EKT: Exercise-aware Knowledge Tracing for Student Performance Prediction

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Abstract—For offering proactive services (e.g., personalized exercise recommendation) to the students in computer supported intelligent education, one of the fundamental tasks is predicting student performance (e.g., scores) on future exercises, where it is necessary to track the change of each student’s knowledge acquisition during her exercising activities. Unfortunately, to the best of our knowledge, existing approaches can only exploit the exercising records of students, and the problem of extracting rich information existed in the materials (e.g., knowledge concepts, exercise content) of exercises to achieve both more precise prediction of student performance and more interpretable analysis of knowledge acquisition remains underexplored. To this end, in this paper, we present a holistic study of student performance prediction. To directly achieve the primary goal of performance prediction, we first propose a general Exercise-Enhanced Recurrent Neural Network (EERNN) framework by exploring both student’s exercising records and the text content of corresponding exercises. In EERNN, we simply summarize each student’s state into an integrated vector and trace it with a recurrent neural network, where we design a bidirectional LSTM to learn the encoding of each exercise from its content. For making final predictions, we design two implementations on the basis of EERNN with different prediction strategies, i.e., EERNN with Markov property and EERNN with Attention mechanism. Then, to explicitly track student’s knowledge acquisition on multiple knowledge concepts, we extend EERNN to an explainable Exercise-aware Knowledge Tracing (EKT) framework by incorporating the knowledge concept information, where the student’s integrated state vector is now extended to a knowledge state matrix. In EKT, we further develop a memory network for quantifying how much each exercise can affect the mastery of students on multiple knowledge concepts during the exercising process. Finally, we conduct extensive experiments and evaluate both EERNN and EKT frameworks on a large-scale real-world data. The results in both general and cold-start scenarios clearly demonstrate the effectiveness of two frameworks in student performance prediction as well as the superior interpretability of EKT.

Index Terms—Intelligent education, knowledge tracing, exercise content, knowledge concept.

1 INTRODUCTION

I\textit{n}telligent education systems, such as Massive Online Open Course, Knewton.com and KhanAcademy.org, can help the personalized learning of students with computer-assisted technology by providing open access to millions of online courses or exercises. Due to their prevalence and convenience, these systems have attracted great attentions from both educators and general publics [1], [25], [55]. Specifically, students in these systems can choose exercises individually according to their needs and acquire necessary knowledge during exercising. Fig. 1 shows a toy example of such exercising process of a typical student. Generally, when an exercise (e.g., $e_1$) is posted, the student reads its content (“If function...”) and applies the corresponding knowledge on “Function” concept to answer it. From the figure, student $s_1$ has done four exercises, where she only answers exercise $e_2$ wrong, which may demonstrate that she has well mastered knowledge concepts “Function” and “Inequality” except the “Probability” concept. We can see that a fundamental task in such education systems is to predict student performance (e.g., score), i.e., forecasting whether or not a student can answer an exercise (e.g., $e_5$) correctly in the future [2]. Meanwhile, it also requires us to track the change of students’ knowledge acquisition in their exercising process [7], [53]. In practice, the success of precise prediction could benefit both student users and system creators: (1) Students can realize their weak knowledge concepts in time and thus prepare targeted exercising [16], [48]; (2) System creators can provide better proactive services to different students, such as learning remedy suggestion and personalized exercise recommendation [23].

In the literature, there are many efforts in predicting student performance from both educational psychology and data mining areas, such as cognitive diagnosis [10], knowledge tracing [7], matrix factorization [43], topic modeling [55], sparse factor analysis [25] and deep learning [34]. Specifically, existing works mainly focus on exploiting the exercising process of students, where each exercise is usually distinguished by the corresponding knowledge concepts in the modeling, e.g., exercise $e_1$ in Fig. 1 is represented as the concept “Function”. In other words, existing works model students’ knowledge states for the prediction only based on their performance records on each knowledge, where two exercises (e.g., $e_1$ and $e_3$) labeled with the same knowledge concept are simply identified as the same (actually, exercise $e_1$ and $e_3$ are quite different according to their contents, and $e_3$ is more difficult than $e_1$). Therefore, these approaches cannot distinguish the knowledge acquisition of
two students if one solves \( e_1 \) but the other solves \( e_3 \) since these knowledge-specific representations underutilize the rich information of exercise materials (e.g., text contents), causing severe information loss [10]. To this end, we argue that it is beneficial to combine both student’s exercising records and the exercise materials for more precisely predicting student performance.

Unfortunately, there are many technical and domain challenges along this line. First, there are diverse expressions of exercises, which requires a unified way to automatically understand and represent the characteristics of exercises from a semantic perspective. Second, students' performance in the future is deeply relied on their long-term historical exercising, especially on their important knowledge states. How to track the historically focused information of students is very challenging. Third, the task of student performance prediction usually suffers from the “cold start” problem [26], [46]. That is, we have to make predictions for new students and new exercises. In this scenario, limited information could be exploited, and thus, leading to the poor prediction results. Last but not least, students usually care about not only what they need to learn but also wonder why they need it, i.e., it is necessary to remind them whether or not they are good at a certain knowledge concept and how much they have already learned about it. However, it is a nontrivial problem to either quantify the impacts of solving each specific exercise (e.g., \( e_1 \)) on improving the student’s knowledge acquisition (e.g., “Function”) or interpretably track the change of student’s knowledge states during the exercising process.

To directly achieve the primary goal of predicting student performance with addressing the first three challenges, in our preliminary work [38], we proposed an Exercise-Enhanced Recurrent Neural Network (EERNN) framework by mainly exploring both student’s exercising records and the corresponding exercise contents. Specifically, for the exercising process modeling, we first designed a bidirectional LSTM to represent the semantics of each exercise by exploiting its content. The learned encodings could capture the individual characteristics of each exercise without any expertise. Then, we proposed another LSTM architecture to trace student states in the sequential exercising process with the combination of exercise representations. For making final predictions, we designed two strategies on the basis of EERNN framework. The first one was a straightforward yet effective strategy, i.e., EERNNM with Markov property, in which the students’ next performance only depended on current states. Comparatively, the second was a more sophisticated one, EERNNA with Attention mechanism, which tracked the focused student states based on similar exercises in the history. In this way, EERNN could naturally predict student’s future performance given her exercising records.

In EERNN model, we summarized and tracked each student’s knowledge states on all concepts in one integrated hidden vector. Thus, it could not explicitly explain how much she had mastered a certain knowledge concept (e.g., “Function”), which meant that the interpretability of EERNN was not satisfying enough. Therefore, in this paper, we extend EERNN and propose an explainable Exercise-aware Knowledge Tracing (EKT) framework to track student states on multiple explicit concepts simultaneously. Specifically, we extend the integrated state vector of each student to a knowledge state matrix that updates over time, where each vector represents her mastery level of a certain concept. At each exercising step of a certain student, we develop a memory network to quantify the different impacts on each knowledge state when she solves a specific exercise. We also implement two EKT based prediction models following the proposed strategies in EERNN, i.e., EKTM with Markov property and EKTA with Attention mechanism. Finally, we conduct extensive experiments and evaluate both EERNN and EKT frameworks on a large-scale real-world dataset. The experimental results in both general and cold-start scenarios clearly demonstrate the effectiveness of two proposed frameworks in student performance prediction as well as the superior interpretability of EKT framework.

2 RELATED WORK

The related work can be classified into following categories from both educational psychology (i.e., cognitive diagnosis and knowledge tracing) and data mining (i.e., matrix factorization and deep learning methods) areas.

Cognitive Diagnosis. In the domain of educational psychology, cognitive diagnosis is a kind of techniques that aims to predict student performance by discovering student states from the exercising records [10]. Generally, traditional cognitive diagnostic models (CDM) could be grouped into two categories: continuous models and discrete ones. Among them, item response theory (IRT), as a typical continuous model, characterized each student by a variable, i.e., a latent trait that describes the integrated knowledge state, from a logistic-like function [11]. Comparatively, discrete models, such as Deterministic Inputs, Noisy-And gate model (DINA), represented each student as a binary vector which denoted whether she mastered or not the knowledge concepts required by exercises with a given Q-matrix (exercise-knowledge concept matrix) prior [9]. To improve prediction effectiveness, many variations of CDMs were proposed by
combining learning information [3], [33], [48]. For example, learning factors analysis (LFA) [3] and performance factors analysis (PFA) [33] incorporated the time factor into the modeling. Liu et al. [27] proposed FuzzyCDM that considered both subjective and objective exercise types to balance precision and interpretability of the diagnosis results.

Knowledge Tracing. Knowledge tracing is an essential task for tracing the knowledge states of each student separately, so that we can predict her performance on future exercising activities, where the basic idea is similar to the typical sequential behavior mining [28], [37]. In this task, Bayesian knowledge tracing (BKT) [7] was one of the most popular models. It was a knowledge-specific model which assumed each student’s knowledge states as a set of binary variables, where each variable represented she had “mastered” or “non-mastered” on a specific concept. Generally, BKT utilized a Hidden Markov Model [35] to update knowledge states of each student separately followed by her performance on exercises. On the basis of BKT, many extensions were proposed by considering other factors, e.g., exercise difficulty [31], multiple knowledge concepts [50] and student individuals [52]. One step further, to improve the prediction performance, other researchers also suggested to incorporate some cognitive factors into traditional BKT model [19], [20].

Matrix Factorization. Recently, researchers have attempted to leverage matrix factorizations from data mining field for student performance prediction [43], [44]. Usually, the goal of this kind of research is to predict the unknown scores of students as accurate as possible given a student-exercise performance matrix with some known scores. For example, Thai et al. [43] leveraged matrix factorization models to project each student into a latent vector that depicted students’ implicit knowledge states, and further proposed a multi-relational adaption model for the prediction in online learning systems. To capture the changes of student’s exercising process, some additional factors are incorporated. For example, Thai et al. [42] proposed a tensor factorization approach by adding additional time factors. Chen et al. [5] noticed the effects of both Learning theory and Ebbinghaus forgetting curve theory and incorporated them into a unified probabilistic framework. Teng et al. [41] further investigated the effects of two concept graphs.

Deep Learning Methods. Learning is a very complex process, where the mastery level of students on different knowledge concepts is not updated separately but related to each other. Along this line, inspired by the remarkable performance of deep learning techniques in many applications [28], such as speech recognition [14], image classification [22], natural language processing [29], network graph embedding [8] and also educational applications like question difficulty prediction [18], some researchers attempted to use deep models for student performance prediction [34], [53]. Among these work, deep knowledge tracing (DKT) was the first attempt, to the best of our knowledge, to utilize recurrent neural networks (e.g., RNN and LSTM) to model student’s exercising process for predicting her performance [34]. Moreover, by bridging the relationship between exercises and knowledge concepts, Zhang et al. [55] proposed a dynamic key-value memory network model for improving the interpretability of the prediction results, and Chen et al. [4] incorporated the knowledge structure information for dealing with the data sparsity problem in knowledge tracing. Experimental results showed that deep models had achieved a great success.

Our work differs from the previous studies as follows. First, existing approaches mainly focus on exploiting students’ historical exercising records for their performance prediction, while ignoring the important effects of exercise materials (e.g., knowledge concepts, exercise content). To the best of our knowledge, this work is the first comprehensive attempt that fully explores both student’s exercising records and the exercise materials. Second, previous studies follow the common sense that student’s next performance only depends on the current states, while our work deeply captures the focused information of students in the history by a novel attention mechanism for improving the prediction. Third, we can well handle the cold-start problem by incorporating exercise correlations without any retraining. Last but not least, our work can achieve good prediction results with interpretability, i.e., we can explain the change of student’s knowledge states on explicit knowledge concepts, which is beneficial for many real-world applications, such as explainable exercise recommendation.

3 Problem and Solution Overview

In this section, we first formally define the problem of student performance prediction in intelligent education. Then, we will give the overview of our study.

Problem Definition. In an intelligent education system, suppose there are $|S|$ students and $|E|$ exercises, where students do exercises individually. We record the exercising process of a certain student as $s = \{ (e_1, r_1), (e_2, r_2), \ldots, (e_T, r_T) \}$, $s \in S$, where $e_t \in E$ represents the exercise practiced by student $s$ at her exercising step $t$ and $r_t$ denotes the corresponding score. Generally, if student $s$ answers exercise $e_t$ right, $r_t$ equals to 1, otherwise $r_t$ equals to 0. In addition to the logs of student’s exercising process, we also consider the materials of exercises (some examples are shown in Fig. 1). Formally, for a certain exercise $e$, we describe it by the text content, which is combined with a word sequence as $e = \{ w_1, w_2, \ldots, w_M \}$. Also, the exercise $e$ contains its corresponding knowledge concept $k$ coming from all $K$ concepts. Please note that each exercise may contain multiple concepts, e.g., $e_5$ in Fig. 1 has two concepts “Function” and “Inequality”. Without loss
of generality, in this paper, we represent each student’s exercising record as $s = \{(e_1, r_1), (e_2, r_2), \ldots, (e_T, r_T)\}$ or $s = \{(k_1, e_1, r_1), (k_2, e_2, r_2), \ldots, (k_T, e_T, r_T)\}$, where the former one does not consider the knowledge concept information. Then the problem can be defined as:

**Definition 1. (Student Performance Prediction Problem).**

Given the exercising logs of each student and the materials of each exercise from exercising step 1 to $T$, our goal is two-fold: (1) track the change of her knowledge states and estimate how much she masters all $K$ knowledge concepts from step 1 to $T$; (2) predict the response score $\hat{r}_{T+1}$ on the next candidate exercise $e_{T+1}$.

**Solution overview.** An overview of the proposed solution is illustrated in Fig. 2. From the figure, given all students’ exercising records $S$ with the corresponding exercise materials $E$, we propose a preliminary Exercise-Enhanced Recurrent Neural Network (EERNM) framework and an improved Exercise-aware Knowledge Tracing (EKT) framework. Then, we conduct two applications with the trained models. Specifically, EERNM directly achieves the goal of student performance prediction on future exercises given her sequential exercising records, and EKT is further capable of explicitly tracking the knowledge acquisition of students.

## 4 EERN: Exercise-Enhanced Recurrent Neural Network

In this section, we first describe the Exercise-Enhanced Recurrent Neural Network (EERN) framework that could directly achieve the primary goal of predicting student performance. EERN is a general framework where we can predict student performance based on different strategies. Specifically, as shown in Fig. 3, we propose two implementations under EERN, i.e., EERNM with Markov property and EERNNA with Attention mechanism. Therefore, both models have the same process for modeling student’s exercising records yet follow different prediction strategies.

### 4.1 Modeling Process of EERN

The goal of the modeling process in EERN framework is to model each student’s exercising sequence (with the input notation $s$). From Fig. 3, this process contains two main components, i.e., Exercise Embedding (marked orange) and Student Embedding (marked blue).

**Exercise Embedding.** As shown in Fig. 3, given the exercising process of a student $s = \{(e_1, r_1), (e_2, r_2), \ldots, (e_T, r_T)\}$, Exercise Embedding learns the semantic representation/encoding $x_i$ of each exercise from its text content $e_i$ automatically.

Fig. 4 shows the detailed techniques of Exercise Embedding. It is an implementation of a recurrent neural network, which is inspired by the typical one called Long Short-Term Memory (LSTM) [14] with minor modifications. Specifically, given the exercise’s content with the $M$ words sequence $e_i = \{w_1, w_2, \ldots, w_M\}$, we first take Word2vec [29] to transform each word $w_i$ in exercise $e_i$ into a $d_w$-dimensional pre-trained word embedding vector. After the initialization, Exercise Embedding updates the hidden state $v_m \in \mathbb{R}^{d_v}$ of each word $w_m$ at the $m$-th word step with the previous hidden state $v_{m-1}$ in a formula as:

$$
\begin{align*}
    i_m &= \sigma(Z_{ww}^E w_m + Z_{we}^E v_{m-1} + b_E^i), \\
    f_m &= \sigma(Z_{ww}^F w_m + Z_{we}^F v_{m-1} + b_E^f), \\
    o_m &= \sigma(Z_{ww}^O w_m + Z_{we}^O v_{m-1} + b_E^o), \\
    c_m &= f_m \cdot c_{m-1} + i_m \cdot \tanh(Z_{wc}^E w_m + Z_{ve}^E v_{m-1} + b_E^c), \\
    v_m &= o_m \cdot \tanh(c_m),
\end{align*}
$$

where $i_m, f_m, o_m$ represent the three gates, i.e., input, forget, output, respectively, $c_m$ is a cell memory vector. $\sigma(x)$ is the non-linear sigmoid activation function and $\cdot$ denotes the element-wise product between vectors. Besides, the input weighted matrices $Z_{we}^E \in \mathbb{R}^{d_e \times d_w}$, recurrent weighted matrices $Z_{we}^F \in \mathbb{R}^{d_e \times d_e}$ and bias weighted vectors $b_E^c \in \mathbb{R}^{d_e}$ are all the network parameters in Exercise Embedding.

Traditional LSTM model learns each word representation by a single direction network and can not utilize the contextual texts from the future word token [40]. To make full use of the contextual word information of each exercise, we build a bidirectional LSTM considering the word sequence in both forward and backward directions. As illustrated in Fig. 4, at each word step $m$, the forward layer with hidden word state $\tilde{v}_m^f$ is computed based on both the previous hidden state $\tilde{v}_{m-1}^f$ and the current word $w_m$; while the backward layer updates hidden word state $\tilde{v}_m^b$ with the future hidden state $\tilde{v}_{m+1}^b$ and the current word $w_m$. As a result, each word’s hidden representation
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4.2 Prediction Output of EERNM

After modeling the exercising process of each student from exercising step 1 to \( T \), we now introduce the detailed strategies of predicting her performance on exercise \( e_{T+1} \). Psychological results have claimed that student-exercise performances depend on both the student states and the exercise characteristics [10]. Following this finding, we propose two implementations of prediction strategies under EERNM framework, i.e., a straightforward yet effective EERNNM with Markov property and a more sophisticated EERNNA with Attention mechanism, based on both the learned student states \( \{h_1, h_2, \ldots, h_T\} \) and the exercise embeddings \( \{x_1, x_2, \ldots, x_T\} \).

**EERNM with Markov Property.** For a typical sequential prediction task, Markov property is a well understood and widely used theory which assumes that the next state depends only on the current state and not on the sequences that precede it [35]. Given this theory, as shown in Fig. 3(a), when an exercise \( e_{T+1} \) at step \( T+1 \) is posted to a student, EERNNM (1) assumes that the student applies current state \( h_T \) to solve the exercise; (2) leverages Exercise Embedding to extract the semantic representation \( \tilde{x}_{T+1} \) from exercise text \( e_{T+1} \); (3) predicts her performance \( \tilde{r}_{T+1} \) on exercise \( e_{T+1} \) as following formulas:

\[
y_{T+1} = ReLU(W_1 \cdot [h_T \oplus \tilde{x}_{T+1}] + b_1),
\]

\[
\tilde{r}_{T+1} = \sigma(W_2 \cdot y_{T+1} + b_2),
\]

where \( y_{T+1} \in \mathbb{R}^{d_y} \) denotes the overall presentation for prediction at \( (T+1) \)-th exercising step. \( \{W_1, W_2, b_1, b_2\} \) are the parameters. \( \sigma(x) \) is the Sigmoid activation function \( \sigma(x) = \frac{1}{1 + \exp(-x)} \) and \( \oplus \) is the concatenation operation.

EERNM presents a straightforward yet effective way for student performance prediction. However, in most cases, since the current student state \( h_T \) is the last hidden state of the LSTM-based architecture in Student Embedding, it may discard some important information when the sequence is too long, which is called the Vanish problem [17]. Thus, the learned student state by EERNM may be somewhat unsatisfactory for future performance prediction. To address
this question, we further propose another sophisticated prediction strategy, i.e., EERNNA with Attention mechanism, to enhance the effects of important student states in the exercising process for prediction.

**EERNNA with Attention Mechanism.** In Fig. 1, students may get similar scores on similar exercises, e.g., student $s_1$ answers the exercises $e_1$ and $e_3$ right due to the possible reason that the both exercises are similar because of the same knowledge concept “Function”.

According to this observation, as the red lines illustrated in Fig. 3(b), EERNNA assumes that the student state at $(T + 1)$-th exercising step is a weighted sum aggregation of all historical student states based on the correlations between exercise $e_{t+1}$ and the historical ones $\{e_1, e_2, \ldots, e_T\}$. Formally, at next step $T + 1$, we define the attentive state vector $h_{att}$ of student as:

$$h_{att} = \sum_{j=1}^{T} \alpha_j h_j, \quad \alpha_j = \cos(x_{T+1}, x_j),$$

where $x_j$ is the exercise embedding at $j$-th exercising step and $h_j$ is the corresponding student state in the history. Cosine Similarities $\alpha_j$ are denoted as the attention scores for measuring the importance of each exercise $e_j$ in the history for new exercise $e_{T+1}$.

After obtaining attentive student state at step $T + 1$, EERNNA predicts the performance of this student on exercise $e_{T+1}$ with the similar operation in Eq. (5) by replacing $h_T$ with $h_{att}$.

Particularly, through Exercise Embedding, our attention scores $\alpha_j$ not only measure the similarity between exercises from syntactic perspective but also capture the correlations from semantic view (e.g., difficulty correlation), benefiting student state representation for student performance prediction and model explanation. We will conduct experimental analysis for this attention mechanism.

### 4.3 Model Learning

The whole parameters to be updated in both proposed models mainly come from three parts, i.e., parameters in Exercise Embedding $\{Z^E_{w_0}, Z^E_{e_0}, b^E_1\}$, parameters in Student Embedding $\{Z^S_{w_s}, Z^S_{e_s}, b^S_1\}$ and parameters in Prediction Output $\{W_s, b_s\}$. The objective function of EERNNA is the negative log likelihood of the observed sequence of student’s exercising process from step 1 to $T$. Formally, at $t$-th step, let $\tilde{r}_t$ be the predicted score on exercise $e_t$ through EERNN framework, $r_t$ is the actual binary score, thus the overall loss for a certain student is defined as:

$$\mathcal{L} = -\sum_{t=1}^{T} (r_t \log \tilde{r}_t + (1 - r_t) \log (1 - \tilde{r}_t)).$$

The objective function is minimized by the Adam optimization [21]. Details will be specified in the experiments.

### 5 EKT: Exercise-aware Knowledge Tracing

EERNNA can effectively deal with the problem of predicting student performance on future exercises. However, during the modeling, we just summarize and track a student’s knowledge states on all concepts in one integrated hidden vector (i.e., $h_t$ in Eq. (4)), and this is sometimes unsatisfied because it is hard to explicitly explain how much she has mastered a certain knowledge concept (e.g., “Function”).

In fact, during the exercising process of a certain student, when an exercise is given, she usually applies her relevant knowledge to solve it. Correspondingly, her performance on the exercise, i.e., whether or not she answers it right, can also reflect how much she has mastered the knowledge [7], [53]. For example, we could conclude that the student in Fig. 1 has well mastered the “Function” and “Inequality” concepts but needs to devote more energy to the less familiar one “Probability”. Thus, it is valuable if we could remind her about this finding so that she could prepare the target training about “Probability” herself. Based on the above understanding, in this section, we further address the problem of tracking student’s knowledge acquisition on multiple explicit concepts. We extend the current EERNNA and propose an explainable Exercise-aware Knowledge Tracing (EKT) framework by incorporating the information of knowledge concepts existed in each exercise.

Specifically, we extend the knowledge states of a certain student from the integrated vectorial representation in EERNN, i.e., $h_t \in \mathbb{R}^{d_h}$, to a matrix with multiple vectors, i.e., $H_t \in \mathbb{R}^{d_h \times K}$, where each vector represents how much she has mastered an explicit knowledge concept (e.g., “Function”). Meanwhile, in EKT, we assume the student’s knowledge state matrix $H_t$ changes over time influenced by both text content (i.e., $e_t$) and knowledge concept (i.e., $k_i$) of each exercise. Fig. 5 illustrates the overall architecture of EKT. Comparing it with EERNN (Fig. 3), besides the Exercise Embedding module, another module (marked green), which we called Knowledge Embedding, is incorporated in the modeling process. With this additional facility, we can naturally extend the proposed prediction strategies EERNMM and EERNNA to EKT with Markov property and EKTA with Attention mechanism, respectively. In the following, we first introduce the way to implement the Knowledge Embedding module, followed by the details of EKTM and EKTA.

**Knowledge Embedding.** Given the student’s exercising process $s = \{(k_1, e_1, r_1), (k_2, e_2, r_2), \ldots, (k_T, e_T, r_T)\}$, the goal of Knowledge Embedding is to explore the impacts of each exercise on improving student states from this exercise’s knowledge concepts $k_i$ and this impact weight is denoted by $\beta_i$. Intuitively, at step $t$, if this exercise is related to the $i$-th concept, we can just consider the impact of this specific concept without others’ influences, i.e., $\beta_i = 1$ if $j = i$, otherwise $\beta_j = 0, 0 \leq i, j \leq K$. However, in educational psychology, some findings indicate that the knowledge concepts in one specific domain (e.g., mathematics) are not isolated but contain correlations with each other [53]. Hence, in our modeling, we assume that learning one concept, for a certain student, could also affect the acquisition of other concepts. Thus, it is necessary to quantify these correlation weights among all $K$ concepts in the knowledge space.

Along this line, as the module (marked in green) shown in Fig. 5, we investigate and propose a static memory network for calculating knowledge impact $\beta_i$. Specifically, it is inspired by the memory-augmented neural network [15], [39], which has been successfully adopted in many applications, such as question answering [49], language modeling [24] and one-shot learning [36]. It usually contains an external memory component that can store the stable.
information. Then, during the sequence, it can read each input and write the storage information from the memory for influencing its long-term dependency. Considering this property, we set up a memory module with a matrix $M \in \mathbb{R}^{d_k \times K}$ to store the representations of $K$ knowledge concepts by $d_k$-dimensional features.

Mathematically, at each exercising step $t$, when an exercise $e_t$ comes, we first set its knowledge concept to be a one-hot encoding $k_t \in \{0, 1\}^K$ with the dimension equaling to the total number $K$ of all concepts. Since the intuitive one-hot representation is too sparse for modeling [13], we utilize an embedding matrix $W_k \in \mathbb{R}^{K \times d_k}$ to transfer the initial knowledge encoding $k_t$ into a low-dimensional vector $v_t \in \mathbb{R}^{d_k}$ with continuous values as: $v_t = W_k^T k_t$.

After that, the impact weight $\beta_t^i$ ($1 \leq i \leq K$) on the $i$-th concept from exercise $e_t$’s knowledge concept $k_t$ is further calculated by the softmax operation of the inner product between the given concept encoding $v_t$ and each knowledge memory vector in the memory module $M_i$ as:

$$
\beta_t^i = \text{Softmax}(v_t^T M_i) = \frac{\exp(v_t^T M_i)}{\sum_{k=1}^{K}(\exp(v_t^T M_k))}.
$$

**(Student Embedding).** With the knowledge impact $\beta_t$ of each exercise, an improved Student Embedding will further specify each knowledge acquisition of a certain student during her exercising process. Thus, EKT could naturally track student’s knowledge states on multiple concepts simultaneously, benefiting the interpretability.

Methodology-wise, at the exercising step $t$, we also update one of a student’s specific knowledge state $H_t^i \in \mathbb{R}^{d_k}$ ($1 \leq i \leq K$) by the LSTM network after she answers the exercise $e_t$:

$$
H_t^i = \text{LSTM}(\tilde{x}_t^i, H_{t-1}^i; \theta_{H_t}),
$$

here we replace the original input $\tilde{x}_t$ with a new joint one $\tilde{x}_t^i$ which is computed in the formula as: $\tilde{x}_t^i = \beta_t^i \tilde{x}_t$, where $\tilde{x}_t$ is the same encoding that combines the effects of both the exercise $e_t$ she practices and the score $r_t$ she gets (Eq. (2)).

After modeling student’s historical exercising process, in the prediction part of EKT, the performance of each student is predicted based on three types of factors, i.e., her historical knowledge states $\{H_1, H_2, \cdots, H_T\}$, the embeddings of the exercises she practiced $\{x_1, x_2, \cdots, x_T\}$, and the materials $k_{T+1}$ and $e_{T+1}$ of the candidate exercise.

**EKTM with Markov property.** Similar to EERNNM, EKT follows the straightforward Markov property that assumes student performance on further exercise only depends on her current knowledge state $H_T$. Specifically, as shown in Fig. 5(a), when the exercise $e_{T+1}$ is posted, EKTM first integrates student’s mastery on this exercise with its knowledge impacts $\beta_{T+1}$ as:

$$
s_{T+1} = \sum_{i=1}^{K} \beta_{T+1}^i H_T^i,
$$

then predicts her performance $\hat{x}_{T+1}$ by changing the similar operation in Eq. (5) as:

$$
y_{T+1} = \text{ReLU}(W_3 \cdot [s_{T+1} \oplus x_{T+1}] + b_3),
\hat{r}_{T+1} = \sigma(W_4 \cdot y_{T+1} + b_4),
$$

where $\{W_3, W_4, b_3, b_4\}$ are the parameters.

**EKTA with Attention mechanism.** EKTA also follows the sophisticated Attention mechanism to enhance the effect of important states in the history for predicting student’s future performance, which is shown in Fig. 5(b). Here, a small modification compared with EERNNA is that we extend the attentive state vector $H_{att}$ of student (Eq. (6)) to a matrix one $H_{att}$, where each knowledge state slot $H_{att}^i$ ($1 \leq i \leq K$) can be computed as:

$$
H_{att}^i = \sum_{j=1}^{T} \alpha_j H_j^i, \quad \alpha_j = \cos(x_{T+1}, x_j).
$$

Then, EKTA generates the prediction on exercise $e_{T+1}$ with Eq. (10) and Eq. (11) by replacing $H_T$ with $H_{att}$.

After that, we can train EKT by minimizing the same objective function in Eq. (7). Please note that during our modeling, EKT framework could enhance the interpretability of the learned matrix $H_t$ through the impact weight $\beta_t$, which could tell us the mastery levels on each concept of a certain student at exercising step $t$, and we will discuss the details in the next section.


6 APPLICATION

After discussing the training stage of both EERNN and EKT, we now present the way to apply EERNN and EKT based models to achieve two motivating goals, i.e., student performance prediction and knowledge acquisition tracking.

Student Performance Prediction. As one of the primary applications in intelligent education, student performance prediction helps provide better proactive services to students, such as personalized exercise recommendation [23]. Both EERNN and EKT can directly achieve this goal.

Specifically, with the trained EERNN (EKT) model $\mathcal{M}$, given an individual student and her exercising record $s^p = \{(k_1^p, e_1^p, r_1^p), (k_2^p, e_2^p, r_2^p), \ldots, (k_T^p, e_T^p, r_T^p)\}$, we could predict her performance on the next exercise $e_{T+1}^p$ by the following steps: (1) apply model $\mathcal{M}$ to fit her exercising process $s^p$ to get the student state at the step $T$ for prediction (i.e., $h_T^p$ in EERNN or $H_T^p$ in EKT); (2) extract exercise representation $x_{T+1}^p$ and knowledge impact $\beta_{T+1}$ by Exercise Embedding and Knowledge Embedding; (3) predict her performance $\hat{r}_{T+1}^p$ with Eq. (5) (Eq. (11)). Similarly, EERNN (EKT) generates the prediction by replacing $h_T^p (H_T^p)$ with $h_{att}^p (H_{att})$.

Please note that student $s^p$ can be either any one that exists in the training stage or a new student that never shows up. Equally, exercise $e_i^p$ in $s^p$ can also be either a learned exercise or any new exercise. Specifically, when a new student without any historical record is coming, at step 1, EERNN (EKT) can model her first state $h_1 (H_1)$ and make performance prediction by the non-personalized prior $h_0$ in Fig. 3 ($H_0$ in Fig. 5), i.e., the state generated from all trained student records. After that, EERNN (EKT) can fit her own exercising process and make personalized predictions on the following exercises. Similarly, when a new exercise is coming, Exercise Embedding (Knowledge Embedding) in EERNN (EKT) can learn its representation (impact) only based on its original content (concept). Last but not least, all the prediction part of EERNN (EKT) do not require any model retraining. Therefore, EERNN (EKT) can naturally deal with the cold-start problem when making predictions for new students and new exercises.

Knowledge Acquisition Tracking. It is of great importance to remind students about how much they have mastered each knowledge concept (e.g., with the mastery level ranges from 0 to 1) as they can be motivated to conduct the target training in time for practicing more efficiently [16]. As mentioned earlier, the EKT framework has a good ability to track student’s knowledge acquisition with the learned states $\{H_1, H_2, \ldots, H_T\}$. Inspired by [53], we introduce the way to estimate the knowledge mastery level of students.

In the prediction part, at each step $t$, please note that Eq. (11) predicts student performance on a specific exercise $e_t$ from two kinds of inputs: the student’s integrated mastery for this exercise (i.e., $s_t$) and the individual exercise embedding (i.e., $x_t$). Thus, if we just want to estimate her mastery of the $i$-th specific concept without any exercise input, we can change $s_t$ by her state in $H_t$ on this concept (i.e., $H_t^i$), and meanwhile, omit the input exercise embedding $x_t$. Fig. 6 shows the detailed process of this mastery level estimation on knowledge concepts. Specifically, given a student’s exercising record $s = \{(k_1, e_1, r_1), (k_2, e_2, r_2), \ldots, (k_T, e_T, r_T)\}$, we first obtain her knowledge state $H_t$ at step $t$ by fitting the record from 1 to $t$ with the trained EKT. Then, to estimate her mastery of the $i$-th specific concept, we construct the impact weight $\beta_i = (0, \cdots, 1, \cdots, 0)$, where the value in $i$-th dimension equals to 1, and also extract her knowledge state $H_t^i$ on $i$-th concept by Eq. (10). After that, we can change Eq. (11) and finally estimate her mastery level $l_t^i$ by:

$$y_t^i = ReLU(W_3 : [H_t^i \oplus 0] + b_3),$$

$$l_t^i = \sigma(W_4 : y_t^i + b_4),$$

where $0 = (0, 0, \cdots, 0)$ is a masked exercise embedding with the same dimension as $x_{T+1}$ in Eq. (11). The given input $\{W_3, W_4, b_3, b_4\}$ are the same to those in Eq. (11) without any retraining of EKT.

Moreover, when estimating the knowledge mastery of students by EKT, we can also endow the correspondence between each learnt vector (i.e., in $M$ and $H_i$) and the knowledge concept. Since each vector $H_t^i$ represents the student’s state on a certain concept based on the observation of her exercising record at step $t$, we can infer the concept meaning of this vector according to the changes of its value. For example, if we notice that the change of a student’s mastery level $l_t^i$ (Eq. (13), computed by $H_t^i$) is consistent with her exercising score record on concept “Function”, the corresponding state $H_t$ could be viewed as her knowledge state on “Function”, and correspondingly $M^i$ stores the “Function” information. We will conduct the detailed analysis about this estimation in the experiment section.

7 EXPERIMENTS

In this section, we conduct extensive experiments to demonstrate the effectiveness of our proposed frameworks and their implementations from various aspects: (1) the prediction performance of EERNN and EKT against the baselines; (2) the effectiveness of attention mechanism in EERNNA and EKT; (3) the illustration of tracking student’s knowledge states by EKT; (4) meaningful visualizations for student performance prediction.

7.1 Experimental Dataset

The dataset supplied by iFLYTEK Co., Ltd. was collected from Zhixue\(^1\), a widely-used online learning system, which provided high school students with a large number of exercise resources for exercising. In this paper, we conduct experiments on students’ records on mathematics because the mathematical dataset is currently the largest and most

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(b) Distribution of exercising records

### Table 1

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Original</th>
<th>Pruned</th>
</tr>
</thead>
<tbody>
<tr>
<td># of records</td>
<td>68,337,149</td>
<td>5,996,075</td>
</tr>
<tr>
<td># of students</td>
<td>1,100,726</td>
<td>84,909</td>
</tr>
<tr>
<td># of exercises</td>
<td>1,825,767</td>
<td>15,045</td>
</tr>
<tr>
<td># of knowledge concepts</td>
<td>37</td>
<td>37</td>
</tr>
<tr>
<td># of knowledge features</td>
<td>550</td>
<td>447</td>
</tr>
<tr>
<td>Avg. exercising records per student</td>
<td>65.9</td>
<td></td>
</tr>
<tr>
<td>Avg. content length per exercise</td>
<td>27.3</td>
<td></td>
</tr>
<tr>
<td>Avg. knowledge concepts per exercise</td>
<td>1.12</td>
<td></td>
</tr>
<tr>
<td>Avg. knowledge features per exercise</td>
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</tr>
<tr>
<td>Avg. exercises per knowledge concept</td>
<td>406.6</td>
<td></td>
</tr>
</tbody>
</table>

### 7.2 Experimental Setup

In this subsection, we clarify the implementation details to set up our EERNN and EKT frameworks. Then, we introduce the comparison baselines and evaluation metrics in the experiments.
For better illustration, we list the detailed characteristics of these models in Table 2. More specifically, in the experiments, we used the open source to implement the BKT model\(^3\), and all other models were implemented by ourselves by PyTorch [32] using Python on a Linux server with four 2.0GHz Intel Xeon E5-2620 CPUs and a Tesla K20m GPU. All models were tuned to have the best performance to ensure the fairness.

For comparison, we chose two models from educational psychology, i.e., *Item Response Theory* (IRT), *Bayesian Knowledge Tracing* (BKT), and three data mining models, i.e., *Probabilistic Matrix Factorization* (PMF), *Deep Knowledge Tracing* (DKT), *Dynamic Key-Value Memory Networks* (DKVMN) for comparison. Then, to highlight the effectiveness of Exercise Embedding in our models, we compared our two EERNN based models, i.e., EERNM and EERNNA, and two EKT based models, i.e., EKTM and EKTA, with many baselines from various perspectives. Specifically, we chose two models from educational psychology, i.e., *Item Response Theory* (IRT), *Bayesian Knowledge Tracing* (BKT), and three data mining models, i.e., *Probabilistic Matrix Factorization* (PMF), *Deep Knowledge Tracing* (DKT), *Dynamic Key-Value Memory Networks* (DKVMN) for comparison. Then, to highlight the effectiveness of Exercise Embedding in our models, i.e., validating whether or not it is effective to incorporate exercise texts for the prediction, we introduced two variants, which are denoted as LSTMM and LSTMA. The details of them are as follows:

- **IRT**: IRT is a popular cognitive diagnostic model that models student’s exercising records by a logistic-like function [10].
- **BKT**: BKT is a typical knowledge tracing model which assumes the knowledge states of each student as a set of binary variables and traces them separately with a kind of hidden Markov model [7].
- **PMF**: PMF is a factorization model that projects students and exercises into latent factors [42].
- **DKT**: DKT is a deep learning method that leverages recurrent neural network (RNN and LSTM) to model students’ exercising process for prediction [34]. The inputs are the one-hot encodings of student-knowledge representations.
- **DKVMN**: DKVMN is a state-of-the-art deep learning method that could track student states on multiple concepts [53]. It contains a key matrix to store concept representation and a value matrix for each student to update the states. However, it does not consider the effect of exercise content in the modeling.
- **LSTMM**: LSTMM is a variant of EERNN framework. Here, in the modeling process, we do not embed exercises from their contents, and only represent them as the one-hot encodings with both 2nd-level and 3rd-level knowledge features\(^2\). Then we leverage traditional LSTM to model students’ exercising process. For prediction, LSTMM follows Markov property strategy similar to EERNM.
- **LSTMA**: LSTMA is another variant of EERNN framework which contains the same modeling process as LSTMM. For prediction, LSTMA follows the strategy of Attention mechanism similar to EERNNA.

For better illustration, we list the detailed characteristics of these models in Table 2. More specifically, in the experiments, we used the open source to implement the BKT model\(^3\), and all other models were implemented by ourselves by PyTorch [32] using Python on a Linux server with four 2.0GHz Intel Xeon E5-2620 CPUs and a Tesla K20m GPU. All models were tuned to have the best performance to ensure the fairness.

2. The one-hot representation is a typical manner in many models. We use knowledge features for representation because the number of them is much larger than the 1st-level ones, ensuring the reliability.

7.2.3 Evaluation Metrics

A qualified model for student performance prediction should have good results from both regression and classification perspectives. In this paper, we evaluated the prediction performance of all models using four widely-used metrics in the domain [12], [47], [48], [54].

From the regression perspective, we selected Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), to quantify the distance between predicted scores and the actual ones. The smaller the values are, the better the results have. Besides, we treated the prediction problem as a classification task, where an exercising record with score 1 (0) indicates a positive (negative) instance. Thus, we used two metrics, i.e., Prediction Accuracy (ACC), Area Under an ROC Curve (AUC), for measuring. Generally, the value 0.5 of AUC or ACC represents the performance prediction result by randomly guessing, and the larger, the better.

7.3 Student Performance Prediction

Prediction in General Scenario. In this subsection, we compare the overall performance of all models on student performance prediction. To set up the experiments, we partitioned the dataset from student’s perspective, where the exercising records of each student are divided into training set and testing set with different percentages. Specifically, for a certain student, we used her first 60%, 70%, 80%, 90% exercising records (with the exercises she practiced and the scores she got) as training sets, and the remains were for testing, respectively. We repeated all experiments 5 times and report the average results using all metrics.

Fig. 9 shows the overall results on this task. There are several observations. First, all our proposed EKT based models and EERNN based models perform better than other baseline methods. The results clearly indicate that both EKT and EERNN frameworks can make full use of both exercising records and exercise materials, benefiting the prediction performance. Second, among our proposed models, we find that EKT based models (EKTA, EKTM) generate better results than EERNN based ones (EERNNA, EERNNM), indicating the effectiveness of tracking student’s knowledge states on multiple concepts ($H_i$ in Fig. (5)) than simply modeling them with an integrated encoding ($h_i$ in Fig. (3)). Third, models with Attention mechanism (EKTA, EERNNA, LSTM) outperform those with Markov property (EKTM, EERNNM, LSTMM), which demonstrates that it is effective to track the focused student embeddings based on similar exercises for the prediction. Next, as our proposed models incorporate an independent Exercise Embedding module for extracting exercise encoding directly from the text content, they outperform their variants (LSTMA, LSTMM) and the state-of-the-arts (DKVMN, DKT). This observation also suggests that both EKT and EERNN alleviate the information loss caused by the feature-based or knowledge-specific representations in existing methods. Last but not least, the traditional models (IRT, PMF and BKT) do not perform as well as deep learning models in most cases. We guess a possible reason is that these RNN based deep models can effectively capture the change of student’s exercising process, and therefore, the deep neural network structures are suitable for student performance prediction.

In summary, all above evidences demonstrate that both EKT and EERNN have a good ability to predict student performance by taking full advantage of both the exercising records and exercise materials. Moreover, EKT shows the superiority of tracking student’s multiple knowledge states for the prediction.

Prediction on Cold-start (new) Exercises. The task of predicting student performance often suffers from the “cold start” problem. Thus, in this part, we conduct detailed experiments to demonstrate the performance of our proposed models in this scenario from the exercise’s perspective (Experimental analysis on the cold-start students will be given in the following subsection). Specifically, we selected the new exercises (that never show up in training) in our experiment. Then we only trained each model on 60%, 70%, 80%, 90% training sets, and tested the prediction results on these new exercises in the corresponding testing sets. Please note that, in this experiment, we did not change any training process and just selected the cold-start exercises for testing, thus all the models do not need any retraining.

For better illustration, we reported the experimental results of all deep learning based models under all metrics in Fig. 10. There are also similar observations as Fig. 9, which demonstrate the effectiveness of both EKT and EERNN frameworks once again. Clearly, from the results, EKT based models, especially EKTA, perform the best, followed by EERNN based models. Also, we find that the improvement of them for prediction on new exercises are more significant.

Thus, we can reach a conclusion that both EKT and EERNN with Exercise Embedding module for representing exercises from the text content could effectively distinguish the characteristics of each exercise. Those models are superior to LSTM based models of using feature representation as well as the state-of-the-art DKVMN and DKT of considering knowledge representation. In summary, both EKT and EERNN can deal with the cold-start problem when predicting student performance on new exercises.
that both EKT and EERNN based models can guarantee long at the first few steps. This finding also demonstrates fitting length is 0). Moreover, they all get better predictions performance of new students without any record (i.e., the 0.5), by the prior student state ACC and AUC (much better than the randomly guessing based models obtain about 0.72 (0.65) on the metrics of both knowledge concepts into modeling, which is superior to benefiting the prediction. Second, EKT framework has bet-

conclusions. First, both EKTM and EERNNM are effective forms EERNNA and EERNNM on both metrics, respectively. More-

results when the fitting sequence of student is short (less than 40), however, as the fitting length increases, EERNNA results when the fitting sequence of student is short (less than 40), however, as the fitting length increases, EERNNA performs better gradually. When the length surpasses about 60, EERNNA outperforms EERNNM significantly. More-

Fig. 11(a) and Fig. 11(b) show the comparison results of them. From the figures, all models perform better and better as the length of fitting sequence increases. Specifically, for EERNNA and EERNNM, we find that they generate similar results when the fitting sequence of student is short (less than 40), however, as the fitting length increases, EERNNA performs better gradually. When the length surpasses about 60, EERNNA outperforms EERNNM significantly. More-

7.4 Effectiveness of Attention

As we have clarified in EKT and EERNN, EKTA (EERNNA) with Attention mechanism has a superior ability than EKTM (EERNNM) because the former ones can track the focused student states and enhance the effect of these states when modeling each student’s exercising process. To highlight the effectiveness of attention, we compared the performance of our proposed models, i.e., EKTA (EERNNA) and EKT (EERNNM). To setup this experiment, we first divided the students into 90%/10% partitions, using the 90% students for training and the remaining 10% for testing. Therefore, the testing students never showed up in training. Then, for each student in the testing process, we fitted her exercising sequence by the trained models with different length step t from 0 to 180 and predicted her scores on the last 10% exercises of her exercising records. We also conducted 10-fold cross validation to ensure the reliability of experimental results. Here, we reported the average performance under ACC and AUC metrics.

7.5 Visualizations

Visualization of Knowledge Acquisition Tracking. The im-

important ability of EKT, which is superior to EERNN, is that it can track student’s knowledge states on multiple concepts to further explain the change of knowledge mastery levels of the student, ensuring the interpretability. To make deep analysis about this claim, we visualize the predicted mastery levels (i.e., (t) in Eq. (13)) of a certain student on explicit knowledge concepts at each step during the exercising process. For better visualization, we made some preprocessing as follows. First, we selected 6 most frequent concepts that the student practiced since it was hard to illustrate clearly if we visualize all 37 concepts in one figure. Second, we just logged students’ performance records on the knowledge
In a quadrilateral ABCD, points E, F, G, H lie on edges AB, BC, CD, DA, if edges EH, FG intersect at point M, which line can go through point M?

Given a sequence $e_1, e_2, e_3, e_4, e_5, e_{20}$ denotes the sum of the first n items in the sequence $a_n$. What is the value of n when $S_n$ is equal to its minimum value?

There are two lines a and b. If a is parallel to b, and b lies on the plane C, what is the position relation between line a and plane C?

In a triangle ABC containing angles A, B, C and edges a, b, c, angles A, B, C form an arithmetic sequence and b=2a cos A, what is the shape of the triangle?

If function $f(x) = (ax^2 + bx + c)$ and x is more than 1, when a=1 and b=3, what is the range of the function $f(x)$?

If a, b, c form a geometric sequence, how many zeros does the function $f(x) = ax^2 + bx + c$ have?

In a triangle containing angles A, B, C and edges a, b, c, angles A, B, C form an arithmetic sequence and $b=2a \cos A$, what is the shape of the triangle?

8 Conclusions

In this paper, we presented a focused study on student performance prediction. Specifically, we first proposed a general Exercise-Enhanced Recurrent Neural Network (EERNN) framework exploring both student’s exercising records and the content of corresponding exercises. Though EERNN could effectively deal with the problem of predicting student performance on future exercises, it can not track student’s knowledge states on multiple explicit concepts. Therefore, we then extended EERNN to an Exercise-aware Knowledge Tracing (EKT) framework by further incorporating the information of knowledge concepts existed in each exercise. For making final predictions, we designed two strategies under both EKT and EERNN, i.e., straightforward EKTM (EERNNM) with Markov property and sophisticated EKTA (EERNNA) with Attention mechanism. Comparatively, EKTA (EERNNA) could track the historically focused information of students for making prediction, which was superior to EKTM (EERNNM). Finally, we conducted extensive experiments on a large-scale real-world dataset, and the results demonstrated the effectiveness and interpretability of our proposed models.

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References


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