

Learning states enhanced knowledge tracing: Simulating the diversity in real-world learning process

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ABSTRACT

The Knowledge Tracing (KT) task focuses on predicting a learner's future performance based on the historical interactions. The knowledge state plays a key role in learning process. However, considering that the knowledge state is influenced by various learning factors in the interaction process, such as the exercises similarities, responses reliability and the learner's learning state. Previous models still face two major limitations. First, due to the exercises differences caused by various complex reasons and the unreliability of responses caused by guessing behavior, it is hard to locate the historical interaction which is most relevant to the current answered exercise. Second, the learning state is also a key factor to influence the knowledge state, which is always ignored by previous methods. To address these issues, we propose a new method named Learning State Enhanced Knowledge Tracing (LSKT). Firstly, to simulate the potential differences in interactions, inspired by Item Response Theory (IRT) paradigm, we designed three different embedding methods ranging from coarse-grained to fine-grained views and conduct comparative analysis on them. Secondly, we design a learning state extraction module to capture the changing learning state during the learning process of the learner. In turn, with the help of the extracted learning state, a more detailed knowledge state could be captured. Experimental results on four real-world datasets show that our LSKT method outperforms the current state-of-the-art methods.

1. Introduction

Knowledge Tracing (KT) is a challenging task as the real learning process of humans involves numerous complex learning behaviors and is influenced by various factors, including the learning state during answering, the difficulty of exercises, and tendencies towards guessing (Papamitsiou et al., 2020) and so on. The key to KT task lies in comprehensively simulating these complex factors and effectively modeling them as real-world learning process.

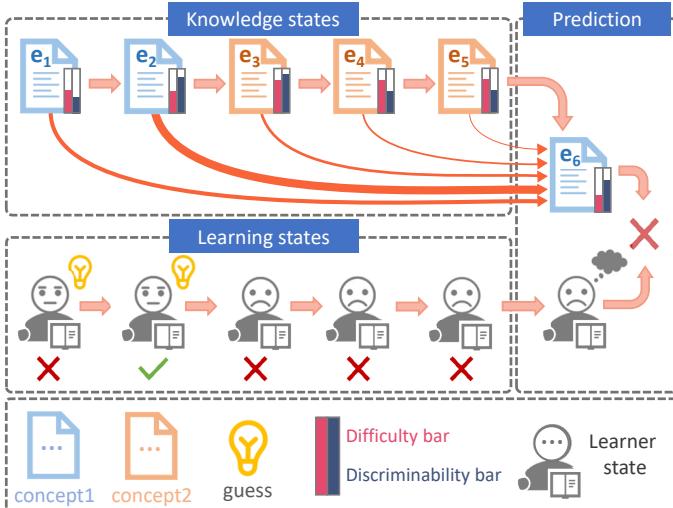
In recent years, the Transformer has shown great potential in the field of KT (Wang et al., 2023, 2024). Many Deep Learning-based Knowledge Tracing (DLKT) models, such as Attention-based DLKT (ATT-DLKT) models, adopts the Transformer to capture the inherent relationships between learners' historical interactions, to accurately estimate their knowledge states. However, these models often have some limitations. Firstly, they usually rely too much on learners' historical performance on similar exercises to assess their knowledge states (Ghosh et al., 2020; Pandey & Karypis, 2019; Yin et al., 2023). Moreover, to alleviate data sparsity problem, many models choose the Knowledge Concepts (KCs) instead of exercises for model training, thus the rich association information between exercises and interactions could be lost. This inevitably increases the difficulty for ATT-DLKT models to accurately identify the key historical

moments and may introduce noise into the model's training. Additionally, due to subjectivity, the unreliable responses caused by learner guessing factors could also inevitably bring in some noise in the interaction. Secondly, the learner's changing learning state is another important factor in the learning process which is always ignored by previous methods. This states is related with the learner's recent performance and can complement the knowledge state, together influencing the learner's next performance. To address these issues, we propose a new ATT-DLKT method named Learning State Enhanced Knowledge Tracing (LSKT). This approach, on one hand, further mines the potential interaction information from exercises and responses to obtain the more precise feature embedding. On the other hand, incorporates the changes in learners' answering process into the capturing of knowledge states. Thereby the performance of our model could be improved.

To better illustrate the above points, we provide a simple example in Figure 1. Figure 1(a) depicts a scenario where a learner answering six consecutive exercises, revealing two main factors influencing learner performance: knowledge state and learning state. Although exercises e_1 and e_2 involve the same knowledge concepts, the various factors including differences difficulty in exercise, discriminability in exercises and the learner's learning state all could affect the performance. From the traditional perspective of knowledge state, exercise e_2 , which shares more similarities in influencing factors with e_6 , would provide more valuable predictions for e_6 ; indicating that e_6 is more likely to be predicted as correct. However, even if e_2 is answered correctly, there still

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(a) Motivation diagram

Timeline	Knowledge Concept	Correct
00:00:25	Square Root	✗
00:01:07	Square Root	✓
00:01:33	Median	✗
00:02:50	Median	✗
00:03:12	Median	✗
00:03:21	Square Root	✗

(b) A learning segment in ASSIST12

Figure 1: Figure (a) illustrates the learning process of a learner. As shown in the figure, during the process of answering these six exercises, the learner is influenced by many factors. We need to observe the learner's performance in e_1 to e_5 , infer their latent knowledge state and learning state, and consider both aspects to predict the learner's performance in exercise e_6 . Figure (b) shows a real slice of the ASSIST12 dataset. It demonstrates that recent learning states have an impact on subsequent performance, even though different concepts are involved, which should be taken into account.

could be possibilities of lucky guesses. Therefore, only relying the similarity may the prediction on e_6 be wrong. Furthermore, the learning state is also a crucial factor which could influence the learner performance. From the perspective of learning state evolution, poor performance on exercises e_1 - e_5 may lead to a decline in the learner's learning state, which could affect their performance on e_6 . In fact, the real answer in e_6 is incorrectly, which implies that during model training, we need to fully consider the knowledge states and learning states to make the model closer to the real-world answering process. Figure 1(b) shows a real slice from the ASSIST12 dataset, detailing the information of e_1 - e_6 as depicted in the left panel. From this slice, it's evident that even with different adjacent interaction knowledge concepts, a learner's recent performance could influence their future performance. This observation is also supported by data analysis in literature (Cui et al., 2023). However, past studies often overlooked the complex factors during the answering process. This prompts us to consider how to effectively model these factors to fully utilize the model's potential, capturing more fine-grained changes in knowledge states, and thus more realistically reflecting the learner's answering process.

To address the issues mentioned above, we proposed LSKT based on ATT-DLKT model. There are three main contributions in this method. Firstly, three feature embedding methods are designed from coarse-grained to fine-grained inspired by IRT paradigm. By combining the potential differences in interactions, the model could not only mitigate the overfitting problem, but also capture the refined difference between interactions. Additionally, we also explored the impact of different embedding paradigm on the performance of the model. Secondly, to extract the changing learning state

during the learning process, due to the ability of natural capturing capability of the interaction information within each moment, the causal convolution layers with different receptive field sizes are leveraged. In this way, the short-term changes and possible patterns in the learning process can be captured, which were overlooked by previous ATT-DLKT models. Thirdly, considering that the learning state is a key fact to influence the knowledge states, we aim to incorporate the learning state into the process of extracting knowledge states, and then a learning state-enhanced knowledge state extraction module is designed.

In summary, our LSKT method could integrate global contextual information, capture long-range dependencies, and introduce sparse attention to the learning state. In this way, the detailed knowledge states and learning states are captured jointly without introducing additional noise and the key contributions are as follows:

The key contributions can be summarized as follows:

- (1) We reveal a potential issue in ATT-DLKT model, which relies heavily on learners' past performances of similar exercises to assess their knowledge state, while failing to adequately consider the dynamic changes in learning state. By integrating the consideration of both states, the model's predictive accuracy and applicability can be significantly improved, making it more consistent with actual learning environments.
- (2) Inspired by IRT, three different personalized level on interaction embedding is designed and compared, simulating realistic differences between interactions. This design not only alleviates the issue of model overfitting caused by data sparsity but also enhances the model's performance and interpretability.

- (3) We proposed a novel learning state extraction module which always ignored by previous methods. This module could capture the learner's learning patterns over multiple time scales during the answering process, so it can effectively represent the learner's learning state at history answer time.
- (4) To capture the precise knowledge state, a learning state-enhanced knowledge state extraction module has been proposed. This module achieves more fine-grained knowledge state by paying sparse attention to the learning states in the process of tracing knowledge states.

The subsequent sections of this article are organized as follows: The second part reviews and analyzes related work. The third part defines KT problems and introduces the specific approach of our model (LSKT). The fourth part reports the experimental results on four public datasets and discusses and summarizes our method.

2. Related work

2.1. Traditional knowledge tracing

Probabilistic models and logical models were two categories of early knowledge tracing models. Probabilistic models used Markov processes (HMM) (Ghahramani, 2001). The Bayesian Knowledge Tracing (BKT) method was a classic example of this (Corbett & Anderson, 1994). This method was proposed by Corbett and Anderson. In this method, the mastery state of knowledge points was modeled as a binary variable (mastered/not mastered), and the learning process was modeled as discrete transitions from the not mastered state to the mastered state. With further research on BKT, subsequent studies incorporated more influencing factors, such as temporal differences in data (Zhu et al., 2018), hierarchical relationships between knowledge points (Käser et al., 2017), exercise difficulty (Pardos & Heffernan, 2011), etc. logical models were based on logical functions and used continuous distributions instead of discrete probabilities to represent learners' knowledge states, thus better capturing learning intensity. The basic principle involved calculating the probability of correctly answering exercises based on learner learning ability parameters and exercise parameters (such as difficulty and discrimination). Performance Factors Analysis (PFA) (Pavlik Jr et al., 2009) and Learning Factors Analysis (LFA) (Cen et al., 2006) were two classic logical models for knowledge tracing. While these traditional knowledge tracing models possess strong interpretability, they often exhibit certain limitations and biases as they rely on domain knowledge annotated by experts as input features. Such models tend to be somewhat one-sided and constrained, making it challenging to fully uncover the hidden information in the data. Consequently, the predictive performance of early models is typically subpar.

Deep learning is getting a lot of attention from researchers because of its excellent ability to extract features. This has led to a new field called Deep Learning Knowledge Tracing (DLKT). Currently, DLKT models mainly adopt three network architectures: Recurrent Neural Networks

(RNNs) (Shen et al., 2021), Memory Networks (Abdelrahman & Wang, 2019), and Attention Networks (Choi et al., 2020). Deep Knowledge Tracing (DKT) (Piech et al., 2015a) was among the first models to base knowledge tracing on deep learning, with one common strategy involving the use of Recurrent Neural Networks. In the DKT model, the hidden units of the RNN were utilized to represent the learner's knowledge state, which was updated as the learner's answering behavior evolved. Another approach was the Dynamic Key-Value Memory Networks (DKVMN) (Zhang et al., 2017), which employed memory networks to depict the learner's knowledge state. This involved using static "key" matrices to represent fixed knowledge concepts and dynamic "value" matrices to reflect the progression of knowledge states. However, the efficacy of DKT and DKVMN was found to be inadequate when dealing with sparse historical data and limited interactions between learners and exercises. To counter this challenge, Pandey et al. introduced a knowledge tracing framework based on self-attention mechanisms, termed Self-Attentive Knowledge Tracing (SAKT) (Pandey & Karypis, 2019). This method was capable of recognizing the state of specific knowledge based on learners' past interactions with exercises and making predictions accordingly.

2.2. Transformer-based knowledge tracing

In recent years, the outstanding performance of Transformer models in fields such as NLP and multimodal information processing (Wang et al., 2021b; Alaparthi & Mishra, 2020; Qian et al., 2023) has sparked researchers' interest in their application to the field of KT. Early studies, such as (Pandey & Karypis, 2019), primarily employed the self-attention mechanism to capture learners' historical learning in order to infer their knowledge state. However, due to significant differences between KT datasets and natural language data, these models did not surpass the performance of traditional DLKT models, such as DKT and DKVMN. Recent research has started to tackle this issue, with models like AKT (Ghosh et al., 2020), DTransformer (Yin et al., 2023), and FKT (Huang et al., 2024). AKT improved model performance by incorporating a monotonic attention mechanism to model learners' forgetting behavior and using embeddings from the Rasch model to capture differences among problems. DTransformer introduced contrastive learning to maintain the stability of knowledge states, alleviating the information bias issues observed in earlier studies. FKT adopted an encoder-decoder-predictor framework and integrated speed prediction as an additional task, enabling fine-grained knowledge tracing. These latest studies have focused on the characteristics of learner-item interaction data, enhancing Transformer-based KT methods, not only improving model performance but also advancing the application of Transformer models in the KT domain.

However, despite efforts by studies like AKT and FGKT (Mao et al., 2023) to consider the actual differences between exercises, limitations persist. For instance, AKT had only distinguished exercises with the same concept by simulating exercise difficulty, but considering only exercise

difficulty information could not fully simulate the subtle differences between exercises, thereby limiting the model's development potential. FGKT uses three traditional fusion functions to model the differences between exercises and concepts, but its lack of theoretical basis makes the model's interpretability poor. To address these issues, our LSKT designs three different granularity differential exercise and interaction embeddings based on item response theory as inputs to the model, and conducted experimental comparisons, thereby improving the performance and interpretability of the model. Additionally, these models had often overlooked an important factor in the learning process, namely, the changes in learners' learning states. Our LSKT introduces consideration of learning states into the process of tracing learners' knowledge states, and combines the two states to jointly predict learners' future exercise performance.

3. METHODOLOGY

This section will introduce our LSKT model. Firstly, the KT task will be clearly defined. Then, we'll provide an overview of LSKT's architecture and detail the three different feature embedding methods we've designed. Next, the learning state extraction module will be introduced and the knowledge state extraction module with enhanced learning states will be discussed in depth. Finally, the final prediction results will be generated through a prediction layer.

3.1. Problem definition

In this section, we present the definition of the KT task and summarize the main parameters' symbols utilized throughout the paper in Table 1. In practical learning scenarios, learners typically answer exercises in the recommended order of the educational system. This interaction process can be represented as $K = \{k_1, k_2, \dots, k_n\}$, where $n \in \mathbb{N}^+$ represents the number of exercises. For a specific learner, the interaction with exercises can be represented as a triplet $k_t = (e_t, c_t, r_t)$, where $e_t \in \mathbb{N}^+$ and $c_t \in \mathbb{N}^+$ denote the exercise index and concept index at time t , respectively, and $r_t \in \{0, 1\}$ represents the response at time t (0 for incorrect and 1 for correct). Since we primarily focus on predictions for individual learners, for readability, we omit the learner index. Thus, the answering process of each learner can be represented as the following sequence:

$$K = \{(e_1, c_1, r_1), \dots, (e_t, c_t, r_t)\} \quad (1)$$

The goals of our LSKT can be primarily divided into two parts. One is to obtain the more accurate knowledge state. Specifically, we propose the learning state $\{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_t\}$ up to time t based on the interaction sequence K of the learner. By fusing with the original knowledge state $\{h_1, h_2, \dots, h_t\}$, the fused state $\{z_1, z_2, \dots, z_t\}$ is obtained. The other is to predict the learner's performance on the task at time $t + 1$, denoted as \hat{r}_{t+1} . Our LSKT utilize the fused state z_t above and exercise e_t are leveraged to participate the downstream task.

Table 1
Notations and explanations.

Notations	Explanations
e	Exercise index
c	Concept index
r	Response index
c_c, c'_c	Concept embedding and its variation
α_e	Deviation degree parameter
r_r, r'_r	Response embedding and its variation
$g_{(c,r)}, g'_{(c,r)}$	Original interaction embedding and its variation
d_e	Discrimination feature
f_c	Guessing factor feature
x	Exercise feature
y	Interaction feature
\hat{y}	Learning state feature
β	Learning state-based similarity distribution
$\gamma_{t,\tau}$	Complete attention scores at time t versus time τ
h	Knowledge state
z	Synthesis of knowledge state and learning state
\hat{r}_{t+1}	Prediction at time $t + 1$

3.2. Model overview

The diagram in Figure 2 illustrates the backbone network of our LSKT along with its components. Our LSKT model consists of four parts: the IRT based feature embedding module, the Learning State Extraction (LSE) module, the learning state enhanced knowledge state extraction module, and the Learner Response Prediction module. Firstly, through the feature embedding module, embedded representations of learners' exercise and interaction features are obtained. Then, the LSE module is utilized to extract the sequence of learning state changes from the embedded interaction sequences of learners. Subsequently, we employ sparse attention calculation based on the k-means clustering method for each moment in the sequence of learning state changes. This allows us to obtain sparse attention scores by masking irrelevant moments of learning state and integrating them into the process of capturing knowledge states, thereby emphasizing similar moments of learning state. Finally, the learning state and knowledge state are fused together to jointly predict learners' performance in answering exercises in the next moment. Unlike the previous ATT-DLKT method, our model simulates the potential differences in interactions and pays attention to the changes in the learner's learning state during the answering process. By introducing consideration of these two key points into the model, it more finely simulates the process of knowledge acquisition in the real world, thereby enhancing the model's effectiveness and interpretability.

3.3. IRT based feature embedding module

In real world educational environment, the number of questions in question banks often far exceeds the number of learners, leading to many questions being answered by only a few learners, resulting in data sparsity issues. To address this problem, many models utilize knowledge concepts to index questions, thus avoiding overfitting. However, these methods often overlook the potential differences embedded in learner interactions, which include the potential distinctions between different exercises under the same knowledge

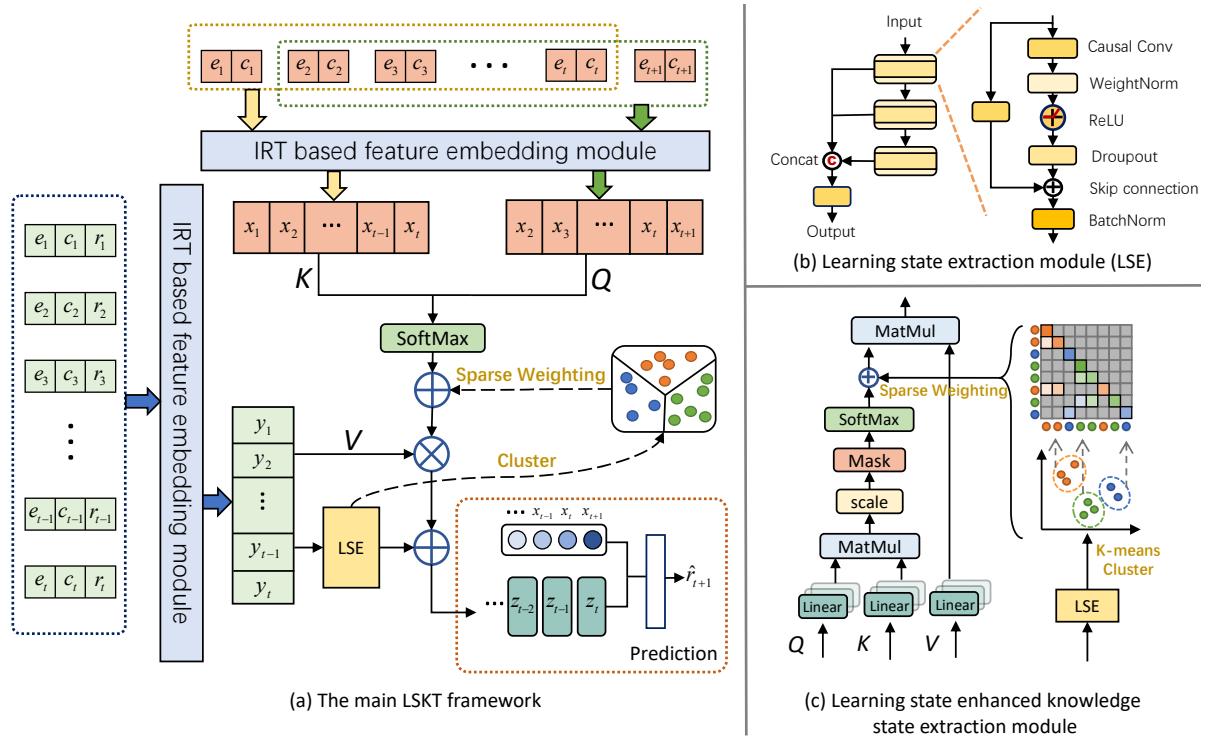


Figure 2: (a) The overall architecture of our LSKT. (b) The learning state extraction module, where we extract and integrate multi-scale learning state information through multi-layer causal convolutions. (c) The learning state enhanced knowledge state extraction module

concept, as well as the unreliability of responses caused by learners' guessing behavior. This oversight undoubtedly limits the potential of knowledge tracing (KT) methods.

To address the above issues, methods for the sequence of exercises and interactions with learners are delved into. We believe that the three-parameter model of Item Response Theory (IRT) can progressively uncover the impact of differences between exercises and interactions on learner performance. Inspired by this, exercise embeddings and interaction embeddings corresponding to these three different levels of refinement in parameter modeling are designed. Our design effectively alleviates the problem of model overfitting and gradually explores the subtle differences between different exercises and interactions under the same concept, thereby fully unleashing the potential of the model. The effects of the three modeling methods on model training in RQ4 will be further compared.

1PL-based embeddings. The LSKT-1PL model corresponds to the IRT one-parameter model, which introduces a difficulty difference parameter among exercises to achieve coarse-grained modeling of exercise characteristics and interaction features. Specifically, the modeling of exercise characteristics is as follows:

$$x_t = [c_{c_t} \| (\alpha_{e_t} \cdot c'_{c_t})] W_1 \quad (2)$$

where $x_t \in \mathbb{R}^D$ represents the feature vector of the exercise at time t . $c_{c_t}, c'_{c_t} \in \mathbb{R}^D$ denote the D -dimensional continuous vectors obtained for the knowledge concept c_t through a Knowledge concept feature extractor, and the corresponding variation obtained through another Knowledge

concept feature extractor, respectively. $\alpha_{e_t} \in \mathbb{R}$ is a learnable scalar parameter representing the difficulty of the exercise e_t , and we use $\alpha_{e_t} \cdot c'_{c_t}$ to simulate the difficulty differences among different exercises. The symbol $\|$ denotes the feature concatenation operation, and $W_1 \in \mathbb{R}^{2D \times D}$ is a learnable parameter matrix. For simplicity of the formula expression, we omit the bias parameter required for the dimensionality reduction operation.

Similarly, the coarse-grained modeling of learner-exercise interaction features is as follows:

$$g_{(c_t, r_t)} = c_{c_t} + r_{r_t} \quad (3)$$

$$g'_{(c_t, r_t)} = c'_{c_t} + r'_{r_t} \quad (4)$$

$$y_t = [g_{(c_t, r_t)} \| (\alpha_{e_t} \cdot g'_{(c_t, r_t)})] W_2 \quad (5)$$

where $r_{r_t}, r'_{r_t} \in \mathbb{R}^D$ represent the D -dimensional continuous vectors obtained from the learner's response r_t through two response different feature extractors, with r_{r_t} denoting the original embedding and r'_{r_t} denoting the corresponding change. $g_{(c_t, r_t)}, g'_{(c_t, r_t)} \in \mathbb{R}^D$ represent the original interaction embedding between context c_t and response r_t , and their corresponding changes, respectively. $W_2 \in \mathbb{R}^{2D \times D}$ is a learnable parameter matrix. $y_t \in \mathbb{R}^D$ represents the interaction feature between the learner and the exercise at time step t .

2PL-based embeddings. LSKT-2PL corresponds to the IRT two-parameter model, which introduces a discrimination parameter between exercises on the basis of LSKT-1PL,

achieving a sub-fine-grained modeling of the differences between exercises and between interactions.

$$x_t = c_{c_t} + [\text{Repeat } (\alpha_{e_t}, D) \| (W_3 \cdot d_{e_t})] W_4 \cdot c'_{c_t} \quad (6)$$

$$y_t = g_{(c_t, r_t)} + [\text{Repeat } (\alpha_{e_t}, D) \| (W_3 \cdot d_{e_t})] W_5 \cdot g'_{(c_t, r_t)} \quad (7)$$

where $\text{Repeat } (\cdot, D)$ represents the repetition of the difficulty scalar parameter to obtain a D -dimensional vector. $d_{e_t} \in \mathbb{R}^D$ denotes a D -dimensional mapping of exercises in the latent space. $W_3 \in \mathbb{R}^{D \times D}$ is a learnable parameter matrix. We use $W_3 \cdot d_{e_t}$ to represent a finer differentiation between exercises, namely the distinctiveness parameter of exercises. Building upon LSKT-1PL, LSKT-2PL integrates the effects of two parameters, namely the difficulty and distinctiveness, on the embedding of exercises at time t and the interaction embedding. $W_4, W_5 \in \mathbb{R}^{2D \times D}$ represent two learnable dimension reduction parameter matrices.

3PL-based embeddings. LSKT-3PL corresponds to the IRT three-parameter model. It builds upon LSKT-2PL by introducing the possibility of learners guessing, which is often overlooked when modeling the answering process. In reality, the impact of answering a exercise truthfully versus guessing should differ in terms of the learner's knowledge state. To simulate learners' guessing behavior, we incorporated random guessing perturbations into the learner interaction sequences, achieving a fine-grained model embedding:

$$f_{c_{t+1}} = c_{c_{t+1}} + \text{Random} \{0, \tilde{r}_{\text{Random} \{0,1\}}\} \quad (8)$$

$$y_t = f_{c_{t+1}} + g_{(c_t, r_t)} + [\text{Repeat } (\alpha_{e_t}, D) \| (W_3 \cdot d_{e_t})] W_6 \cdot g'_{(c_t, r_t)} \quad (9)$$

where $\text{Random} \{0, \tilde{r}_{\text{Random} \{0,1\}}\}$ represents randomly selecting whether to introduce a guessing factor, where 0 indicates no guessing, and $\tilde{r}_{\text{Random} \{0,1\}} \in \mathbb{R}^D$ represents randomly introducing a D -dimensional learner response embedding vector. Here, a 0-valued embedding vector represents an incorrect guess, while a 1-valued embedding vector represents a correct guess. In the entire formula, $f_{c_{t+1}}$ denotes whether to introduce the guessing factor for the next exercise, indicating the possibility of guessing or not guessing, and the possibility of guessing correctly or incorrectly. We choose to model the guessing factor for the next exercise because the goal of Knowledge Tracing (KT) is to predict the learner's performance on the next exercise based on the current knowledge state. Therefore, the knowledge state at time t should include the guessing factor for time $t+1$. $W_6 \in \mathbb{R}^{2D \times D}$ is a learnable parameter matrix. The learner's actual answering process can be better simulated by introducing the guessing factor in the interaction sequence y_t . The 3PL embedding modeling does not modify the exercise feature x_t , based on the 2PL embedding modeling.

3.4. Learning state extraction module (LSE)

In the actual answering process, the learner's state is changing, influenced by various complex factors. e.g., continuous wrong answers might dent their confidence, making them more prone to errors even when facing questions they have not fully mastered. A study (Cui et al., 2023) suggests that learners' recent performance significantly impacts their

next steps in real test environments. However, existing ATT-DLKT models often overlook this aspect. Therefore, to capture learners' learning states, we've devised the LSE module.

Figure 2(b) illustrates the structure of LSE. The structure of LSE consists of three residual blocks arranged sequentially to capture the learner's learning states at different scales, and finally achieves feature fusion through skip connections. The 1×1 convolutional layer is utilized for dimensionality reduction, yielding the comprehensive learning state of the learner. Each residual block comprises a causal convolutional layer, weight normalization layer, ReLU function, dropout layer, and skip connection. Layer normalization is applied between adjacent residual blocks.

The primary function of LSE is to perform causal convolution operations on the learner's historical interaction sequences. Since causal convolution strictly relies on past temporal information for prediction, for a historical interaction sequence y and a one-dimensional convolutional kernel s , the mathematical expression of the causal convolution process can be represented as:

$$\hat{y}_t = \sum_{m=0}^M y_{t-m} \cdot s_{M-m} \quad (10)$$

Here, \hat{y}_t represents the output value of the convolution at time step t , M denotes the size of the convolutional kernel, y_{t-m} represents the value of the interaction sequence y at time step $t - m$, and s_m is the weight of the convolutional kernel s at position m . Then, \hat{y}_t goes through three residual blocks for feature extraction, and the fused learning state feature \hat{y}_t , which incorporates the learner's multi-scale learning patterns, is obtained by merging the output features of each residual block.

Through the LSE module, the model is able to capture the learner's learning patterns over multiple time scales during the answering process. The LSE module does not aggregate useful information through the similarity between exercises, but obtains a cross-knowledge concept learning pattern through the learner's recent performance. We believe that \hat{y}_t can effectively describe the learner's learning state at time t .

3.5. Learning state enhanced knowledge state extraction module

Through the LSE module, we obtained the learning state sequence of learners. However, the differences in the learner's states during the answering process is not involved in the process of extracting knowledge states. To take it into consideration, A learning state enhanced knowledge state extraction module was designed, as shown in Figure 2(c).

In the learner's exercise-answer interactions, the learning state may change due to various complex factors. However, not all past learning states are equally important for prediction. Due to the nature of the softmax function, even historical states with relatively small relevance to the current prediction may receive some attention, which could introduce additional noise in the process of extracting knowledge

states. To address this issue, we adopted a sparse attention-weighted approach to incorporate consideration of the learning state into the process of extracting knowledge states.

To exclude historically irrelevant moments, The k -means algorithm is used to group the historical learning state sequences, with different groups of historical moments being treated as irrelevant and masked. To obtain stably updated clustering clusters and ensure no leakage of future information, A fixed-size pool X_{pool} with a size of μ is designed by us to store the learning states of the most recent μ learners (excluding learners from the current batch). Subsequently, by applying the k -means algorithm to divide the learning states of all learners in the pool into n groups, we obtain n cluster centers for learning states $\{l_1, \dots, l_i, \dots, l_n\}$, where $l_n \in \mathbb{R}^{1 \times D}$. Then, based on these n cluster centers, the learning states of learners in the current batch are divided into clusters to obtain the corresponding cluster labels. The formula is as follows:

$$\text{Label}(\hat{y}_t) = \arg \min_i \sqrt{\sum_{p=1}^D (\hat{y}_{tp} - l_{ip})^2} \quad (11)$$

In the above formula, \hat{y}_t represents the learning state of the current learner at time step t . Using this formula, we can determine the cluster to which this learning state belongs, denoted as $\text{Label}(\hat{y}_t)$.

Next, we will use the learning state information of the current batch of learners to update the pool.

$$X_{pool} = \text{deque}([X_{pool}, \hat{y}], \text{ maxlen } = \mu) \quad (12)$$

where deque is a double-ended queue, and μ is the fixed size of the pool. The most recent μ learner learning state sequences are always retained for stable updates to the clustering center, earlier information will be popped out of the pool.

Once the cluster to which each learner belongs is ascertained, we begin to identify crucial historical moments by calculating the similarity of the historical learning state sequence at each time step.

$$\beta_t = \frac{\hat{y}_t \hat{y}_{history}^T}{\sqrt{D}} \quad \hat{y}_{history} = \{\hat{y}_1, \dots, \hat{y}_t\} \quad (13)$$

where β_t represents the similarity distribution calculated based on the learning state \hat{y}_t at time t .

By masking the attention scores of different clusters, we achieve sparse attention learning of states. Using $\text{Mask}(\cdot)$ to represent a masking operation that selects features within the same group, we can obtain a sparse similarity score matrix for learning state interactions along the sequence.

$$\text{Mask}(\beta_{t,\tau}) = \begin{cases} \beta_{t,\tau} & \text{if } \text{Label}(\hat{y}_t) = \text{Label}(\hat{y}_\tau) \\ -\infty & \text{Otherwise} \end{cases} \quad (14)$$

where $\text{Label}(\hat{y}_t) = \text{Label}(\hat{y}_\tau)$ indicates that \hat{y}_t and \hat{y}_τ belong to the same cluster, and attention scores between learning states in different clusters will be masked. $\beta_{t,\tau}$ represents the similarity score of \hat{y}_τ with respect to \hat{y}_t .

Next, we merge the sparse similarity score matrix of learning states with its corresponding exercise similarity score matrix to achieve enhanced knowledge state capture

from learning states. To prevent future information leakage, interaction sequences beyond time step t should not be included in the calculation and thus need to be masked. The formula is as follows:

$$\gamma_{t,\tau} = \begin{cases} \frac{e^{q_t k_\tau^T / \sqrt{D}}}{\sum_{\tau=1}^N e^{q_t k_\tau^T / \sqrt{D}}} + \frac{e^{\text{Mask}(\beta_{t,\tau})}}{\sum_{\tau=1}^N e^{\text{Mask}(\beta_{t,\tau})}} & \text{if } \tau \in (1, t) \\ 0 & \text{if } \tau \in (t+1, N) \end{cases} \quad (15)$$

Here, the exercise feature x_t at time t is utilized by us as the query item q_t , and the exercise feature x_τ at time τ is taken as the key item k_τ . Through the dot product operation, we obtain the attention distribution of the exercise sequence. Next, this attention distribution is integrated with the attention distribution of the learning state sequence, thereby incorporating the learner's state changes during the learning process, resulting in a comprehensive attention score distribution γ . The focus of this approach lies in emphasizing historical moments with similar learning states, further refining the modeling of the answering process, and successfully introducing the diversity of learning state changes into the model. This will help improve the performance of the model.

Key moment information from the historical interaction sequence can be extracted to obtain the final knowledge state by utilizing the complete attention score matrix:

$$h_t = \sum_{\tau=1}^N \gamma_{t,\tau} v_\tau \quad (16)$$

where $v_\tau \in \mathbb{R}^{1 \times D}$ represents the interaction feature y_τ of the learner at time τ as the value, while $h_t \in \mathbb{R}^{1 \times D}$ represents the final acquired knowledge state, which includes historical priors of learning performance.

Subsequently, we fuse the knowledge state with the learning state, with the formula as follows:

$$z_t = [h_t \parallel \hat{y}_t] W_7 \quad (17)$$

where $z_t \in \mathbb{R}^{1 \times D}$ represents the fusion of two states, and $W_7 \in \mathbb{R}^{2D \times D}$ is a learnable parameter matrix. We will utilize z_t for the final prediction of the KT task.

3.6. Prediction

The final step involves predicting the learner's response to the next exercise at the subsequent time step. The module's inputs comprise the comprehensive state feature z_t at the current time step and the embedding vector x_{t+1} of the subsequent exercise.

$$\hat{r}_{t+1} = \sigma([z_t \parallel x_{t+1}] W_8) \quad (18)$$

Here, σ is the Sigmoid function, and $W_8 \in \mathbb{R}^{D \times D}$ is a learnable parameter matrix. These inputs are fused through a fully connected network, and ultimately, a sigmoid function is applied to generate the predicted probability \hat{r}_{t+1} of the learner answering the current exercise correctly, where $\hat{r}_{t+1} \in [0, 1]$.

$$\text{Loss} = -\sum_{t=1}^T (r_{t+1} \log \hat{r}_{t+1} + (1 - r_{t+1}) \log (1 - \hat{r}_{t+1})) \quad (19)$$

In the entire LSKT method, all learnable parameters are trained in an end-to-end manner by minimizing the binary cross-entropy loss of all learner responses.

Table 2

Dataset statistics.

Statistics	ASSIST09	ASSIST12	ASSISTChall	algebra05
Interactions	346,860	2,711,813	942,816	809,694
Learners	4,217	29,018	1709	574
Exercises	26,688	53,091	3,162	1,084
Concepts	123	265	102	138
Avg.Length	82.25	93.45	873.79	1,410.62

4. EXPERIMENTAL RESULTS

In this section, a detailed presentation of the experimental results of LSKT on four real-world educational datasets is provided, accompanied by extensive discussions and analysis for the evaluation of the model performance. We address the following research questions:

- **RQ1.** How does LSKT perform compared to baseline methods in predicting learners' future performance?
- **RQ2.** What is the role of the key model components of LSKT in the entire method framework?
- **RQ3.** How does the learning state promote more fine-grained knowledge state extraction?
- **RQ4.** What impact does the feature modeling of three granularities based on IRT have on model embedding?

4.1. Datasets

To evaluate the performance of our LSKT model, we conducted experiments on four real-world publicly available datasets, including ASSIST09¹, ASSIST12², ASSISTChall³, and algebra05⁴. The ASSIST09 dataset (Feng et al., 2009) was created and collected by the online tutoring system ASSISTment in 2004. Another dataset from the same platform is ASSIST12, which collected data from 2012 to 2013 and has been regarded as one of the benchmark datasets for KT research over the past decade. The ASSISTChall (Patikorn et al., 2018) dataset was released in a data mining competition in 2017, containing longer sequences of learner interactions and allowing multiple attempts for a single problem. The algebra0 (Yu et al., 2010) dataset was released in the KDDcup 2010 Educational Data Mining Challenge, comprising learner responses to algebra problems from 2005 to 2006.

For fairness, these datasets were preprocessed based on prior research (Yin et al., 2023), with data modeling issues being addressed and duplicate records being removed. As the ASSIST09 dataset lacks timestamp information, we followed previous studies (Xu et al., 2023; Sun et al., 2024) and sorted learners' answering sequences based on order ID. The detailed statistical results of the processed datasets are presented in Table 2.

¹<https://sites.google.com/site/assistmentsdata/home/2009-2010-assistment-data>

²<https://sites.google.com/site/assistmentsdata/datasets/2012-13-school-data-with-affect>

³<https://sites.google.com/view/assistmentsdatamining/>

⁴<https://pslcdatashop.web.cmu.edu/KDDCup/>

4.2. Baseline methods

To evaluate the effectiveness of LSKT, this section will select several classic or state-of-the-art methods as baseline methods, such as DKT (Piech et al., 2015a), DKVMN (Zhang et al., 2017), SAKT (Pandey & Karypis, 2019), AKT (Ghosh et al., 2020), DTransformer (Yin et al., 2023), and FKT (Huang et al., 2024).

Among them, DKT was a milestone method that introduced recursive neural networks into the field of knowledge tracing, and it outperformed traditional knowledge tracing models. DKVMN further advanced the development of KT by storing knowledge state in a dynamic key-value memory network and updating it at different interaction moments. CKT attempted for the first time to use Convolutional Neural Networks (CNN) to perform knowledge tracing prediction tasks, simulating personalized learning rates for each learner through convolutional operations. SAKT applied transformer encoders to KT and proposed a self-attention mechanism-based method, treating the target problem as a query and the history exercise-answer pairs as keys and values. AKT continued this approach by encoding knowledge state and exercises using self-attention neural networks, and then utilizing a knowledge retriever to retrieve future knowledge states. DTransformer was built upon AKT and designed a knowledge-level diagnostic extractor that could explicitly diagnose learners' proficiency levels. Contrastive learning was introduced during training to maintain the stability of knowledge state. FKT divided the KT prediction task into three steps: obtaining historical knowledge state, inferring future latent features, and predicting future performance. It developed an encoder-decoder-predictor framework to further improve the accuracy of knowledge tracing.

4.3. Implementation details

In our experiment, following the data preprocessing method from previous work (Yin et al., 2023), we split the learning records of 80% of the learners as the training set and 20% as the test set. For all data, the learners' learning records were first sorted according to the timestamp, then, as per work (Ghosh et al., 2020; Yin et al., 2023), learner response sequences with a length exceeding 200 were truncated. For shorter sequences, zero padding was employed to pad them to a fixed length of 200, a process that aids in improving computational efficiency.

The AdamW optimizer with a learning rate of 0.001 and a batch size of 16 is leveraged to train the model, where the dimensions of the exercise embeddings, interaction embeddings, and the answer embeddings are all set to 128. For the hyperparameters, we set the parameter M in Equation (10) to 3 and the parameter μ in Equation (12) to the batch size 16. After adjusting the number of clustering clusters n from 1 to 10, we set the value of n to 4. For fair comparison, all models have been fine-tuned to achieve the best performance. We set the threshold for predicting the response answer to 0.5 (Nagatani et al., 2019; Piech et al., 2015b; Wang et al., 2021a), where responses with a probability greater than 0.5 are considered correct answers;

Table 3

Comparison results with baseline methods on the AUC and ACC metrics. The best and the second-best results are marked in boldface and underlined, respectively.

Dataset	Metric	Baseline							LSKT-NI	LSKT
		DKT	DKVMN	CKT	SAKT	AKT	DTransformer	FKT		
ASSIST09	AUC	0.7908	0.7891	0.8072	0.7783	0.8162	0.8171	—	<u>0.8206</u>	0.8369
	ACC	0.6482	0.7458	0.7622	0.7418	0.7639	<u>0.7655</u>	-	0.7650	0.7785
	RMSE	0.4387	0.4161	0.4089	0.4194	0.4065	0.4005	-	<u>0.3966</u>	0.3886
	MAE	0.4105	0.3132	0.3121	0.3342	0.3109	0.3069	-	<u>0.3043</u>	0.2896
ASSIST12	AUC	0.7060	0.7137	0.7310	0.7021	0.7632	0.7598	<u>0.7692</u>	0.7348	0.7781
	ACC	0.6998	0.7295	0.7365	0.7232	0.7415	0.7392	<u>0.7485</u>	0.7339	0.7559
	RMSE	0.4456	0.4422	0.4234	0.4420	0.4199	0.4223	<u>0.4144</u>	0.4243	0.4098
	MAE	0.3655	0.3634	0.3612	0.3663	0.3476	0.3565	<u>0.3321</u>	0.3585	0.3139
ASSISTChall	AUC	0.6809	0.7024	0.7262	0.6726	0.7556	0.7512	<u>0.7584</u>	0.7244	0.7917
	ACC	0.6971	0.6775	0.6924	0.6735	0.7112	0.7052	<u>0.7133</u>	0.6896	0.7341
	RMSE	0.4543	0.4543	0.4455	0.4609	0.4355	0.4389	<u>0.4311</u>	0.4474	0.4197
	MAE	0.4143	0.4064	0.3864	0.4207	0.3733	0.3767	<u>0.3695</u>	0.3967	0.3451
algebra05	AUC	0.7558	0.7857	0.7899	0.7819	0.7966	0.7932	<u>0.7981</u>	0.7969	0.8063
	ACC	0.8263	0.8315	0.8384	0.8337	0.8414	0.8406	<u>0.8421</u>	0.8412	0.8448
	RMSE	0.3798	0.3424	0.3417	0.3465	0.3406	0.3415	<u>0.3394</u>	0.3398	0.3360
	MAE	0.3498	0.2315	0.2281	0.2304	0.2252	0.2221	0.2266	0.2420	0.2211

otherwise, they are considered incorrect answers. Then, the accuracy of predicting response answers was evaluated using area under the curve (AUC), accuracy (ACC), root mean square error (RMSE), and mean absolute error (MAE).

4.4. Performance prediction (RQ1)

As shown in Table 3, to evaluate the predictive performance of the LSKT model, we compared it with seven methods in the KT domain. Among them, LSKT-NI indicates not using three embedding methods based on the IRT model, but directly utilizing knowledge concept embedding features to train the model. Noteworthily, due to the training of the FKT model requires the use of timestamp labels to obtain response times, and the ASSIST09 dataset lacks such timestamp label information, we only conducted experiments on the FKT model on the other three datasets excluding ASSIST09.

From Table 3, we can see that the proposed model achieves superior performance across four different datasets. Specifically, compared with the current state-of-the-art methods, our model shows an improvement of 1.98% in AUC on the ASSIST09 dataset, 0.89% on the ASSIST12 dataset, 3.33% on the ASSISTChall dataset, and 0.82% on the algebra05 dataset. Besides excelling in the AUC metric, our model also exhibits advantages in other performance evaluation metrics, further proving its robust capability in performing knowledge tracing tasks. However, if we do not adopt a strategy to model the differences between interactions but directly use knowledge concept embeddings, the performance of the model on these four datasets will significantly decline. It is noteworthy that baseline models based on Transformers, such as AKT, DTransformer, and FKT, all to model the differences between exercises to some

Table 4

Comparison of AUC and ACC among three embedding modeling methods. The best and the second-best results are marked in boldface and underlined, respectively.

Dataset	Metric	LSKT-1PL	LSKT-2PL	LSKT-3PL
ASSIST09	AUC	0.8217	<u>0.8289</u>	0.8369
	ACC	0.7669	<u>0.7740</u>	0.7785
ASSIST12	AUC	0.7754	<u>0.7769</u>	0.7781
	ACC	0.7530	<u>0.7532</u>	0.7559
ASSISTChall	AUC	0.7776	<u>0.7904</u>	0.7917
	ACC	0.7220	<u>0.7336</u>	0.7341
algebra05	AUC	0.7982	0.8096	<u>0.8063</u>
	ACC	0.8455	0.8471	<u>0.8448</u>

degree, which is also one of the reasons for their performance superiority over SAKT. All of these highlight the importance of modeling exercise differences for knowledge tracing tasks, especially for the ATT-DLKT model. In RQ2, more detailed ablation experiment results will be further discussed.

4.5. Ablation experiments (RQ2)

In order to investigate the impact of each key component in LSKT on the model's predictive results, we further conducted ablation experiments.

We first compared the effects of three different granularity levels of differential embedding modeling on the performance of the knowledge tracing model. As shown in Table 4, we employed three embedding modeling methods: LSKT-1PL, LSKT-2PL, and LSKT-3PL. The LSKT-1PL model simulates the differences between exercises by introducing difficulty distinctions among exercises into the modeling of

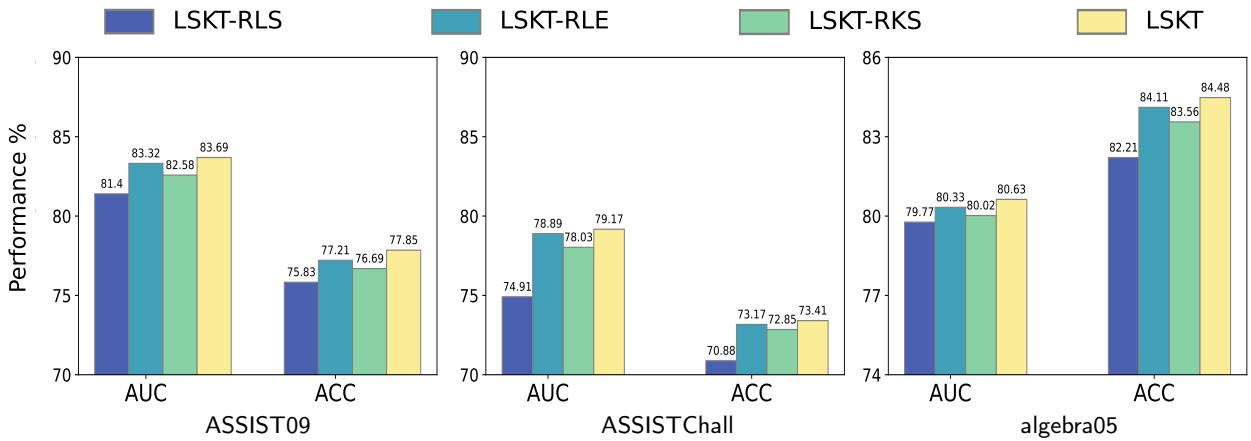


Figure 3: Comparison of ablation experiment results on three datasets. Different colors are used to distinguish between different ablation models, and the specific experimental results are labeled at the top of each bar chart.

exercise features and interaction features, thus modeling the differences between exercises at a coarse granularity. LSKT-2PL, building on the introduction of difficulty distinctions, further models the differentiation between exercises on the same knowledge concept by utilizing a higher-dimensional exercise mapping feature, achieving a sub-fine-grained modeling of the differences between exercises. The LSKT-3PL model introduces a random guessing factor based on LSKT-2PL, enabling a finer-grained simulation of the complex learning behaviors of learners during the answering process. Experimental results show that the LSKT-3PL model achieves the best performance on the ASSIST09, ASSIST12, and ASSISTChall datasets, while its performance on the algebra05 dataset is suboptimal. This suggests that for datasets with fewer exercise types such as algebra05, modeling the differences between exercises at a finer granularity does not necessarily lead to better predictive performance. Perhaps the sub-fine-grained modeling of the LSKT-2PL embedding modeling is sufficient to simulate the differences between exercises on the same concept. Therefore, we compared these three different granularity levels of differential modeling to find a balance between model performance and granularity of modeling. In RQ4, the differences between these three modeling approaches and their impact on embedding features will be further analyzed.

Next, we will analyze the effectiveness of various key components of the LSKT model. We compared the differences in ablation study in Table 5 and the ablation results on the ASSIST09, ASSISTChall, and algebra05 datasets are shown in Figure 3.

- RLS (i.e., Removal of Learning State Extraction Module) disregards the impact of changes in learning state on the model.
- RLE (i.e., Removal of Learning State Enhancement) retains both learning state and knowledge state for model prediction but does not consider the influence of learning state on acquiring knowledge state.
- RKS (i.e., Removal of Knowledge State Extraction Module) disregards capturing knowledge state from

Table 5
Different variants of comparative settings.

Methods	Learning state extraction	Learning state enhancement	knowledge state extraction
LSKT-RLS	✗	✗	✓
LSKT-RLE	✓	✗	✓
LSKT-RKS	✓	✗	✗
LSKT	✓	✓	✓

the history of responses and only utilizes learning state for prediction tasks.

The experimental results are displayed in Figure 3. It can be observed that, firstly, the absence of either the knowledge state or the learning state leads to a decrease in model performance. Only by comprehensively considering both factors can the model's performance reach its optimum. This indicates that the knowledge state and the learning state can complement each other well. Secondly, introducing the distinction of learner state during the extraction of knowledge state can also enhance the model's performance. It is noteworthy that the features of the learning state have a more significant impact on the model's predictive effect. This phenomenon may be due to the influence of forgetting factors in human's actual learning process, which makes the learner's performance at any given moment more affected by recent learning interactions rather than the cumulative interactions of a long history. This explains why the AUC of the LSKT-RKS model is generally superior to that of the LSKT-RLS model on all datasets, a finding that meets our perception.

To investigate the impact of varying the number of clustering clusters n on the knowledge tracing performance of LSKT, we systematically increased n from 1 to 10 and documented the corresponding changes in AUC across four datasets. The experimental findings, depicted in Figure 4, showcase the relationship between the number of clustering clusters and the AUC percentage. Here, the horizontal axis delineates the progression of clustering clusters, while the

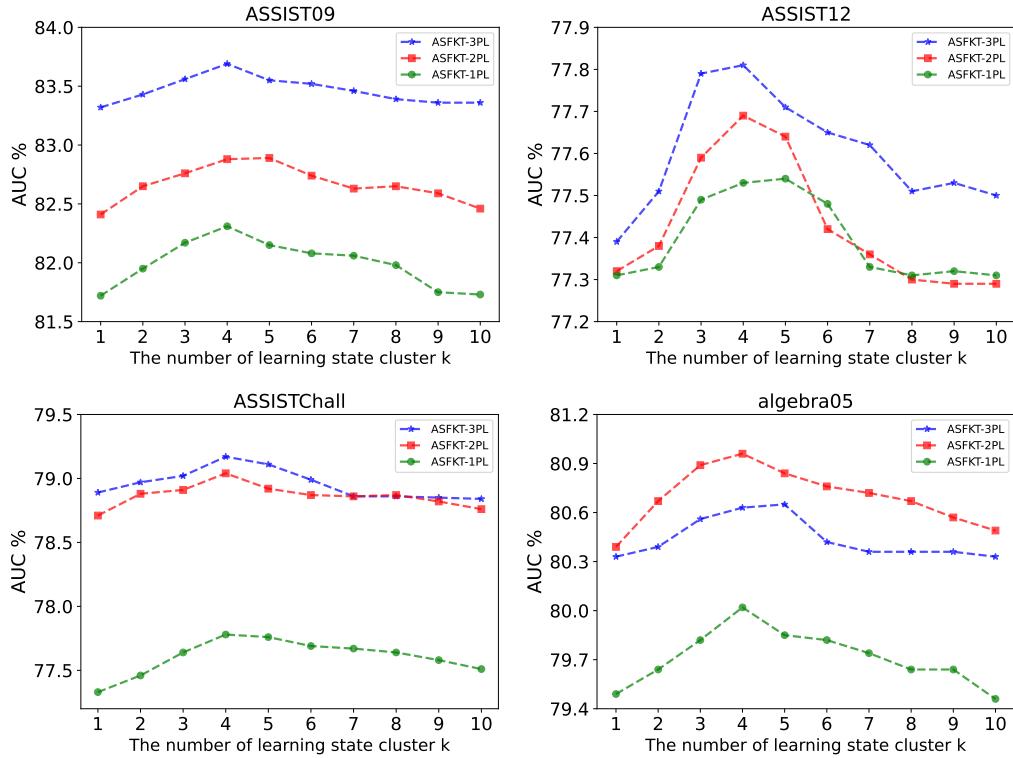


Figure 4: The influence of different clustering quantities on the AUC values of three embedding models. The horizontal axis shows the change in k values from 1 to 10, while the vertical axis displays the percentage of AUC values. Three different colors distinguish the three embedding methods in the graph.

vertical axis illustrates the fluctuations in AUC. The three distinctively colored lines denote three diverse embedding modeling methodologies. Upon scrutinizing the outcomes, we draw the following conclusions: irrespective of the embedding modeling approach, an optimal AUC is attained when n is set to 4 across all four datasets. Nevertheless, deviations from this value, either upwards or downwards, lead to a decline in clustering accuracy. Specifically, when n is less than 4, certain inconsequential historical instances are still accommodated by the model via the softmax function, thus introducing superfluous noise during model training. Conversely, when n exceeds 4, pivotal moment information tends to be overlooked. Hence, to ensure the optimal performance of our proposed LSKT, we consistently maintain n at 4 throughout the entirety of this paper's experiments.

4.6. Fine-grained knowledge state (RQ3)

To capture more fine-grained knowledge states, this paper firstly models three different types of feature embeddings. However, considering only the differences at the level of problem features and interaction features cannot fully simulate the complex answering process of humans. In the real answering process, the change in the learner's state is also a hidden factor that needs to be considered. For example, even if there are multiple exercises similar to the current one in the historical sequence, the learner's current learning state may be significantly different from the learning state when answering some similar exercises in history due to the continuous change in the process of doing the exercises.

Intuitively, if the learner answers a exercise incorrectly, the quality of the learner's state may reflect different levels of mastery of this exercise. Therefore, it is necessary to introduce the change in learning state into the process of extracting knowledge states.

To address the issue, a learning state enhanced knowledge state extraction module is proposed in this approach. This module further distinguishes the differences in learners' historical learning states during the process of capturing knowledge states. This module emphasizes that when capturing the learner's knowledge state, it is necessary to not only consider the similarity between the current required answer exercises and historical exercises, but also to consider whether the learner's learning state at the current moment is consistent with that at the corresponding historical moment. By integrating changes in the learning state into the process of capturing learner knowledge states, we can obtain a more detailed understanding of the knowledge state.

In Figure 5, a random selection of 64 learners' knowledge state sequences from the ASSIST09 dataset's test set was made, and T-SNE (Van der Maaten & Hinton, 2008) technology was employed for visualization. Different features of learning state classes were indicated by different colors. Figure 5(a) demonstrates that without considering the learning states, the knowledge state features tend to mix with each other. Figure 5(b) displays the distribution of learning state features at each time step when considering the learning states. On the other hand, Figure 5(c) shows the distribution

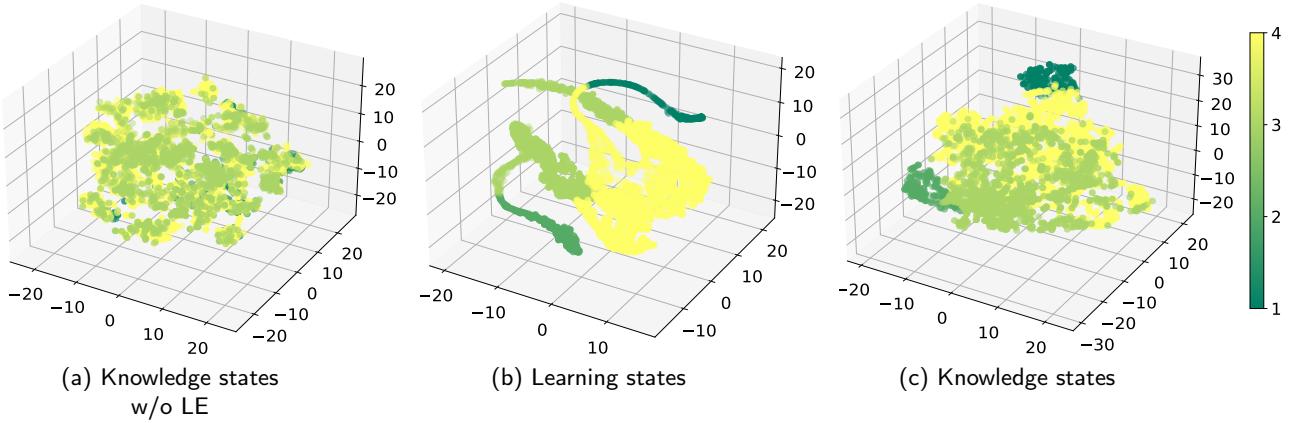


Figure 5: Visualization of Knowledge State and Learning State. Figure (a) represents the distribution of knowledge state features extracted without the guidance of a learning state. Figure (b) illustrates the feature distribution corresponding to the learning state. Figure (c) depicts the distribution of knowledge state features extracted with the guidance of a learning state.

of knowledge state features after incorporating the learning states into the knowledge state extraction process. It can be observed that by introducing learning states as guidance, the knowledge states are classified more precisely. Specifically, under the same learning state, the learning state features at corresponding time steps tend to cluster together rather than being mixed. This result confirms the importance of learning states in interaction performance. By guiding with learning states, we are able to explore more intrinsic and fine-grained knowledge states.

4.7. Embeddings visualization(RQ4)

We utilize the T-SNE algorithm to perform dimensionality reduction and visualize embeddings containing only exercise concept information, as well as embeddings proposed by LSKT based on modeling differences in three levels of granularity. The aim of this approach was to assess the impact of modeling differences between exercises and between interactions on the interpretability of model embedding features. On the ASSIST09 test set, an equal number of exercises were randomly selected for this visualization experiment, and the results are presented in Figure 6.

As shown in Figure 6(a), a large number of exercise embedding features and interaction embedding features are mixed together, indicating that if only the concept of exercises is considered without modeling differences, the model will struggle to distinguish certain concept features, thereby increasing the difficulty of capturing effective associative information between exercises.

To address the above issues, we attempted to gradually model the differences between interactions. Inspired by the IRT-1PL model, new exercise embedding method and corresponding interaction embedding method were designed. The visualization results, as shown in Figure 6(b), indicate that exercise features and interaction features are linearly clustered in the two-dimensional space. This suggests that the LSKT-1PL method can enable the model to capture some continuity relationships in exercise concepts, such as the progressive relationship of exercise difficulty. However, due

to this linear clustering, there is a lack of clear differentiation boundaries between exercise and interaction features. As a result, some exercise representations intertwine with each other in the feature space, making it difficult for the model to determine the relationship and distinction between exercises and interactions.

Inspired by the IRT-2PL model, we designed a new embedding method that further refines the modeling of feature differences. The visualization results, as shown in Figure 6(c), demonstrate that exercises with the same knowledge concepts are clustered closely together in the feature space, while those with different concepts are farther apart. This indicates that the model can effectively differentiate between exercises and interactions with different concepts. However, although differential modeling has been applied to exercises and interactions with the same concepts, the embedding features between exercises and interactions with the same concept still appear very similar, closely aggregated together. This suggests the possibility of overfitting in the model, which is not the expected outcome.

Finally, we chose to introduce the learner's guess factor into the interactive sequence embedding. By simulating the unreliability of responses, we reduced the degree of overfitting of the model on unreliable interactions. The visualization results, as shown in Figure 6(d), demonstrate that the clusters formed by exercise features of the same concept are no longer as concentrated as in Figure 6(c), and the differences between different exercises can be better identified. This explains why the LSKT-3PL model performs better on most datasets.

Through visualizing embedding features without modeling differences and respectively modeling differences at coarse-grained, sub-fine-grained, and fine-grained levels, we can observe the impact of the differential modeling on the ATT-DLKT model. This validates the importance of differentially modeling embedding features for the knowledge tracing task.

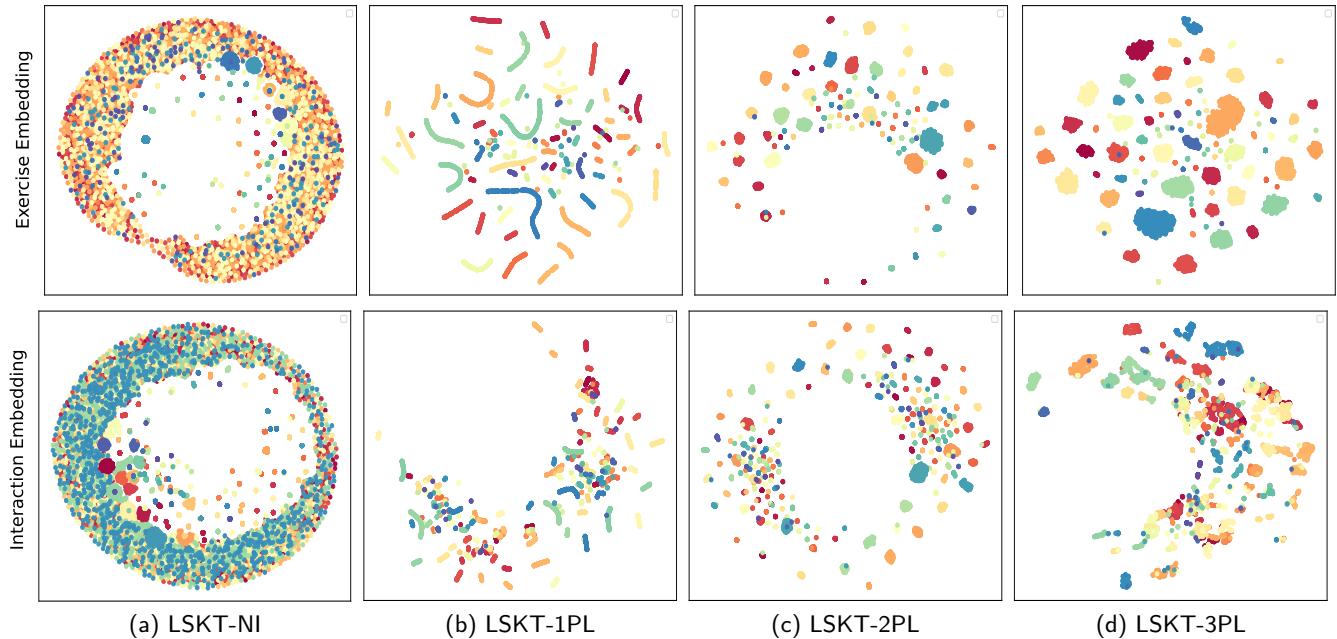


Figure 6: Comparison of four embedding methods on the ASSIST09 dataset. Figure (a) depicts using only conceptual knowledge for embedding features, while figures (b), (c), and (d) illustrate three proposed embedding modeling approaches. The upper and lower graphs respectively show exercise and learner interaction embedding results, with exercises sharing the same knowledge concepts highlighted in the same color.

4.8. Visualization of knowledge state variation

Predicting the changes in knowledge state is one of the important goals of knowledge tracing tasks. To explore the effect of exercise difference modeling and learning state on the evolution of knowledge state, we show a visualization example of the changes in knowledge state on the continuous 30-exercise records of 5 knowledge concepts in the ASSIST09 dataset in Figure 7. The indexes of these 5 knowledge concepts are {15, 19, 30, 99, 86} respectively. Each row in the figure shows the estimated evolution of the knowledge state of a single corresponding knowledge concept in the answer sequence. Each column shows the changes in knowledge and learning state after completing one exercise answer.

Figure 7(a) illustrates the evolution of learners' knowledge and learning states while completing a continuous sequence of 30 exercises. The blue process at the top represents the evolution of learners' mastery levels of individual skills. It can be observed that when learners correctly (incorrectly) complete an exercise, the mastery level of the corresponding knowledge concept increases (decreases). The red process at the bottom represents the evolution of learners' learning states. It can be seen that learning states change as the learning process progresses; when learners frequently answer exercises correctly, their learning state improves, and when they frequently answer exercises incorrectly, their learning state declines, which aligns with common intuition. Our LSKT simultaneously considers the influence of both knowledge states and learning states on learners' performance, which better reflects the real answering process.

In Figure 7(b), we show the differences in the evolution of knowledge mastery for different exercises with the same

knowledge concept {15}, which are {2962, 2967, 2976, 2979}. Although these exercises belong to the same knowledge concept, the evolution of their knowledge mastery is not exactly the same. This difference more closely aligns with our perception that, even though exercises belong to the same concept, their mastery levels can differ due to the complexity of different factors such as difficulty and discrimination of the exercises. This variability in modeling needs to be considered.

Through this experiment, we can see that LSKT is able to assess learners' mastery of each knowledge concept effectively. By modeling the differences between exercises and learners' actual learning states, LSKT can provide a more nuanced reflection of the genuine process of learners' knowledge acquisition.

4.9. Discussion and conclusion

This paper explores two crucial factors that are often overlooked in the existing ATT-DLKT model, namely, the modeling of latent differences in interactive features and the changes in learners' state during the answering process. Specifically, we propose a more fine-grained model, LSKT, which models these two factors during the feature extraction and training process, and integrates them into the KT task. This not only improves the accuracy of the model, but also models a process more in line with the actual answering process. In addition, this paper conducts a visual comparative study of knowledge concept embedding features and three different granularities of exercise and interaction embedding features, the results of which highlight the importance of

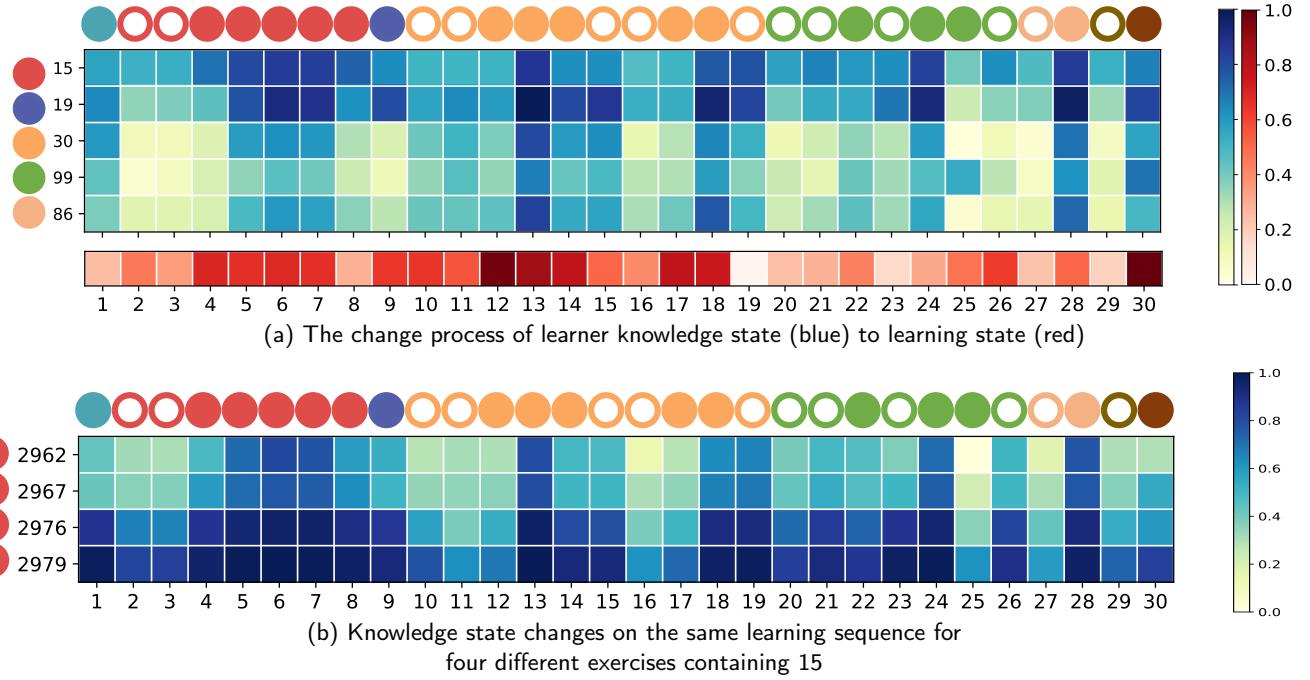


Figure 7: The different knowledge concepts in the graph correspond to circles of different colors. The circle at the top of the image represents the knowledge concept of the exercise being done at that moment. Hollow circles indicate that the learner answered incorrectly, while solid circles indicate that the learner answered correctly. Figure (a) shows the evolution of the learner's knowledge state (blue) and learning state (red) during the continuous 30 exercises, where the deeper the color, the better the learner's mastery of the knowledge concept or the better the learning state. Figure (b) shows the differences in the evolution of mastery level on 5 different exercises involving knowledge concept 15, where each row number represents the real exercise number.

differential modeling in the feature extraction process. Experimental results on four standard datasets prove that our model outperforms other baseline models.

In our future work, we plan to delve into the differences between exercises under the same knowledge concept and the connections between exercises under different knowledge concepts. We hope to fully exploit the potential information in the dataset to further enhance the performance and applicability of our model.

CRediT authorship contribution statement

Shanshan Wang: Conceptualization, Methodology, Writing – review & editing. **Xueying Zhang:** Methodology, Validation, Investigation, Writing – original draft. **Xun Yang:** Conceptualization, Supervision, Resources. **Xingyi Zhang:** Supervision, Resources. **Keyang Wang:** Supervision, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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