over time?" To answer that question, we need to consider experience curves [2, 3] and how they can help determine the likelihood that an individual has a particular skill or attribute even if it has been a long time since being assessed, or if the most recent assessments simply occurred on a bad day.

Rather than focusing on a particular point on the curve that represents the user's proficiency score at that moment, experience is more interested in the area under the curve since that represents a measure of proficiency over all time periods. The shaded area in Figure 2 shows the fluctuation in demonstrable experience as a learner initially learns and later re-learns a skill.

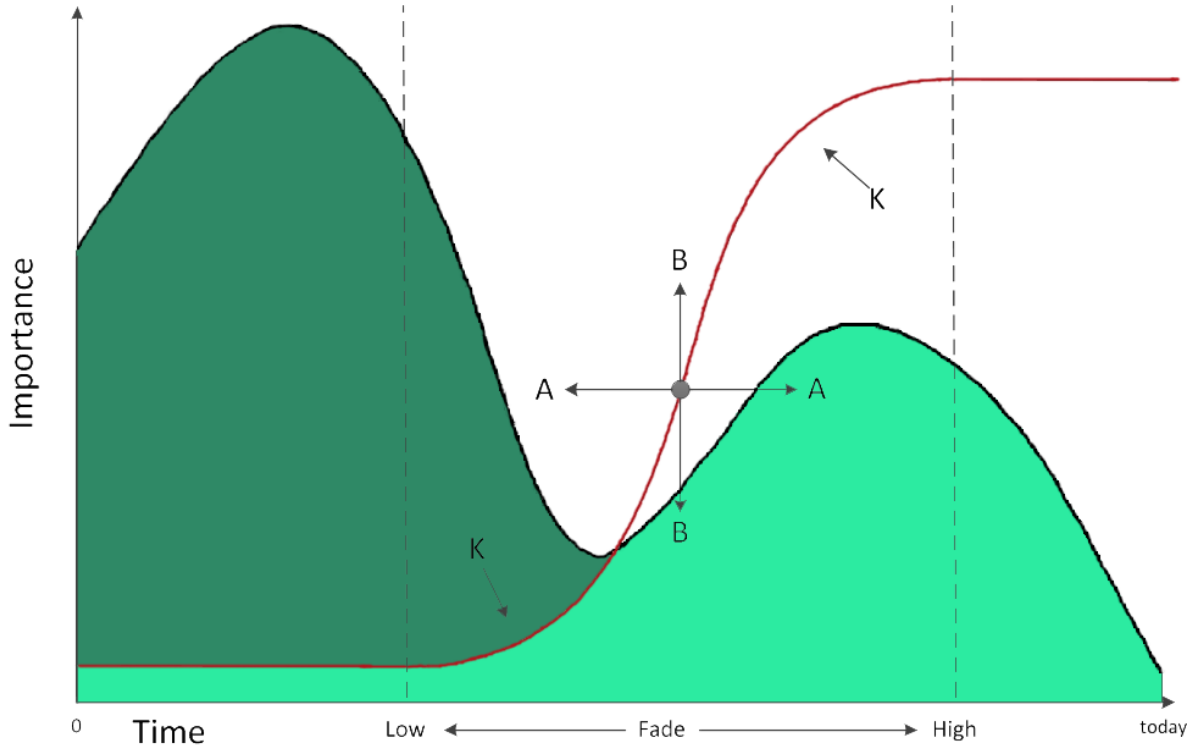

Figure 2: Time-Dependent Experience Curve

The area under the first peak of the curve represents initial learning and skill building until the peak is reached. At that point, the learner has stopped learning new material and the skills begin to decay. At the bottom of the valley, the learner begins to refresh the skill by relearning some of the forgotten material, so the experience curve moves back up and the cycle continues.

However, that is only half of the equation. Skill relevance varies over time too. In many cases, skills once known at a high lever tend to fade over time if not practiced on a regular basis. The sigmoid curve shown in red in Figure 2 represents an adaptable relevance function that applies time sensitive discounting to older experiences (dark green) and gives preference to newer experiences (light green). This relevance curve can be adjusted to account for variations in the life expectancy of different skills. By using empirical data from large groups learners, the bounding edges and shape of the relevance curve can be adjusted to

suit virtually every skill retention scenario from continuous retention to instantaneous skill loss, and every variation in between.

The combination of an individual's demonstrated skills, the associated persistence and decay factors, and empirically derived relevance adjustments can all be leveraged to provide more accurate estimates of an individual's skill and knowledge that are obtained over the course of a lifetime. This provides an effective method of answering the critical career oriented questions "What does this individual know about a particular skill?" and "What is the optimum schedule for refreshing previously learned skills?"

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