PYKT: A Python Library to Benchmark Deep Learning based Knowledge Tracing Models

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Abstract

Knowledge tracing (KT) is the task of using students' historical learning interaction data to model their knowledge mastery over time so as to make predictions on their future interaction performance. Recently, remarkable progress has been made of using various deep learning techniques to solve the KT problem. However, the success behind deep learning based knowledge tracing (DLKT) approaches is still left somewhat unknown and proper measurement and analysis of these DLKT approaches remain a challenge. First, data preprocessing procedures in existing works are often private and custom, which limits experimental standardization. Furthermore, existing DLKT studies often differ in terms of the evaluation protocol and are far away real-world educational contexts. To address these problems, we introduce a comprehensive python based benchmark platform, PYKT, to guarantee valid comparisons across DLKT methods via thorough evaluations. The PYKT library consists of a standardized set of integrated data preprocessing procedures on 7 popular datasets across different domains, and 10 frequently compared DLKT model implementations for transparent experiments. Results from our fine-grained and rigorous empirical KT studies yield a set of observations and suggestions for effective DLKT, e.g., wrong evaluation setting may cause label leakage that generally leads to performance inflation; and the improvement of many DLKT approaches is minimal compared to the very first DLKT model proposed by Piech et al. [25]. We have open sourced PYKT and our experimental results at https://pykt.org/. We welcome contributions from other research groups and practitioners.

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1 Introduction

The increasingly digitalized education tools and the popularity of online learning have produced an unprecedented amount of data that provides us with invaluable opportunities for applying AI in education. Knowledge tracing (KT) is the task of *using students' historical learning interaction data to model their knowledge mastery over time so as to make predictions on their future interaction performance*. Such predictive capabilities can potentially help students learn better and faster when paired with high-quality learning materials and instructions, which is crucial for building next-generation smart and personalized education.

The KT related research has been studied since 1990s where Corbett and Anderson, to the best of our knowledge, were the first to estimate students' current knowledge with regard to each individual knowledge component (KC) [8]. A KC is a description of a mental structure or process that a learner uses, alone or in combination with other KCs, to accomplish steps in a task or a problem[2]. Since then, many attempts have been made to solve the KT problem, such as probabilistic graphical models [13] and factor analysis based models [3, 14, 35]. Recently, due to the rapid advances of deep neural networks, deep learning based knowledge tracing (DLKT) models have become the de facto KT framework for modeling students' mastery of KCs [1, 7, 10, 12, 15, 16, 19, 21, 22, 23, 24, 25, 29, 30, 31, 36, 37, 44, 45, 46, 47].

Although DLKT approaches have constituted new paradigms of the KT problem [10, 22, 25, 30, 46] and achieved promising results, recent studies [15, 16, 25, 34] seem to resemble each other with very limited nuances from the methodological perspective. Most existing work only provides coarse evaluation and both the contributing factors leading to the success of DLKT and how the DLKT models perform in the real-world educational contexts still remain somewhat unknown. Furthermore, evaluations of existing DLKT work are not standardized and reported AUC results of the same approach on the same dataset vary surprisingly from 0.709 to 0.86 [2] (details discussed in Section 3.3). Therefore, there is a substantial need for a standardized DLKT benchmark platform, which ensures that methods can be compared in a fair and transparent manner. Researchers need to be able to evaluate their proposed approaches against a wide range of state-of-the-art (SOTA) methods on both publicly available and private datasets and practitioners need to be capable of differentiating advantages and disadvantages of the DLKT algorithms in real-world educational contexts.

In order to accelerate research in building advanced KT approaches, we systematically design PYKT, a fine-grained python based benchmark library that brings us closer to the requirements of real-world KT applications in educational contexts. Overall this paper makes the following contributions:

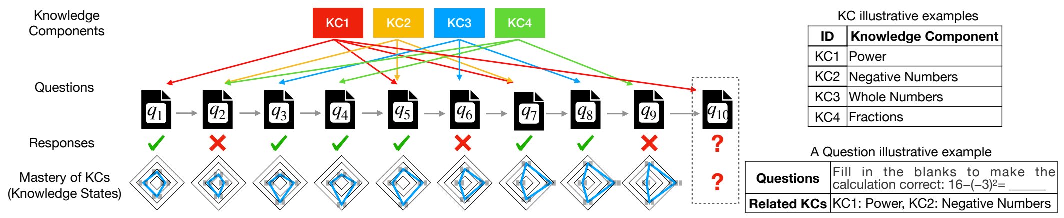
- We carefully and comprehensively assess the progress of recently developed DLKT algorithms through the lens of empirical evaluation of critical experimental setup and design considerations on a variety of public datasets. Through the empirical studies, we attempt to provide answers to the following research questions:
  - **RQ1**: What is a reasonable, reliable and realistic evaluation process for DLKT algorithms?
  - **RQ2**: How do different characteristics of student data, model design and prediction scenario affect the model performance?
- To ensure reproducibility and foster future research, we develop PYKT, an easy-to-use and end-to-end PyTorch benchmark library that includes critical data preprocessing, standardized dataset splitting, SOTA DLKT implementations, and real-world evaluation protocols in educational contexts. We hope the use of PYKT will greatly relieve the burden of comparing existing baselines and developing new algorithms. The PYKT library is open-sourced at `https://pykt.org/`.

Please note that there have been several KT related survey papers [2, 17, 27, 28]. However, to the best of our knowledge, none of the existing work provides rigorous empirical evidence of DLKT approaches on the standardized experimental evaluation in real-world educational contexts.

2 Problem Statement

Let $\mathcal{Q}$, and $\mathcal{C}$ be the sets of questions, and KCs respectively. Let each student $\mathbf{s}$ be a chronologically ordered collection of historical learning interactions, i.e., $\mathbf{s} = \{\mathbf{e}_j\}_{j=1}^{n}$ where $\mathbf{e}_j$ is the jth interaction

[2]A KC is a generalization of everyday terms like concept, principle, fact, or skill.


Knowledge Components
KC1
KC2
KC3
KC4
Questions
q_1 q_2 q_3 q_4 q_5 q_6 q_7 q_8 q_9 q_{10}
Responses
✓ ✗ ✓ ✓ ✓ ✗ ✓ ✓ ✗ ?
Mastery of KCs (Knowledge States)
?

KC illustrative examples

ID	Knowledge Component
KC1	Power
KC2	Negative Numbers
KC3	Whole Numbers
KC4	Fractions

A Question illustrative example

Questions	Fill in the blanks to make the calculation correct: $16-(-3)^2=$ ______
Related KCs	KC1: Power, KC2: Negative Numbers

Figure 1: The graphical illustration of the KT problem.

and n is the total number of interactions for $\mathbf{s}$. We denote an interaction $\mathbf{e}$ as a 4-tuple, i.e., $\mathbf{e} =< q, \{c\}, r, t >$, where $q, \{c\}, r, t$ represent the specific question, the associated KC set, the binary valued student response[3], and student's response timestamp respectively. As illustrated in Figure 1, in this work, our objective is to predict the values ($\hat{y}_{x_*}$) of mastery levels of questions or KCs for the target student $\mathbf{s}$ given his/her past learning interaction data where x_* can be arbitrary questions or KCs, i.e., $x_* = q_*$ or k_*, where $q_* \in \mathcal{Q}$ and $k_* \in \mathcal{C}$.

Please note that in real-world educational contexts, the number of questions is substantially larger than the number of KCs. To avoid the over parameterization, the majority of existing DLKT approaches conduct mastery predictions of questions indirectly by aggregated predicted mastery levels of KCs [10]. When KC information is not available, mastery levels of questions can be directly modeled on question-response data.

3 The DLKT Benchmark

3.1 Representative DLKT Methods

To carefully assess the progress of DLKT model-wise and application-wise, we surveyed existing DLKT related publications in top AI/ML venues[4] from 2015-2021[5] and collected all the baselines compared in these research works and selected the most frequently mentioned DLKT baselines as our representative DLKT methods[6]. In addition, we include some recently proposed approaches to cover a very wide range of DLKT models with different design focus. Please note that there are a few newly developed DLKT focusing on either utilizing more auxiliary information such as LPKT that utilizes time spent on questions [29], or solving data isolation problems in KT via federated learning [42]. The generalization of these approaches are limited to specific datasets and are out of scope in this paper. These representative DLKT methods[7] can be categorized as follows:

- **Deep sequential models**: the chronologically ordered interaction sequence is captured by deep sequential models such as LSTM and GRU [4, 12, 15, 16, 20, 21, 25, 34, 45]. Selected approaches are **DKT** [25], **DKT+** [45], **DKT-F** [21], and **KQN** [15].
  - **DKT**: leverages an LSTM layer to encode the student knowledge state to predict the students' response performances [25].
  - **DKT+**: an improved version of DKT to solve the reconstruction and non-consistent prediction problems [45].
  - **DKT-F**: an extension of DKT that model the students' forgetting behaviors [21].
  - **KQN**: uses student knowledge state encoder and skill encoder to predict the student response performance via the dot product [15].
- **Memory augmented models**: the latent relations between KCs are explicitly modeled by an external memory that is updated iteratively [1, 29, 46]. Selected approach is **DKVMN** [46].
  - **DKVMN**: designs a static key matrix to store the relations between the different KCs and a dynamic value matrix to update the students' knowledge state [46].

[3]Student response is a binary valued indicator variable where 1 represents the student correctly answered the question, and 0 otherwise.

[4]Venues include NeurIPS, ICML, ICLR, AAAI, IJCAI, KDD, WWW, SIGIR, MM, WSDM, ICDM, CIKM.

[5]The very first deep knowledge tracing model is proposed by Piech et al. at NIPS 2015 [25].

[6]The comprehensive DLKT baseline frequency summary is listed in Appendix A.1.

[7]We also include detailed model explanation in the PYKT library docs at `https://pykt-toolkit.readthedocs.io/en/latest/models.html`.

- **Adversarial based models**: the adversarial training techniques such as adversarial perturbations are applied into the original student interaction sequence to reduce the risk of DLKT overfitting and limited generalization problem [12]. Selected approach is **ATKT** [12].
  - **ATKT**: performs adversarial perturbations into student interaction sequence to improve DLKT model's generalization ability [12].
- **Graph based models**: the response interactions between students and questions and the knowledge associations between questions and KCs form a tripartite graph and graph based techniques are applied to aggregate such relations [22, 37, 44]. Selected approach is **GKT** [22].
  - **GKT**: utilizes the graph structure to predict the student response performance [22].
- **Attention based models**: dependence between interactions is captured by the attention mechanism and its variants [10, 24, 26, 47]. Selected approaches are **AKT** [10], **SAKT** [23] and **SAINT** [7].
  - **AKT**: leverages an attention mechanism to characterize the time distance between questions and the past interaction of students [10].
  - **SAKT**: utilizes a self-attention mechanism to capture relations between exercises and the student responses [23].
  - **SAINT**: uses the Transformer-based encoder-decoder architecture to capture students' exercise and response sequences [7].

Please note that the above categorizations are not exclusive and related techniques can be combined. For example, Ghodai and Qing proposed a sequential key-value memory network to unify the strengths of recurrent modeling capacity and memory capacity [1].

3.2 Datasets

We select 7 widely used datasets to evaluate the performance of the popular models. The original raw data download links are listed in Appendix A.2. We will briefly introduce the details of each dataset and the data statistics are shown in Table 1.

- **Statics2011**: This dataset is collected from an engineering statics course taught at the Carnegie Mellon University during Fall 2011 [33]. Recommended by [6, 10, 46], a unique question is constructed by concatenating the problem name and step name.
- **ASSISTments2009**: This dataset is made up of math exercises, collected from the free online tutoring ASSISTments platform in the school year 2009-2010. The dataset is widely used and has been the standard benchmark for KT methods over the last decade [1, 9, 10, 23, 43, 46].
- **ASSISTments2015**: Similar to ASSISTments2009, this dataset is collected from the ASSISTments platform in the year of 2015. This dataset has the largest number of students among the other ASSISTments datasets.
- **Algebra2005**: This dataset is from the KDD Cup 2010 EDM Challenge that contains 13-14 year old students' responses to Algebra questions [32]. It contains detailed step-level student responses. The unique question construction is similar to the process used in Statics2011.
- **Bridge2006**: This dataset is also from the KDD Cup 2010 EDM Challenge and the unique question construction is similar to the process used in Statics2011.
- **NIPS34**: This dataset is from the Tasks 3 & 4 at the NeurIPS 2020 Education Challenge. It contains students' answers to multiple-choice diagnostic math questions and is collected from the Eedi platform [40]. For each question, we choose to use the leaf nodes from the subject tree as its KCs.
- **POJ**: This dataset consists of programming exercises and is collected from Peking coding practice online platform. The dataset is originally scraped by Pandey and Srivastava [24].

3.3 The Standardized Evaluation Protocol

A standardized evaluation protocol is one of the most important basis of AI research and it impacts model performance, fairness, and robustness. Even with many public KT datasets, due to the lack of agreed upon training and evaluation procedures, the published DLKT results surprisingly diverge. For example, the reported AUC scores of DKT and AKT on ASSISTments2009 range from 0.73

Table 1: Data statistics of 7 datasets in PYKT. “Original” and “After Preprocessing” refer to the initial and preprocessed data statistics. “avg KCs” denotes the number of average KCs per question.

Datasets	Original					After Preprocessing				
	interactions	sequences	questions	KCs	avg KCs	interactions	sequences	questions	KCs	avg KCs
Statics2011	194,947	333	1,224	-	-	189,292	1,034	1,223	-	-
ASSISTments2009	346,860	4,217	26,688	123	1.1969	337,415	4,661	17,737	123	1.1970
ASSISTments2015	708,631	19,917	-	100	-	682,789	19,292	-	100	-
Algebra2005	809,694	574	210,710	112	1.3634	884,098	4,712	173,113	112	1.3634
Bridge2006	3,679,199	1,146	207,856	493	1.0136	1,824,310	9,680	129,263	493	1.0136
NIPS34	1,382,727	4,918	948	57	1.0148	1,399,470	9,401	948	57	1.0148
POJ	996,240	22,916	2,750	-	-	987,593	20,114	2,748	-	-

to 0.821 [20, 45] and from 0.747 to 0.835 in [10, 38] respectively. To this end, we standardize the prediction scenarios (Section 3.3.1), data preprocessing, training and testing sets splitting (Section 3.3.2) and evaluation metric (Section 3.3.3).

3.3.1 Real-world Prediction Scenarios

Train DLKT models on KCs but evaluate them on questions. In real-world educational scenarios, the question bank is usually much bigger than the set of KCs. For example, the number of questions is more than 1500 times larger than the number of KCs in Algebra2005 (see Table 1). Therefore, to effectively learn and fairly evaluate the DLKT models from such highly sparse question-response data, a recommended process[8] is listed as follows (also shown in Figure 2):

- **Step 1**: Train the DLKT models on KC-response data, which is artificially generated from question-response data by expanding each question-level interaction into multiple KC-level interactions when the question is associated with a set of KCs.
- **Step 2**: Use the learned DLKT models to predict on the above expanded KC-response data first and then output the final question-level predictions by aggregating predicted mastery levels of its KCs.

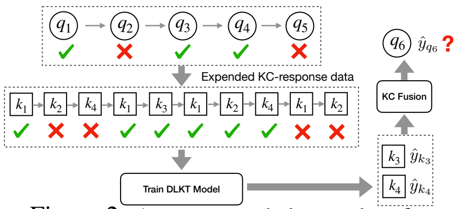


Figure 2: A recommended procedure for training and evaluating the DLKT models.

Although predictions at both question level and KC level are very important and useful for building personalized educational applications, when conducting offline model comparisons, it is recommended that the DLKT models are evaluated on prediction tasks at the question level instead of at the KC level. This is because (1) we only observe student responses on questions and have no ground truth about KCs; (2) a question may be associated with multiple KCs and evaluation results on at the KC level may overestimate or underestimate the real model performance [41].

Specifically, implementing the above evaluation procedure of “step 2” in practice is worthy of serious attention: *predictions of mastery level of KCs within a question should be predicted in an “all-in-one” manner*. The “all-in-one” prediction approach requires to simultaneously estimate the mastery level of all the KCs under each specific question. As illustrated in Figure 2, when predicting the outcome of q_6 that is associated with both k_3 and k_4, we should estimate $\hat{y}_{k_3}$ and $\hat{y}_{k_4}$ independently at the same time. Surprisingly, this crucial issue is neglected in some existing works, whose open sourced implementations conduct one-by-one evaluation on the expanded KC-response sequence, i.e., predicting $\hat{y}_{k_{t+1}}$ given all the responses (or labels) of $\hat{y}_{k_1}, \hat{y}_{k_2}, \cdots, \hat{y}_{k_t}$ are known. Unfortunately, this will cause the leakage of the ground truth since consecutive KCs like k_t and k_{t+1} may be associated with the same questions, which is referred to as the **label leakage** problem. Such dependent predictions will artificially boost prediction performance [41] and empirical analysis on this issue is discussed in Section 4.1.

KC prediction aggregation. To conduct a fine-grained, comprehensive and fair model comparison, we consider 4 different ways of aggregating the KC predictions in the above recommended process (depicted in the “KC Fusion” module in Figure 2), which include (1) **early fusion** that uses the averaged hidden states of all associated KCs to predict the question-level response, i.e., *EF*; (2) **late fusion - average** that uses the averaged prediction probabilities of all KCs as the question-level prediction probability, i.e., *LF-AVG*; (3) **late fusion - majority vote** that conducts majority votes based on all KC prediction results, i.e., *LF-MV*; (4) **late fusion - strict** that predicts positive if and only if all the related KCs’ predicted labels are positive, i.e., *LF-S*.

[8]The below procedure is also briefly mentioned by Ghosh et al. [10].

One-step and multi-step ahead KT predictions. To make the benchmark close to the real application scenarios, we divide our prediction scenarios into two settings: (1) one-step ahead prediction; and (2) multi-step ahead prediction. Specifically, the one-step ahead prediction task only predicts the student's response on the last question given the student's historical interaction sequence (depicted in Figure 3(a)). While the multi-step ahead prediction task predicts a span of student's responses given the student's historical interaction sequence (depicted in Figure 3(b)). Accurate one-step ahead prediction will largely improve the real-time educational recommender systems and the multi-step ahead prediction will provide constructive feedback to learning path selection and construction and help teachers adaptively adjust future teaching materials as well.

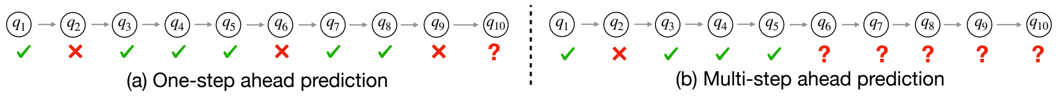

(a) One-step ahead prediction
(b) Multi-step ahead prediction

Figure 3: Two different prediction scenarios: one-step ahead and multi-step ahead predictions.

3.3.2 Data Preprocessing

Another challenge of reproducing existing DLKT research is the lack of standardized data preprocessing procedure. Aforementioned public KT datasets are far away from the ready-to-use stage and require many data preprocessing steps such as removing duplication, handling null or invalid values, and re-constructing the chronological interaction order. Furthermore, such steps are rarely described in existing publications and many open-sourced packages do not include data scripts. Therefore, in this work, our PYKT benchmark aims to outline a reasonable data preprocessing procedure for DLKT research. Specifically, the procedure includes: (1) data filtering: filter out interactions if no student id or any type of information of our 4-tuple interaction representation is not available or missing and filter out students if their sequences have less than 3 interactions. (2) data splitting: 20% students (their interaction sequences) are randomly withheld as the test set. The rest 80% students are randomly and evenly split into 5 folds: 4 folds for training and 1 fold for validation. (3) KC subsequence generation for training and validation. Expand original question-response sequence into KC level by repeating responses multiple times when a question has more than one KCs, one for each KC. Truncate the expanded KC level response sequence into shorter subsequences of length m, where m is the pre-defined max training sequence length. Sequences or subsequences whose length is less than m will be padded with -1. The data statistics of the aforementioned 7 datasets after preprocessing are shown in Table 1.

3.3.3 Evaluation Metric

Similar to all existing DLKT research works [1, 4, 10, 12, 15, 16, 20, 21, 22, 24, 25, 26, 29, 34, 37, 44, 45, 46, 47], we use the area under the receiver operating characteristics curve (AUC) as the main metric to evaluate the performance of DLKT models on predicting binary-valued future learner responses to either questions or KCs. Meanwhile, we also include detailed model performance in terms of accuracy in Appendix.

4 Empirical Studies

Let AS2009, AS2015, AL2005, BD2006 represent datasets ASSISTments2009, ASSISTments2015, Algebra2005, and Bridge2006 respectively in the following section.

Experimental setup. Since we have both question related and KC related information available for datasets of AS2009, AL2005, BD2006, and NIPS34, we conduct offline experiments following the recommended procedure discussed in Section 3.3.1. For experiments on datasets such as Statics2011, AS2015, and POJ that question related or KC related information is missing, both the training and testing procedures are conducted on question-response data. The details of training, validation and test sets are described in Section 3.3.2. By default, we choose to use LF-AVG for KC prediction fusion and all experiments are conducted in the one-step ahead prediction setting and the detailed analysis of multi-step ahead prediction is discussed in Observation 5 in Section 4.1. The pre-defined max training sequence length m is set to 200.

Implementation details. We use the Bayesian search method to find the best hyperparameter and stop searching when the number of the tuned hyperparameter combinations in each data fold is larger than

200 and there is no AUC improvement in the last 50 rounds. For each hyperparameter combination, we adopt the Adam optimizer to train all models with the early stop heuristic. We compute the AUC score on the development set for every epoch and update the best AUC score if needed. We stop the training process when the AUC score doesn't improve in the last 10 iterations or the number of training epochs reaches 200. Experiments are conducted at `https://wandb.ai/`. Please note that all the following AUC results are slightly different (less than 0.005) compared to the results in the original version since we re-run all the experiments under a more consistent hyperparameter search space. Detailed can be found in Appendix A.3.

4.1 Results

We provide extensive experiments and analyses to demonstrate the value of PYKT benchmark. Insights, findings and suggestions are summarized as observations described as follows.

Observation 1. Attention mechanism greatly affects DLKT model performance. The DKT model that first applies deep learning into the KT problem is still superior.

Table 2 summarizes the overall AUC performance results. Specifically, for datasets, i.e., AS2009, AL2005, BD2006, and NIPS34 in which both question and KC related information is available, the DLKT model performance is evaluated on both the original observed question-response data and the expended KC-response data. We have performed 5-fold cross validation for all of our experiments and the averaged AUC score is reported. The score standard deviations and the accuracy scores are reported in Appendix A.4 due to space limit. From Table 2, we find the following results: (1) AKT outperforms (almost) all other methods on all datasets. Since AKT proposes a monotonic attention mechanism to capture short-term dependencies on the past at different time scales, it outperforms the standard self-attention based baselines like SAKT and SAINT. Furthermore, AKT learns the Rasch model-based embeddings that implicitly model question difficulties when both question and KC information is available. This significantly improves its prediction performance and AKT is 3.06%, 1.50%, 1.62% and 1.60% better than the second best approach on AS2009, AL2005, BD2006 and NIPS34 datasets. Meanwhile, it only exceeds the second best approach by 0.30% and 1.08% on Statics2011 and POJ that either question information or KC information is missing. (2) The majority of recently proposed DLKT approaches cannot beat the vanilla DKT model and the performance between DKT and the best performing model for each dataset is shown in the bottom line ($\Delta_{\mathbf{DKT}}$) in Table 2. (3) Deep sequential models, i.e., DKT, DKT+, DKT-F, KQN, outperform the self-attention based model SAKT and SAINT in majority cases. We believe this is because different from the most NLP tasks that require capturing the long-term dependencies, faraway historical interactions have little influence on students' future performance prediction. This also indicates that the recency and forgetting effects need to be considered in the DLKT model design. (4) KT prediction on programming exercises is much harder compared to KT tasks on math questions. DLKT models are able to achieve 0.8ish AUC scores but only get 0.6ish AUC on the POJ dataset. (5) There is little difference in prediction results on BD2006 and NIPS34 datasets at question level and KC level. This is because most questions in these two datasets only contain one KC and the averaged numbers of KCs per question are 1.0136 and 1.0148 in BD2006 and NIPS34 respectively. (6) The original ATKT implementation utilizes the future ground truth to predict the mastery level of the current question, which is problematic. The published promising results cannot be reproduced when this problem gets fixed. The fixed results are reported in this paper and details are discussed in Appendix A.5.

Table 2: The overall prediction performance in terms of AUC at both question level and KC level. Marker $*$, $\circ$ and $\bullet$ indicates whether the AKT model is statistically superior/equal/inferior to the compared method (using paired t-test at 0.01 significance level). The last column shows the total numbers of win/tie/loss for AKT against the compared method (e.g., #win is how many times AKT significantly outperforms that method).

Model	Question Level(All-in-One)				KC Level(ALL-in-One)				Statics2011	AS2015	POJ	AKT
	AS2009	AL2005	BD2006	NIPS34	AS2009	AL2005	BD2006	NIPS34				#win/#tie/#loss
DKT	0.7541*	0.8149*	0.8015*	0.7689*	0.7419*	0.8146●	0.8013*	0.7681*	0.8222*	0.7271*	0.6089*	10/0/1
DKT+	0.7547*	0.8156*	0.8020*	0.7696*	0.7424*	0.8144●	0.8019*	0.7689*	0.8279*	0.7285●	0.6173*	9/0/2
DKT-F	-	0.8147*	0.7985*	0.7733*	-	0.8163●	0.7984*	0.7727*	0.7839*	-	0.6030*	7/0/1
KQN	0.7477*	0.8027*	0.7936*	0.7684*	0.7361*	0.8005*	0.7935*	0.7677*	0.8232*	0.7254*	0.6080*	11/0/0
DKVMN	0.7473*	0.8054○	0.7983*	0.7673*	0.7330*	0.7891*	0.7981*	0.7668*	0.8093*	0.7227*	0.6056*	10/1/0
ATKT	0.7470*	0.7995*	0.7889*	0.7665*	0.7337*	0.7964*	0.7885*	0.7658*	0.8055*	0.7245*	0.6075*	11/0/0
GKT	0.7424*	0.8110*	0.8046*	0.7689*	0.7227*	0.8025*	0.8045*	0.7681*	0.8040*	0.7258*	0.6070*	11/0/0
SAKT	0.7246*	0.7880*	0.7740*	0.7517*	0.7085○	0.7682*	0.7738*	0.7516*	0.7965*	0.7114*	0.6095*	10/1/0
SAINT	0.6958*	0.7775*	0.7781*	0.7873*	0.6865*	0.6662*	0.7779*	0.7860*	0.7599○	0.7026*	0.5563*	10/1/0
AKT	0.7853	0.8306	0.8208	0.8033	0.7650	0.8091	0.8206	0.8017	0.8309	0.7281	0.6281	-
$\Delta_{\mathbf{DKT}}$	0.0312	0.0157	0.0193	0.0344	0.0231	0.0017	0.0193	0.0336	0.0087	0.0014	0.0192	-

Observation 2. One-by-one evaluation on expanded KC sequences causes label leakage problem that leads to performance inflation.

Table 3: The boosted DLKT AUC results due to label leakage. The exaggerated gains (Δ_{Gain}) are computed by subtracting AUC scores of one-by-one predictions (left part in Table 3) from AUC scores of all-in-one predictions at KC level (middle part in Table 2).

Model	KC Level(One-by-One)				Exaggerated Performance Gains (Δ_{Gain})			
	AS2009	AL2005	BD2006	NIPS34	AS2009	AL2005	BD2006	NIPS34
DKT	0.8262	0.9218	0.8028	0.7742	0.0843	0.1072	0.0015	0.0061
DKT+	0.8268	0.9221	0.8032	0.7748	0.0844	0.1077	0.0013	0.0059
DKT-F	-	0.9220	0.7997	0.7787	-	0.1057	0.0013	0.0060
KQN	0.8216	0.9179	0.7949	0.7736	0.0855	0.1174	0.0014	0.0059
DKVMN	0.8213	0.9190	0.7993	0.7723	0.0883	0.1299	0.0012	0.0055
ATKT	0.8210	0.9156	0.7902	0.7718	0.0873	0.1192	0.0017	0.0060
GKT	0.8171	0.9208	0.8057	0.7741	0.0944	0.1183	0.0012	0.0060
SAKT	0.7806	0.9115	0.7740	0.7532	0.0721	0.1433	0.0002	0.0016
SAINT	0.7605	0.9050	0.7787	0.7910	0.0740	0.2388	0.0008	0.0050
AKT	0.8493	0.9305	0.8218	0.8084	0.0843	0.1214	0.0012	0.0067

As discussed in Section 3.3.1, label leakage happens when the target KC prediction $\hat{y}_{k_{j+1}}$ depends on the ground truth of the previous KC k_j in the expanded KC sequence and at the same time, k_j and k_{j+1} belong to the same question. During our journey of building PYKT, we found many publicly available DLKT implementations overlook this leakage issue [10, 23, 46], which artificially boosts prediction performance. We reproduce such "wrong" evaluation procedure and report the exaggerated results in the left part in Table 3. Furthermore, we explicitly show the exaggerated AUC gains (Δ_{Gain}) in the right part of Table 3 by computing the AUC scores difference between results of one-by-one predictions at KC level (values in Table 3) and results of all-in-one predictions at KC level (middle part in Table 2). The related accuracy results are reported in Appendix A.6. As we can see that, the leakage issue is much worse in AS2009 and AL2005, i.e., the mean values of Δ_{Gain} is 8.38% and 13.09% respectively. This is because questions in AS2009 and AL2005 have more KCs associated and their average KC numbers per question is 1.1970 and 1.3634 compared to the value of 1.0136 and 1.0148 in BD2006 and NIPS34. Experimental results and conclusions impacted by the leakage problem need to be re-validate and we believe this is the reason why we cannot reproduce the results of many DKLT models on AS2009 and AL2005 [10, 23, 46]. In summary, we do not recommend to conduct KT evaluations at KC level in the above one-by-one manner.

Observation 3. DLKT models behaves differently for students who have very long interaction sequences.

In the real educational scenarios, the length of historical learning interactions varies a lot. Therefore, we split the test set into two parts: (1) students with long interaction sequences (sequence length is larger than 200), denoted as L; and (2) students with short interaction sequences (sequence length is less than or equal to 200), denoted as S. We choose 200 as the cutoff threshold because the pre-defined max training sequence length m is set to 200 as well in all experiments. We evaluate the DLKT performance on L and S respectively (shown in Table 4). Its full version with standard deviations and the results in terms of accuracy are reported in Appendix A.7 and Appendix A.8. Generally speaking, DLKT models perform quite differently on L and S. For example, the difference of AUC scores on POJ ranges from 5% to 14%. Meanwhile, DLKT models perform alike on Statics2011 and AS2015. By digging into these two datasets, we find that these two datasets have very high numbers of KC co-occurrence on L and S, i.e., the appearance of one KC is often accompanied by another KC. Such adjacent interactions will largely influence the model performance and the role of long-term contextual information reduces quite a lot. As a result, there are no obvious AUC performance difference on L and S student subgroups.

Table 4: Prediction performance in terms of AUC for students with different lengths of interactions.

Model	Statics2011		AS2009		AS2015		AL2005		BD2006		NIPS34		POJ	
	L	S	L	S	L	S	L	S	L	S	L	S	L	S
DKT	0.8219	0.8314	0.7351	0.7650	0.7106	0.7281	0.8160	0.7623	0.8010	0.8563	0.7740	0.7430	0.5979	0.6629
DKT+	0.8276	0.8364	0.7357	0.7657	0.7113	0.7296	0.8168	0.7600	0.8015	0.8593	0.7748	0.7436	0.6045	0.6782
DKT-F	0.7859	0.7465	-	-	-	-	0.8158	0.7597	0.7980	0.8467	0.7784	0.7480	0.5915	0.6606
KQN	0.8230	0.8280	0.7259	0.7604	0.7064	0.7266	0.8038	0.7466	0.7931	0.8515	0.7738	0.7414	0.5944	0.6774
DKVMN	0.8086	0.8294	0.7271	0.7588	0.7039	0.7240	0.8067	0.7429	0.7978	0.8540	0.7725	0.7414	0.5924	0.6732
ATKT	0.8046	0.8295	0.7249	0.7605	0.7029	0.7262	0.8004	0.7564	0.7884	0.8464	0.7711	0.7438	0.5960	0.6687
GKT	0.8044	0.8004	0.7224	0.7535	0.7111	0.7266	0.8122	0.7528	0.8042	0.8535	0.7741	0.7431	0.5977	0.6577
SAKT	0.7958	0.8179	0.6989	0.7403	0.6857	0.7134	0.7891	0.7347	0.7734	0.8239	0.7570	0.7253	0.6001	0.6544
SAINT	0.7592	0.7845	0.6687	0.7112	0.6617	0.7060	0.7788	0.7097	0.7776	0.8189	0.7912	0.7687	0.5294	0.6702
AKT	0.8305	0.8466	0.7781	0.7878	0.7113	0.7292	0.8317	0.7771	0.8204	0.8643	0.8074	0.7829	0.6137	0.6949

Observation 4. Prediction results of different ways of KC aggregation resemble each other and the "late fusion - average" is slightly better compared to other approaches.

Generally speaking, there are 4 different ways of aggregating KC predictions in the "KC Fusion" module in Figure 2. Therefore, we conduct extensive experiments to empirically evaluate their impacts on the final prediction performance (shown in Table 5). Due to the space limit, we choose to use DKT and AKT as the representative approaches from the deep sequential DLKT models and attention based DLKT models. The full results of all the baselines are shown in Appendix A.9. Please note that since DKT, ATKT and GKT inherently don't use individual hidden states to model each KC,

Table 5: Impact on different KC fusion mechanisms.
Marker $*$, $\circ$ and $\bullet$ indicates whether the LF-AVG mechanism is statistically superior/ equal/inferior to the compared fusion method (using paired t-test at 0.01 significance level).

Model	Dataset	Fusion Mechanisms				Δ_{Fusion}
		LF-AVG	LF-MV	LF-S	EF	
DKT	AS2009	0.7541	0.7526*	0.7524*	-	0.0015
	AL2005	0.8149	0.8123*	0.8131*	-	0.0018
	BD2006	0.8015	0.8015$\circ$	0.8015$\circ$	-	0.0000
	NIPS34	0.7689	0.7687*	0.7688*	-	0.0001
DKVMN	AS2009	0.7473	0.7458*	0.7456*	0.7454*	0.0015
	AL2005	0.8054	0.8022*	0.8021*	0.7961*	0.0032
	BD2006	0.7983	0.7983$\circ$	0.7983$\circ$	0.7983$\circ$	0.0000
	NIPS34	0.7673	0.7672*	0.7673$\circ$	0.7673$\circ$	0.0000
ATKT	AS2009	0.7470	0.7440*	0.7466*	-	0.0004
	AL2005	0.7995	0.7963*	0.7974*	-	0.0021
	BD2006	0.7889	0.7888*	0.7889$\circ$	-	0.0000
	NIPS34	0.7665	0.7663*	0.7665$\circ$	-	0.0000
GKT	AS2009	0.7424	0.7376*	0.7401*	-	0.0023
	AL2005	0.8110	0.8072*	0.8072*	-	0.0038
	BD2006	0.8046	0.8046$\circ$	0.8046$\circ$	-	0.0000
	NIPS34	0.7689	0.7686*	0.7689$\circ$	-	0.0000
AKT	AS2009	0.7853	0.7794*	0.7847*	0.7825*	0.0006
	AL2005	0.8306	0.8228*	0.8275*	0.8177*	0.0031
	BD2006	0.8208	0.8208$\circ$	0.8208$\circ$	0.8208$\circ$	0.0000
	NIPS34	0.8033	0.8028*	0.8033$\circ$	0.8034$\bullet$	-0.0001
#win/#tie/#loss		-	16/4/0	11/9/0	4/3/1	

EF approach is inapplicable on these methods. Similar to Table 2, we use markers $*$, $\circ$ and $\bullet$ to indicate whether the **LF-AVG** model is significantly better/equal to/worse than the compared method at 0.01 significance level. The difference (Δ_{Fusion}) is computed by subtracting AUC scores of LF-AVG from the best AUC score from LF-MV, LF-S, and EF. The last row shows the total number of win/tie/loss for LF-AVG against the compared method. As we can see, (1) though statistically significant, the performance difference between different fusion mechanisms is very small. The LF-AVG approach outperforms or perform alike other approaches across all 4 datasets. (2) Δ_{Fusion} is much larger on AL2005, we believe this is because the AL2005 dataset has the largest the number of KCs per question (shown in Table 2). Averaging probabilities of KCs within a question will stabilize the DLKT model performance.

Observation 5. The choice of accumulative or non-accumulative prediction vastly influences the DLKT performance in the multi-step ahead prediction scenario.

As discussed in Section 3.3.1, accurate predictions in the multi-step ahead prediction scenario are also very important from educational perspectives. Practically, there are two different approaches, i.e., accumulative prediction and non-accumulative prediction. The accumulative prediction approach uses the last predicted values for the current prediction while the non-accumulative prediction predicts all future values all at once. To have a fine-grained analysis in the multi-step ahead prediction scenario, we further experiment with DLKT models on different portions of observed student interactions. Specifically, we vary the observed percentages of student interaction length from 20% to 90% with step size of 10%. Due to the space limit, we select DKT/DKVMN/ATKT/GKT/AKT and AS2009/BD2006/POJ as the representative approaches and datasets and the results are shown in Figure 4. The full AUC and accuracy results are shown in Appendix A.10 and Appendix A.11.

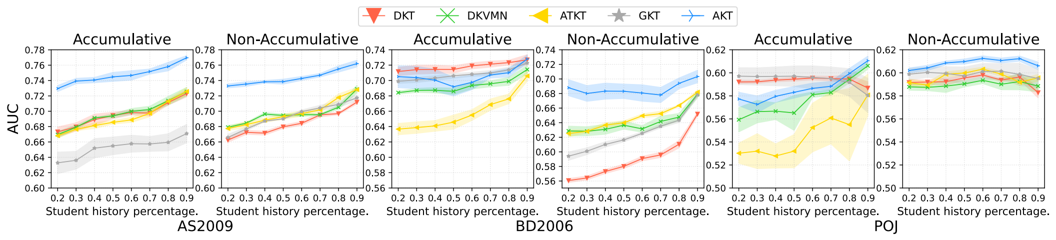


Figure 4: Accumulative and non-accumulative predictions in the multi-step ahead scenario in terms of AUC on AS2009, BD2006, and POJ.

We make the following observations: (1) accumulative performance is mostly worse than non-accumulative performance on the POJ dataset. This is because the DLKT approaches only achieve 0.6ish AUC (shown in Table 2) and the previous prediction errors are aggregated and propagated to the future prediction tasks in an accumulative fashion. (2) the performance of non-accumulative predictions on BD2006 drops a lot compared to its accumulative prediction results. We believe this is because the BD2006's has the largest average sequence length. When conducting non-accumulative predictions with different percentages of student historical interactions, it actually needs to predict questions in the very farway future all in once. The DLKT performance downgrades when there is not enough contextual information of the target question. (3) with the increase of student historical interactions, the DLKT performance gradually improves in both the accumulative and non-accumulative settings.

5 Limitation

While PYKT is able to standardize and accelerate research in DLKT, we are aware of some potential limitations described as follows:

- **Binary response assumption**. Most existing DLKT research relies on the binary response assumption and existing publicly available datasets only contain the binary labels, i.e., correct or incorrect. We believe this is because the binary valued data is (sort of) the most objective assessment labels that can be easily collected from either the online learning platforms or the offline classrooms in a large scale. However, we deeply believe that having more fine-grained student assessment labels beyond binary value of correct and incorrect would definitely push the boundary of this research field. Some research works such as option tracing [11] aim to extend existing KT methods beyond correctness prediction to the task of predicting the exact option students select in multiple choice questions. This only works for multiple choice questions and it generalizes the traditional KT prediction from binary classification to the multi-class classification settings. The PYKT library is well modularized and different loss functions or evaluation metrics can be easily added. Hence, it is flexible to extend the existing benchmark to non-binary prediction settings such as multi-class classification or real-valued regression problems.
- **Auxiliary side information**. All existing baselines don't utilize the rich auxiliary side information in educational contexts. Various auxiliary side information could be extracted as external knowledge and integrated with the DLKT models. Such auxiliary knowledge is expected to improve DLKT performance, which can be considered as follows:
  - **Question side info.**: (1) question text content [16, 34]; (2) latent question variations with respect to each KC [10]; (3) question difficulty level [10, 18, 47]; and (4) relations among questions [18, 24, 47].
  - **Student side info.**: (1) historical successful and failed attempts [47]; (2) recent attempts [47]; (3) students' learning ability [20]; and (4) individualized prior knowledge of students [30].
  - **KC side info.**: (1) latent knowledge representation [10, 15]; and (2) relations among KCs [18].

6 Conclusion

Outlook: We describe concrete ongoing and future work towards expanding PYKT. Specifically,

- We will keep adding newly developed DLKT approaches into our DLKT model zoo and provide ready-to-use benchmark results for both researchers and practitioners. We will incorporate more diverse datasets into the PYKT platform.
- We will explore new DLKT opportunities such as modeling external side information from the student side, KC side and question side. For example, we would like to apply the successful pre-training techniques into the KT domain to better capture the heterogeneous educational data.

Conclusion: We present PYKT, a systematic and comprehensive python library standardizing previous efforts in DLKT research with a focus on accessibility, reproducibility and practical usage in real-world educational contexts, thereby paving the way towards a deeper understanding of different DLKT components. Through its modularized and standardized data preprocessing components, rigorous and real-world prediction scenario formulation, and experiment management, PYKT is able to greatly relieve the burden of comparing existing baselines and developing new algorithms and highlights several future directions in building more practical, generalizable, and robust DLKT models.

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References

[1] Ghodai Abdelrahman and Qing Wang. Knowledge tracing with sequential key-value memory networks. In Benjamin Piwowarski, Max Chevalier, Éric Gaussier, Yoelle Maarek, Jian-Yun Nie, and Falk Scholer, editors, *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, Paris, France, July 21-25, 2019*, pages 175–184. ACM, 2019.

[2] Ghodai Abdelrahman, Qing Wang, and Bernardo Pereira Nunes. Knowledge tracing: A survey. *ArXiv preprint*, abs/2201.06953, 2022.

[3] Hao Cen, Kenneth Koedinger, and Brian Junker. Learning factors analysis–a general method for cognitive model evaluation and improvement. In *International Conference on Intelligent Tutoring Systems*, pages 164–175. Springer, 2006.

[4] Penghe Chen, Yu Lu, Vincent W Zheng, and Yang Pian. Prerequisite-driven deep knowledge tracing. In *2018 IEEE International Conference on Data Mining*, pages 39–48. IEEE, 2018.

[5] Song Cheng, Qi Liu, Enhong Chen, Zai Huang, Zhenya Huang, Yiying Chen, Haiping Ma, and Guoping Hu. DIRT: deep learning enhanced item response theory for cognitive diagnosis. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management, Beijing, China, November 3-7, 2019*, pages 2397–2400. ACM, 2019.

[6] Benoît Choffin, Fabrice Popineau, Yolaine Bourda, and Jill-Jênn Vie. DAS3H: Modeling student learning and forgetting for optimally scheduling distributed practice of skills. In *International Conference on Educational Data Mining*, 2019.

[7] Youngduck Choi, Youngnam Lee, Junghyun Cho, Jineon Baek, Byungsoo Kim, Yeongmin Cha, Dongmin Shin, Chan Bae, and Jaewe Heo. Towards an appropriate query, key, and value computation for knowledge tracing. In *Proceedings of the Seventh ACM Conference on Learning@Scale*, pages 341–344, 2020.

[8] Albert T Corbett and John R Anderson. Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-adapted Interaction*, 4(4):253–278, 1994.

[9] Mingyu Feng, Neil Heffernan, and Kenneth Koedinger. Addressing the assessment challenge with an online system that tutors as it assesses. *User Modeling and User-adapted Interaction*, 19(3):243–266, 2009.

[10] Aritra Ghosh, Neil T. Heffernan, and Andrew S. Lan. Context-aware attentive knowledge tracing. In Rajesh Gupta, Yan Liu, Jiliang Tang, and B. Aditya Prakash, editors, *The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020*, pages 2330–2339. ACM, 2020.

[11] Aritra Ghosh, Jay Raspat, and Andrew Lan. Option tracing: Beyond correctness analysis in knowledge tracing. In *International Conference on Artificial Intelligence in Education*, pages 137–149. Springer, 2021.

[12] Xiaopeng Guo, Zhijie Huang, Jie Gao, Mingyu Shang, Maojing Shu, and Jun Sun. Enhancing knowledge tracing via adversarial training. In *Proceedings of the 29th ACM International Conference on Multimedia*, pages 367–375, 2021.

[13] Tanja Käser, Severin Klingler, Alexander G Schwing, and Markus Gross. Dynamic bayesian networks for student modeling. *IEEE Transactions on Learning Technologies*, 10(4):450–462, 2017.

[14] Elise Lavoué, Baptiste Monterrat, Michel Desmarais, and Sébastien George. Adaptive gamification for learning environments. *IEEE Transactions on Learning Technologies*, 12(1):16–28, 2018.

[15] Jinseok Lee and Dit-Yan Yeung. Knowledge query network for knowledge tracing: How knowledge interacts with skills. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, pages 491–500, 2019.

[16] Qi Liu, Zhenya Huang, Yu Yin, Enhong Chen, Hui Xiong, Yu Su, and Guoping Hu. EKT: Exercise-aware knowledge tracing for student performance prediction. *IEEE Transactions on Knowledge and Data Engineering*, 33(1):100–115, 2019.

[17] Qi Liu, Shuanghong Shen, Zhenya Huang, Enhong Chen, and Yonghe Zheng. A survey of knowledge tracing. *ArXiv preprint*, abs/2105.15106, 2021.

[18] Yunfei Liu, Yang Yang, Xianyu Chen, Jian Shen, Haifeng Zhang, and Yong Yu. Improving knowledge tracing via pre-training question embeddings. In Christian Bessiere, editor, *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence*, pages 1577–1583. ijcai.org, 2020.

[19] Ting Long, Yunfei Liu, Jian Shen, Weinan Zhang, and Yong Yu. Tracing knowledge state with individual cognition and acquisition estimation. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 173–182, 2021.

[20] Sein Minn, Yi Yu, Michel C Desmarais, Feida Zhu, and Jill-Jenn Vie. Deep knowledge tracing and dynamic student classification for knowledge tracing. In *2018 IEEE International Conference on Data Mining*, pages 1182–1187. IEEE, 2018.

[21] Koki Nagatani, Qian Zhang, Masahiro Sato, Yan-Ying Chen, Francine Chen, and Tomoko Ohkuma. Augmenting knowledge tracing by considering forgetting behavior. In Ling Liu, Ryen W. White, Amin Mantrach, Fabrizio Silvestri, Julian J. McAuley, Ricardo Baeza-Yates, and Leila Zia, editors, *The World Wide Web Conference, San Francisco, CA, USA, May 13-17, 2019*, pages 3101–3107. ACM, 2019.

[22] Hiromi Nakagawa, Yusuke Iwasawa, and Yutaka Matsuo. Graph-based knowledge tracing: Modeling student proficiency using graph neural network. In *2019 IEEE/WIC/ACM International Conference on Web Intelligence*, pages 156–163. IEEE, 2019.

[23] Shalini Pandey and George Karypis. A self-attentive model for knowledge tracing. In *12th International Conference on Educational Data Mining*, pages 384–389. International Educational Data Mining Society, 2019.

[24] Shalini Pandey and Jaideep Srivastava. RKT: relation-aware self-attention for knowledge tracing. In Mathieu d'Aquin, Stefan Dietze, Claudia Hauff, Edward Curry, and Philippe Cudré-Mauroux, editors, *The 29th ACM International Conference on Information and Knowledge Management, Virtual Event, Ireland, October 19-23, 2020*, pages 1205–1214. ACM, 2020.

[25] Chris Piech, Jonathan Bassen, Jonathan Huang, Surya Ganguli, Mehran Sahami, Leonidas J Guibas, and Jascha Sohl-Dickstein. Deep knowledge tracing. *Advances in Neural Information Processing Systems*, 28, 2015.

[26] Shi Pu, Michael Yudelson, Lu Ou, and Yuchi Huang. Deep knowledge tracing with transformers. In *International Conference on Artificial Intelligence in Education*, pages 252–256. Springer, 2020.

[27] Sergio Ramirez, Nour El Mawas, and Jean Heutte. Machine learning techniques for knowledge tracing: A systematic literature review. In *Proceedings of the 13th International Conference on Computer Supported Education*. Science and Technology Publications, Lda, 2021.

[28] Sami Sarsa, Juho Leinonen, and Arto Hellas. Deep learning models for knowledge tracing: Review and empirical evaluation. *ArXiv preprint*, abs/2112.15072, 2021.

[29] Shuanghong Shen, Qi Liu, Enhong Chen, Zhenya Huang, Wei Huang, Yu Yin, Yu Su, and Shijin Wang. Learning process-consistent knowledge tracing. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 1452–1460, 2021.

[30] Shuanghong Shen, Qi Liu, Enhong Chen, Han Wu, Zhenya Huang, Weihao Zhao, Yu Su, Haiping Ma, and Shijin Wang. Convolutional knowledge tracing: Modeling individualization in student learning process. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1857–1860, 2020.

[31] Dongmin Shin, Yugeun Shim, Hangyeol Yu, Seewoo Lee, Byungsoo Kim, and Youngduck Choi. SAINT+: Integrating temporal features for EdNet correctness prediction. In *11th International Learning Analytics and Knowledge Conference*, pages 490–496, 2021.

[32] J Stamper, A Niculescu-Mizil, S Ritter, G Gordon, and K Koedinger. Algebra I 2005-2006 and Bridge to Algebra 2006-2007. Development data sets from KDD Cup 2010 Educational Data Mining Challenge, 2010.

[33] Paul Steif and Norman Bier. Oli engineering statics-fall 2011, 2014.

[34] Yu Su, Qingwen Liu, Qi Liu, Zhenya Huang, Yu Yin, Enhong Chen, Chris Ding, Si Wei, and Guoping Hu. Exercise-enhanced sequential modeling for student performance prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

[35] Nguyen Thai-Nghe, Lucas Drumond, Tomáš Horváth, Artus Krohn-Grimberghe, Alexandros Nanopoulos, and Lars Schmidt-Thieme. Factorization techniques for predicting student performance. In *Educational Recommender Systems and Technologies: Practices and Challenges*, pages 129–153. IGI Global, 2012.

[36] Zejie Tiana, Guangcong Zhengc, Brendan Flanaganb, Jiazhi Mic, and Hiroaki Ogatab. BEKT: Deep Knowledge Tracing with Bidirectional Encoder Representations from Transformers.

[37] Shiwei Tong, Qi Liu, Wei Huang, Zhenya Huang, Enhong Chen, Chuanren Liu, Haiping Ma, and Shijin Wang. Structure-based Knowledge Tracing: An Influence Propagation View. In *2020 IEEE International Conference on Data Mining*, pages 541–550. IEEE, 2020.

[38] Chenyang Wang, Weizhi Ma, Min Zhang, Chuancheng Lv, Fengyuan Wan, Huijie Lin, Taoran Tang, Yiqun Liu, and Shaoping Ma. Temporal cross-effects in knowledge tracing. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, pages 517–525, 2021.

[39] Fei Wang, Qi Liu, Enhong Chen, Zhenya Huang, Yuying Chen, Yu Yin, Zai Huang, and Shijin Wang. Neural cognitive diagnosis for intelligent education systems. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 6153–6161, 2020.

[40] Zichao Wang, Angus Lamb, Evgeny Saveliev, Pashmina Cameron, Yordan Zaykov, José Miguel Hernández-Lobato, Richard E Turner, Richard G Baraniuk, Craig Barton, Simon Peyton Jones, et al. Instructions and guide for diagnostic questions: The NeurIPS 2020 education challenge. *ArXiv preprint*, abs/2007.12061, 2020.

[41] Kevin H Wilson, Yan Karklin, Bojian Han, and Chaitanya Ekanadham. Back to the basics: Bayesian extensions of IRT outperform neural networks for proficiency estimation. *International Educational Data Mining Society*, 2016.

[42] Jinze Wu, Zhenya Huang, Qi Liu, Defu Lian, Hao Wang, Enhong Chen, Haiping Ma, and Shijin Wang. Federated deep knowledge tracing. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, pages 662–670, 2021.

[43] Xiaolu Xiong, Siyuan Zhao, Eric G Van Inwegen, and Joseph E Beck. Going deeper with deep knowledge tracing. *International Educational Data Mining Society*, 2016.

[44] Yang Yang, Jian Shen, Yanru Qu, Yunfei Liu, Kerong Wang, Yaoming Zhu, Weinan Zhang, and Yong Yu. GIKT: A graph-based interaction model for knowledge tracing. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 299–315. Springer, 2020.

[45] Chun-Kit Yeung and Dit-Yan Yeung. Addressing two problems in deep knowledge tracing via prediction-consistent regularization. In *Proceedings of the Fifth Annual ACM Conference on Learning@Scale*, pages 1–10, 2018.

[46] Jiani Zhang, Xingjian Shi, Irwin King, and Dit-Yan Yeung. Dynamic Key-Value Memory Networks for Knowledge Tracing. In Rick Barrett, Rick Cummings, Eugene Agichtein, and Evgeniy Gabrilovich, editors, *Proceedings of the 26th International Conference on World Wide Web, Perth, Australia, April 3-7, 2017*, pages 765–774. ACM, 2017.

[47] Moyu Zhang, Xinning Zhu, Chunhong Zhang, Yang Ji, Feng Pan, and Changchuan Yin. Multi-Factors Aware Dual-Attentional Knowledge Tracing. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 2588–2597, 2021.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 5
   (c) Did you discuss any potential negative societal impacts of your work? [N/A] Our work has no potential negative societal impacts.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] All codes, datasets and detailed instructions can be found at `https://pykt.org`.

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] Training details can be found in the Section 4. The hyperparameter search space is provided in Appendix A.3.

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We use 5-fold cross validation to evaluate each models and report the average scores with standard deviations in result tables in Appendix.

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

   (a) If your work uses existing assets, did you cite the creators? [Yes]

   (b) Did you mention the license of the assets? [Yes] The datasets used in our work are publicly released and we have well cited the corresponding papers and implicitly mentioned their download links.

   (c) Did you include any new assets either in the supplemental material or as a URL? [N/A]

   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes]

   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] The datasets we used don't contain personally identifiable information or offensive content.

5. If you used crowdsourcing or conducted research with human subjects...

   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]