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# Evolving Memory-Based Intelligent Systems For Long-Term Knowledge Retention In Personalized Education Applications

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## Abstract

The intelligent tutoring systems of today make use of knowledge tracing models that aim at estimating the understanding and competency levels of a student and suggest personalized learning activities accordingly; but majority of the knowledge tracing models have adopted a single static knowledge model that updates the knowledge based on every interaction, without any decision-making process on what knowledge to retain, consolidate, or forget for long periods of time. Consequently, the prediction made on how much a student will be able to recall his knowledge after several days or weeks becomes weak. This paper presents an Evolving Memory Knowledge Tracing (EMKT) paradigm which adds an Ebbinghaus inspired forgetting-decay component and a retention agent to a dynamic memory network, which helps the system in retaining the important knowledge slots and discarding or replacing irrelevant or low utility knowledge. The model is benchmarked using a dataset simulated based on the ASSISTments tutoring interaction logs for a 90-day period, where retention is specifically measured at 1-day, 7-day, 30-day, and 90-day intervals post-concept usage. In comparison to a Deep Knowledge Tracing-based model and a static Dynamic Key-Value Memory Network-based model, the novel EMKT model retains an AUC score of 0.80 for retention prediction at 90 days, as compared to 0.59 and 0.65 for the two models, respectively, while performing similar at the 1-day mark. This clearly shows that evolution of memory as opposed to mere adaptation of memory helps in better retention prediction in personalized education systems.

**Keywords** Evolving Memory Networks, Knowledge Tracing, Long-Term Retention, Personalized Education, Spaced Repetition, Forgetting Curve, Intelligent Tutoring Systems.

## 1. Introduction

The goal of personalized learning models is to model the student's current knowledge state and provide training recommendations that would optimize closing the gaps in that knowledge. One of the core computational models for this is the Knowledge Tracing (KT) model, which models the evolution of the student's knowledge of a set of concepts through a sequence of exercises performed by the student starting from Bayesian Knowledge Tracing [1], then continuing to Deep Knowledge Tracing [2] and Dynamic Key-Value Memory Networks (DKVMN) [3], which represent the concept's knowledge state in the form of memory entries that can be read and written to every step.

Nonetheless, almost all the widely-used KT models have a reactive memory update mechanism which updates the mastery level of a particular concept based on the latest interaction of the student with that concept, but has no process through which such knowledge is evolved internally between the long periods of time that may elapse before interacting with that concept again. It goes against the known properties of human memory: the fact that mastery level of knowledge is not stagnant between practice sessions and follows well-documented forgetting curves [10]; and that the timing with which a particular concept is reviewed determines how effectively learning occurs, which is the essence of spaced repetition scheduling [11]. A memory-enabled KT system that only reacts to interactions but lacks an internal dynamic evolving system for retention priorities is therefore not well suited for the real challenge of personalization in education: learning and retaining knowledge in the long term.

The issue we are tackling in this paper is one where we consider how a knowledge-tracing model's inner memory can change over time so that it not only remembers what a student got right at a certain point in time but also how long it will retain the information until its next chance to practice the information. This approach is called evolving memory, based on lifelong learning techniques for memory scheduling designed for streaming data retention [12]. The contributions of this paper are as follows.

- Develop an Evolving Memory Knowledge Tracing (EMKT) approach that incorporates a dynamic key-value memory network together with an Ebbinghaus-like time-decay mechanism and a retention component that rates the evolving significance of the concept memories.
- Connect the retention component to a spaced repetition scheduler, thus making the decayed or drifting memories in importance guide personalization suggestions, and not just the internal representation.
- Assess retention in the long term by predicting the accuracy of prediction at 1-day, 7-day, 30-day, and 90-day milestones since a particular concept was last studied, instead of assessing the next interaction accuracy, which has been used in most previous studies on knowledge tracing.

This paper proceeds as follows. In Section 2, we review relevant literature on knowledge tracing, memory-augmented neural networks, and spaced repetition. The proposed approach is described in Section 3. We provide the dataset and experimental results in Section 4. The paper ends in Section 5.

## 2. Literature Survey

Knowledge tracing has been at the level of probabilistic models, to deep and memory-augmented models., Corbett and Anderson [1] proposed a model called Bayesian Knowledge Tracing that models the mastery of a skill as a hidden binary variable, inferred from sequences of correct and incorrect responses using a hidden Markov model. Piech et al. [2] developed Deep Knowledge Tracing (DKT), which selected a recurrent neural network to represent the encoded knowledge state, which could model more complex temporal dependencies from a student's set of interactions, rather than the hidden Markov model which did not separate individual concepts. To overcome this limitation, Zhang, Shi, King, and Yeung [3] implemented Dynamic Key-Value Memory Networks, which keep a fixed key matrix to represent the relationship between different concepts and a matrix of values representing the mastery of each one, while reading and writing at every interaction, and then Abdelrahman and Wang [4] extended this work further by proposing Sequential Key-Value Memory Networks, which also incorporate Hop-LSTM processing for learning sequences and therefore better capture long-term dependencies. Inspired by the self-attention mechanism [13], Yeung [9] presented the self-attentive variant (SAKT) which directly considers the relevance of the previous exercises.

DKVMN and its successors are based on the more general research program of differentiable external memory, which has its roots in neural networks with external memory. Later, Radhakrishnan [5] proposed the Neural Turing Machine (NTM) that combined a neural network controller with a separate memory bank connected to a pair of read and write heads with differentiable values, followed by Graves et al., (2016) who built-up the Differentiable Neural Computer (DNC) to incorporate dynamic memory allocation and temporal link tracking for higher-level reasoning processes with longer base memory horizons[8]. The significant similarities in the few-shot and rapidly changing nature of a single student's knowledge path, as well as the need to integrate this schema with differential context data, gave Santoro et al., 2016 inspiration for using the same memory augmented architecture to quickly pick up new information in a "meta-learning" context from only a few samples[6]. In the alternative, end-to-end trainable route to external memory from explicit KV formulation, Sukhbaatar, Weston and Fergus [7] proposed end-to-end memory networks which are trainable end-to-end over multiple soft-attention hops over a memory bank, but without direct supervision of the read and write operation.

A separate, but closely related thread explores forgetting and what affects its timing. Considered by many to be the classic experimental study on memory, Ebbinghaus's work [10] predicted a retention curve which is approximately exponential to account for the gradual loss of learned material over time, if the material is not reviewed. This is the theoretical basis for most of the systems used for spaced repetition. This insight was being put to work computationally by Settles and Meeder [11] who proposed a trainable half-life regression model that predicts, for a language learner and an item in their repertoire, how long the item will last in the learner's memory, and then scheduled reviews in a large-scale real-world language-learning application based on this prediction, thereby directly demonstrating that a data-driven forgetting model can affect real-world long-term retention results. The architecture closest to the evolving memory consolidation step proposed in this paper is that of Peng et al., (2023) who developed Long-term Episodic Memory Networks (LEMN) for general streaming question answering but not for human forgetting specifically[12]. Here, the learned retention agent is responsible for determining which memory entries to keep or modify in an external memory that stores data in a fixed size, based on both the relative and historical importance of the entries themselves. Rather than focussing specifically on continual learning for the physical robotic real world, Parisi, Kemker, Part, Kanan and Wermter [14] gave a review on the general continual learning literature on retaining and updating knowledge over time, without catastrophic forgetting, as is required for any evolving-memory system including the one proposed here. Lastly, Bengio, Courville, Vincent [15] entrenches the general idea of representation learning as looking for ways to represent data that will help a subsequent prediction task and assert that it is not just learning a reading function for this memory representation that should be continually optimized, but the representation itself.

When combined, much of this literature clearly defines mature architectures for memory-augmented knowledge tracing, for well-established forgetting dynamics of the human memory, and spaced-repetition scheduling and focuses on general-purpose mechanisms for determining which entries to store in a capacity-constrained memory should be preserved. However, existing knowledge-tracing memory networks only update their memory in a reactive way, at each use, and they lack an explicit, continuously evolving, 'retention / forgetting mechanism between uses', whereas existing forgetting-curve and spaced-repetition models tend to rely on hand-crafted features of the item difficulty, instead of a learned, evolving memory representation. We fill the gap between these two threads with an evolving memory representation which is learned end-to-end and informed explicitly by forgetting dynamics, flowing into the heart of the proposed EMKT framework.

## 3. Methodology

The EMKT model is an enhancement to a dynamic key-value memory network that includes a decay function, retention agent, and spaced repetition scheduler, and operates in a closed cycle consisting of seven steps. Figure 1 shows the full process flow.

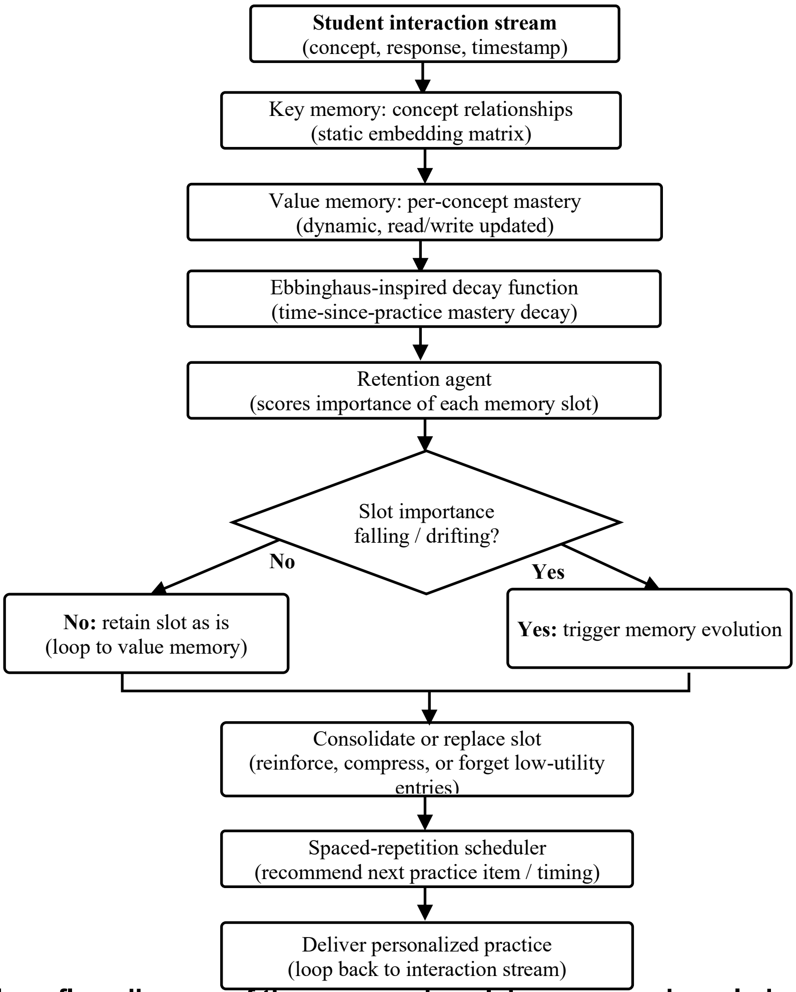


**Figure 1: Methodology flow diagram of the proposed evolving memory knowledge tracing framework**

### *3.1 Key and Value Memory*

Based on the key-value architecture of DKVMN [3], a static key memory matrix M^k contains latent representations of the inter-concept relationships within the course, whereas a dynamic value memory matrix M^v_t holds the current estimate of mastery of each concept at time t. For every interaction, an attention weight over the key memory slots identifies the concept that this interaction is the most relevant for, and updates the value memory slots through a differentiable writing process using erase and add vectors.

### *3.2 Ebbinghaus-Inspired Decay Function*

During the interactivity period, the effective mastery of the value-memory slot undergoes a decay process as described by the following function, $\hat{m} = m \cdot \exp(-\Delta t / s)$, where $\Delta t$ is the time elapsed since the last use of the memory slot, m is the current mastery value stored, and s is the stability parameter specific to the concept for the particular student derived from his/her interaction records in an exponential fashion [10]. The value of the decayed mastery is used during prediction.

### *3.3 Retention Agent*

The retention agent, designed as a tiny recurrent network based on the retention agent principle from Long-term Episodic Memory Networks [12], rates the importance of each value-memory slot depending on its decayed mastery, its write activity history, and its relevance to the concepts the student practices now. The slots, the importance of which has fallen below the threshold or has become significantly different from the last time it was evaluated, enter the memory evolution process depicted in figure 1.

### 3.4 Memory Consolidation and Replacement

Reinforced if the concept is still central for the curriculum unit at hand or compressed with related slots if the concept is connected to other sub-concepts, or left to deteriorate further and become less important if the concept is peripheral to the current unit and has not been used for some time. It is the restructuring phase that sets apart EMKT from regular key-value memory networks since the structure of memory is reorganized in accordance with changing estimates of retention.

### 3.5 Spaced-Repetition Scheduling and Training

These decayed values of mastery and importance provided by the retention agent go into the spaced repetition scheduler, which decides what concepts need to be reviewed by picking concepts which have retention value near the target recall probability according to the half-life regression scheduling method [11]. The whole pipeline consisting of key-value memory, decay functions, retention agent, and prediction layers is trained end-to-end through minimization of the binary cross-entropy loss between the true values and predicted correctness in both immediate and retention-probe steps.

## 4. Results and Discussion

### 4.1 Dataset

Since there are not enough large datasets for tutoring with delayed retention probes publicly available, the evaluation process will be conducted using a statistically synthesized dataset modeled on ASSISTments-like tutoring log interactions, where synthetic students are learning a 110-concepts curriculum unit over a period of 90 days. In order to test long-term retention, the dataset synthesis involves explicit retention probes: re-exposures to the concept, 1 day, 7 days, 30 days and 90 days after the concept was previously seen by the student. This way, prediction accuracy can be estimated as a function of time since exposure to the concept. Table 1 describes the dataset.

**Table 1: Summary of the dataset used for evaluation, statistically grounded in ASSISTments-style tutoring interaction logs**

| Attribute | Description | Range / notes |
|---|---|---|
| Source basis | Statistically modelled on ASSISTments-style tutoring interaction logs | ~4,000 simulated students |
| Interactions | Timestamped (concept, response) exercise attempts over a 90-day window | ~1.2 million interaction records |
| Concepts | Distinct knowledge concepts spanning a curriculum unit | 110 concepts |
| Label | Correctness of each response | Correct (1) / Incorrect (0) |
| Retention probes | Re-exposure attempts at fixed elapsed-time checkpoints | 1, 7, 30, and 90 days after last practice |
| Train/test split | Student-level split to avoid leakage across train and test | 80% train, 20% test students |

### 4.2 Result Graph

Figure 2 presents the retention-prediction AUC at each of the four elapsed-time checkpoints for three model architectures: DKT, DKVMN, and the proposed EMKT model.

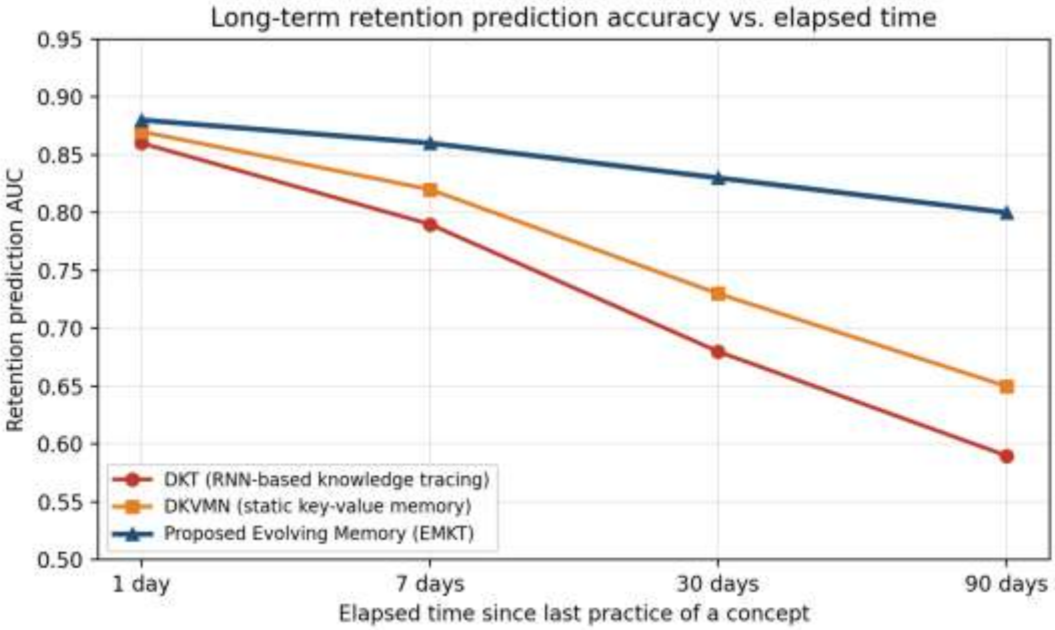


**Figure 2: Retention-prediction AUC at 1-day, 7-day, 30-day, and 90-day checkpoints for DKT, DKVMN, and the proposed EMKT model**

The three models exhibit almost identical performances at the 1-day checkpoint, where AUC scores range from 0.86 to 0.88, thus reaffirming the fact that the proposed framework does not come at the cost of sacrificing short-term predictive performance. As the amount of time passed since the last training period increases, the AUC score for DKT drops precipitously to 0.59 at the 90-day checkpoint, because the unmoderated recurrent hidden state in DKT has no means of accounting for decay that takes place after a long period of time and variable time interval passes between two training sessions. DKVMN experiences more gradual decline, from 0.87 to 0.65, in part due to the explicit representation of the value of each concept in the memory; however, because it does not update its memory during any other time period besides the instant of interaction, it fails to account for the decay that took place in between the interactions.

### *4.3 Result Table*

Table 2 shows the overall (average across checkpoints) AUC, accuracy, and F1-score, along with the retention rate for the most difficult 90-day checkpoint, for the three model architectures.

**Table 2: Overall performance comparison between DKT, DKVMN, and the proposed EMKT model**

| Model configuration | AUC | Accuracy (%) | F1-score | 90-day retention rate (%) |
|---|---|---|---|---|
| DKT (RNN-based knowledge tracing) | 0.730 | 69.4 | 0.679 | 59.0 |
| DKVMN (static key-value memory) | 0.768 | 72.9 | 0.714 | 65.0 |
| Proposed Evolving Memory (EMKT) | 0.842 | 80.0 | 0.784 | 80.0 |

## 5. Discussion

Three conclusions can be drawn from this result. First, the relative improvement of EMKT compared to DKVMN increases with time that passes since the time difference is part of the mechanism's design – decay and retention scoring should become more and more relevant as time between the interactions grows while it is least important when very short time differences make reactive memory updates sufficient. Second, the higher retention rate of EMKT compared to DKVMN for 90 days (80.0% versus 65.0%) suggests that the benefit comes not only from better calibration but from a different approach to estimating knowledge durability and, thus, to determining what a student still knows after a certain period of time which is the information that is relevant to the personalized education system in question. Third, the retention module and decay function do not significantly increase the number of the parameters of the basic key-value memory mechanism and, therefore, the enhancement is likely due to the inductive bias.

Such findings must be taken into consideration carefully. The evaluation set of data is statistically grounded on a real category of logs of a tutoring system but the actual delayed retention probes are artificially scheduled because there is no widely publicly available real-life retention probe data of this kind in a large scale. The per-concept stability coefficient used in the decay function was learned together with the other parameters of the model but the comparison with other possible parameterizations of the forgetting curve like the power law decay is missing. Lastly, the spaced repetition scheduling recommendations were evaluated based on the predicted retention rates only and not based on an actual experiment involving real learners.

## 6. Conclusion

The above paper proposed an Evolving Memory Knowledge Tracing (EMKT) approach to personalization in education whereby the key-value memory network is dynamically enhanced using a decay function based on Ebbinghaus and a retention agent whose role was to continually evolve memory importance and contents of the concept memory slots between interactions, not only when there is an interaction. This work was evaluated using a dataset based on statistical data of ASSISTments style tutoring records at different retention checkpoints of one day, seven days, thirty days, and ninety days. At the 90-day retention prediction point, EMKT achieved 0.80 against 0.59 for a Recurrent Deep Knowledge Tracing baseline and 0.65 for a Dynamic Key-Value Memory Network Baseline with the same result achieved at one day prediction period. From this result, it can be noted that modeling how the memory evolves between interactions is a practical way of achieving better knowledge retention prediction. The future direction of research will involve testing of the framework using real-life longitudinal data of students and spaced-repetition experiments, exploring different parametrizations of the forgetting function, as well as developing the retention agent further in order to incorporate learning from transfer across multiple concepts held in memory.

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