DAS3H: Modeling Student Learning and Forgetting for Optimally Scheduling Distributed Practice of Skills

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DAS3H: Modeling Student Learning and Forgetting for Optimally Scheduling Distributed Practice of Skills [Talk submission]

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Abstract. Spaced repetition consists in temporally distributing exposure to an information so as to improve long-term memorization for a human learner. However, most adaptive spacing algorithms rely on expert-defined heuristics and are limited to pure memorization, e.g. foreign language learning. In this article, we propose a new student model for human skill learning and forgetting, called DAS3H. We provide empirical evidence on three real-world educational datasets that DAS3H, which incorporates both exercise-skill relationships and forgetting effect, outperforms other state-of-the-art student models that consider one or the other.

Keywords: Student modeling, adaptive spacing, memory, optimal scheduling

1 Motivation

Human learners have to manage their studying time wisely: they constantly have to make a trade-off between acquiring new knowledge and reviewing previously encountered learning material. Considering that learning often involves building on old knowledge and that efforts undertaken in studying new concepts may be significant, this issue should not be taken lightly. Fortunately, there are simple yet robust learning strategies that help students efficiently manage their learning time and improve long-term memory retention at a small cost. The *spacing effect* states that temporally distributing learning episodes is more beneficial to long-term memory than learning in a single massed study session. The *testing effect* basically consists in self-testing after being exposed to new knowledge instead of simply reading the lesson again.

Recent research effort has been put on developing adaptive and personalized spacing schedulers for improving long-term retention of flashcards[3] [5,4,1] among human learners. Adaptive spacing schedulers sequentially decide which item (or question, exercise) to ask the student at any time based on the student's past study history. Compared to non-adaptive schedulers, they show substantial improvement of the learners' retention at immediate and delayed tests [2]. A common approach for designing spaced repetition adaptive schedulers consists in modeling human memory statistically and recommending the item whose memory strength is closest to a fixed value θ [1,3].

However, and to the best of our knowledge, there is no work on extending these algorithms when knowledge to be remembered concerns the application of underlying skills. In

[3] Cards on which one side contains the question (e.g. *What is the correct translation of "manger" in English?*) and the other side contains the answer.

this case, specific items are the only way to practice one or multiple skills, because we do not have to memorize the content directly. Furthermore, most student models involve multiple skills, but do not model forgetting.

The goal of the present article is to start filling this gap by developing a student learning and forgetting model for inferring skills knowledge state and memory dynamics and predicting student future performance based on past performance data. This model will serve as a basis for the future development of adaptive and personalized skill practice scheduling algorithms for improving human learners' long-term memory.

2 Our model DAS3H

We developed a new student learning and forgetting model: DAS3H stands for item Difficulty, student Ability, Skill, and Student Skill practice History, and builds on the DASH model from Lindsey et al. [1]. Specifically, DAS3H extends DASH to items with multiple skills and allows the influence of past practice on present performance to differ from one skill to another. We also leverage the recent Knowledge Tracing Machines (KTMs) framework [6] to enrich the DASH model by embedding the features in d dimensions and model pairwise interactions between those features.

For an embedding dimension of $d=0$, our model DAS3H reads:

$$\mathbb{P}(Y_{s,j,t}=1)=\sigma(\alpha_s-\delta_j+\sum_{k\in KC(j)}\beta_k+h_\theta(\mathrm{t}_{s,j,1:l},\mathrm{y}_{s,j,1:l-1}))$$

with $Y_{s,j,t}\in\{0,1\}$ the binary correctness of student s answering item j at time t, σ the logistic function, α_s the ability of student s, δ_j the difficulty of item j, $KC(j)$ the set of skill indices involved by item j, β_k the easiness of skill k and h_θ a function parameterized by θ (learned by DAS3H) that summarizes the effect of the $l-1$ previous attempts where student s reviewed item j ($\mathrm{t}_{s,j,1:l-1}$) and the binary outcomes of these attempts ($\mathrm{y}_{s,j,1:l-1}$). Data consists of student-item interactions (student and item ids, skills, timestamps, outcomes). Following Lindsey et al. [1], we choose:

$$h_\theta(\mathrm{t}_{s,j,1:l},\mathrm{y}_{s,j,1:l-1})=\sum_{k\in KC(j)}\sum_{w=0}^{W-1}\theta_{k,2w+1}\log(1+c_{s,k,w})-\theta_{k,2w+2}\log(1+a_{s,k,w}).$$

In h_θ, w denotes the index of the time window, $c_{s,k,w}$ and $a_{s,k,w}$ respectively denote the amount of times that skill k has been correctly recalled and encountered in window w by student s earlier. The time windows w are not disjoint and span increasing time intervals. Intuitively, h_θ can be seen as a sum of memory strengths, one for each skill involved in item j. The use of log counts induces diminishing returns of practice inside a given time window and difference of log counts formalizes a power law of practice.

For higher embedding dimensions $d>0$, we use probit as the link function; all features are embedded in d dimensions and their interaction is modeled in a pairwise manner.

3 Experiments and results

To evaluate the performance of DAS3H, we compared it to 4 state-of-the-art student models (DASH, IRT, PFA and AFM) within the KTM framework and with 3 different feature embedding dimensions (0, 5 and 20). Three different educational datasets were used: ASSISTments 2012-2013, Bridge to Algebra 2006-2007 and Algebra I 2005-2006.

We performed 5-fold cross-validation at the student level for our experiments. Following previous work [6] we used hierarchical distributional assumptions when $d>0$ and L2 regularization when $d=0$ on the features to help model training and avoid overfitting. We used the same time windows as Lindsey et al. [1]: $\{1/24, 1, 7, 30, +\infty\}$. Time units are expressed in days.

Python code for replicating our results is freely available on GitHub[4] and results on all datasets are reported in Table 1. By lack of space, only AUC metrics for an embedding dimension $d=0$ are given. Metrics are averaged over 5 folds and standard deviations are reported. On each dataset, DAS3H outperforms the other student models.

model	algebra05	bridge06	assist12
DAS3H	**0.826**±0.003	**0.790**±0.004	**0.739**±0.001
DASH	0.773±0.002	0.749±0.002	0.703±0.002
IRT	0.771±0.007	0.747±0.002	0.702±0.001
PFA	0.744±0.004	0.739±0.003	0.668±0.002
AFM	0.707±0.005	0.692±0.002	0.608±0.002

Table 1. AUC comparison on all datasets, for an embedding dimension $d=0$.

4 Discussion and conclusion

These results show that DAS3H is able to more accurately model student performance when multiple skill and temporal information is at hand. Unexpectedly, the impact of the multidimensional embeddings and the pairwise interactions seems to be very small yet unclear. Further analyses underline that adding time windows features and assuming different learning and forgetting curves for different skills significantly boosts AUC performance.

In a real-world educational setting, exercises generally involve multiple skills at the same time. In such a situation, how should one select the next item to recommend a user so as to maximize their long-term memory retention? Further work will consist in investigating item selection strategies in this context.

References

1. Lindsey, R.V., Shroyer, J.D., Pashler, H., Mozer, M.C.: Improving students' long-term knowledge retention through personalized review. Psychological science 25(3), 639–647 (2014)
2. Mettler, E., Massey, C.M., Kellman, P.J.: A comparison of adaptive and fixed schedules of practice. Journal of Experimental Psychology: General 145(7), 897 (2016)
3. Metzler-Baddeley, C., Baddeley, R.J.: Does adaptive training work? Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition 23(2), 254–266 (2009)
4. Reddy, S., Levine, S., Dragan, A.: Accelerating human learning with deep reinforcement learning. In: NIPS'17 Workshop: Teaching Machines, Robots, and Humans (2017)
5. Tabibian, B., Upadhyay, U., De, A., Zarezade, A., Schölkopf, B., Gomez-Rodriguez, M.: Enhancing human learning via spaced repetition optimization. Proceedings of the National Academy of Sciences 116(10), 3988–3993 (2019)
6. Vie, J.J., Kashima, H.: Knowledge Tracing Machines: Factorization Machines for Knowledge Tracing. In: Proceedings of the 33th AAAI Conference on Artificial Intelligence. p. to appear (2019), `http://arxiv.org/abs/1811.03388`

[4] `https://github.com/BenoitChoffin/das3h`