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Priority Guided Explanation for Knowledge Tracing with Dual Ranking and Similarity Consistency

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Abstract

Knowledge tracing plays a pivotal role in enabling personalized learning on online platforms. While deep learning-based approaches have achieved impressive predictive performance, their limited interpretability poses a significant barrier to practical adoption. Existing explanation methods primarily focus on specific model architectures and fall short in 1) explicitly prioritizing critical interactions to generate fine-grained explanations, and 2) maintaining similarity consistency across interaction importance. These limitations hinder actionable insights for improving student outcomes. To bridge the gap, we propose a model-agnostic approach that provides enhanced explanations applicable to diverse knowledge tracing methods. Specifically, we propose a novel ranking loss designed to explicitly optimize the importance ranking of past interactions by comparing their corresponding perturbed outputs. Furthermore, we introduce a similarity loss to capture temporal dependencies, ensuring consistency in the assigned importance scores for conceptually similar interactions. Extensive experiments conducted on various knowledge tracing models and benchmark datasets demonstrate substantial enhancements in explanation quality.

1 Introduction

Knowledge Tracing (KT) aims to predict learners' future performance based on their past learning records. Deep learning-based knowledge tracing (DLKT) has achieved remarkable performance. However, the lack of interpretability in DLKT models hinders their broader adoption in real-world online education systems. Consequently, developing effective methods to explain DLKT predictions is crucial for the practical application of knowledge tracing.

Current explanation methods for knowledge tracing can be broadly categorized into two types: intrinsic explanations and feature attribution explanations, as illustrated in Figure 1. Intrinsic explanation approaches [Yeung, 2019; Su *et al.*, 2021; Minn *et al.*, 2022; Chen *et al.*, 2023; Huang *et al.*, 2024] utilize interpretable prediction structures based on educational theories, such as item response theory [McDonald, 2000] or selective perception [Simon, 1978], to provide explanations through educational concepts, such as exercise difficulty. This is illustrated in Figure 1(a). Although such explanations assist researchers in verifying the reasonableness of knowledge tracing model structures, they often constrain model flexibility, leading to a trade-off with performance [Li *et al.*, 2022]. Moreover, these methods cannot be directly utilized to improve learning plans. Instead of explaining model structures, feature attribution methods highlight significant past interactions that contribute to DLKT's prediction, as shown in Figure 1(b). Here feature refers to an interaction, representing a student's completion of an exercise along with the associated score. In knowledge tracing, attention-based methods [Pandey and Karypis, 2019; Ghosh *et al.*, 2020] are the primary approach for assessing the impact of each past interaction. However, within the explainable artificial intelligence research community, attention-based explanations remain controversial due to their potential to generate misleading explanations for humans [Bastings and Filippova, 2020; Lopardo *et al.*, 2024].

While only a few feature attribution methods are specifically tailored for knowledge tracing, they have been extensively developed in other research fields, such as time series prediction [Sundararajan *et al.*, 2017; Crabbé and van der Schaar, 2021; Bhalla *et al.*, 2023]. A promising direction of research has focused on learning a mask to perturb the input, where the mask encodes the feature importance at each time step for prediction [Fong and Vedaldi, 2017; Crabbé and van der Schaar, 2021; Bhalla *et al.*, 2023]. We refer to these methods as mask optimization methods, which serve as the foundation of our proposed approach. Our empirical observations reveal that applying these methods to knowledge tracing leads to suboptimal performance, primarily due to two key challenges. *Firstly*, existing methods fail to account for the unique temporal dependencies in knowledge tracing compared to other domains. For example, in time series prediction, temporal dependencies are largely determined by the positional relationships within a sequence. Contrastively, knowledge tracing considers temporal dependencies influenced by both the positions within the sequence and the similarity between interactions. *Secondly*, these methods

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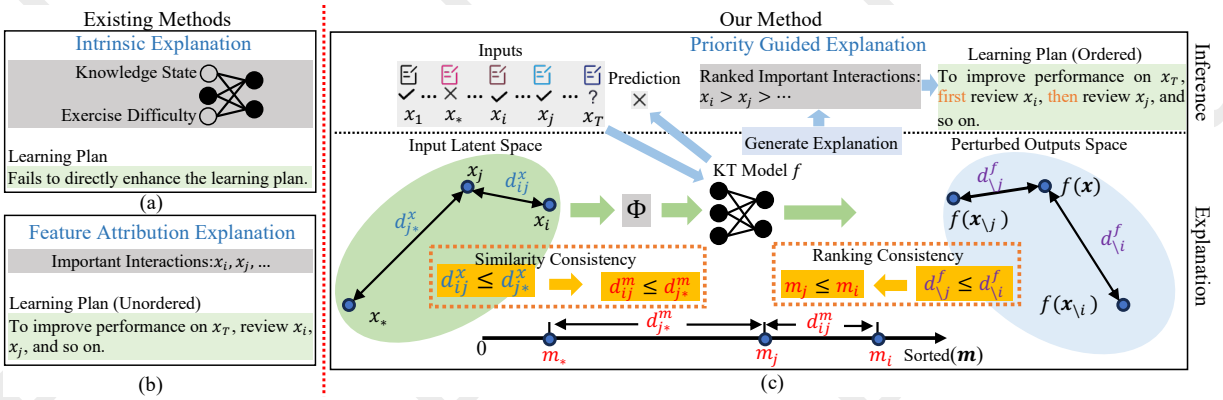

Figure 1: Explanation for Knowledge Tracing: x_i denotes an individual interaction at time step i, and $d^f_{\setminus i}$ represents the distance between the perturbed output $f(\boldsymbol{x}_{\setminus i})$, which removes interaction x_i, and the original output $f(\boldsymbol{x})$.

often reduce interactions to a binary classification of important or unimportant, failing to provide precise rankings of their importance scores. In knowledge tracing, however, fine-grained explanations that identify and prioritize important interactions are preferred, as they allow students to develop personalized learning plans based on these rankings, thereby improving learning outcomes. As shown in Figure 1(c), if a student learns that x_i is a more important interaction than x_j for their performance on x_T based on the explanation, they can devise an efficient learning plan, which first reviews x_i and then x_j to improve their performance on x_T.

Motivated by the above observations, we propose two novel consistency assumptions, namely similarity consistency and ranking consistency, to enhance feature attribution explanation methods and address the aforementioned challenges. We formulate the problem as a mask optimization task, where the method optimizes a mask to represent the importance of each interaction in the prediction process. To capture temporal dependencies, we introduce a similarity consistency loss, ensuring that the distances between interaction importance scores align with the distances of the interactions in the latent feature space. For instance, if an interaction x_i is more similar to x_j than x_*, the discrepancy in their corresponding importance scores d^m_{ij} should also be smaller than d^m_{j*}. To achieve a fine-grained ranking of the importance scores, we propose a ranking consistency loss, which ensures that the importance ranking of interactions is accurately reflected in the perturbed output space. Specifically, if the perturbed output $f(\boldsymbol{x}_{\setminus j})$, which excludes feature j, is closer to the original output than $f(\boldsymbol{x}_{\setminus i})$, it suggests that feature i is more important than feature j and should therefore be assigned a higher m_i. Our method is model-agnostic and produces improved explanations that are valuable for enhancing learning plans. Here we summarize the main contributions of this paper as follows:

- To the best of our knowledge, we present the first model-agnostic and priority-guided explanation method for knowledge tracing, which is able to provide high-quality and fine-grained explanation for various knowledge tracing methods.
- We propose two novel consistency assumptions to explicitly capture the relationships between interactions and their importance scores, in the input latent space and the perturbed output space, respectively.
- We conduct extensive experiments to compare to 7 explanation methods across 4 knowledge tracing models and 2 benchmark datasets, with results showcasing its superior performance and generalization capability.

2 Related Work

Knowledge Tracing. We present the development of knowledge tracing methods based on their underlying deep learning architectures. Long short-term memory networks [Hochreiter and Schmidhuber, 1997] have been employed in numerous studies to model students' knowledge states [Piech *et al.*, 2015; Long *et al.*, 2021; Liu *et al.*, 2023; Abdelrahman *et al.*, 2023]. Memory-augmented neural networks with two external memory matrices [Graves *et al.*, 2014], designed to store knowledge concept representations and mastery levels separately, have also been adopted in various studies [Zhang *et al.*, 2017; Wang and Sahebi, 2023]. Additionally, attention mechanisms [Vaswani *et al.*, 2017] have been widely applied to model the relevance between interactions and predict student performance [Pandey and Karypis, 2019; Ghosh *et al.*, 2020; Pandey and Srivastava, 2020; Lee *et al.*, 2022; Wang *et al.*, 2023; Li *et al.*, 2024].

Model Interpretability. Based on the application domains of explanation methods, we categorize existing approaches into static and temporal methods. Static methods are typically applied in domains without time dependencies, such as image classification. Gradient-based methods have been employed to measure the influence of each feature by calculating the gradient of features with respect to the model's output [Simonyan *et al.*, 2014; Sundararajan *et al.*, 2017]. Other approaches assess the contribution of each feature by examining how perturbations to input features affect the model's output [Ribeiro *et al.*, 2016; Jalwana *et al.*, 2020; Ren *et al.*, 2023]. However, these methods often overlook time dependencies inherent in temporal models, which leads to expla-

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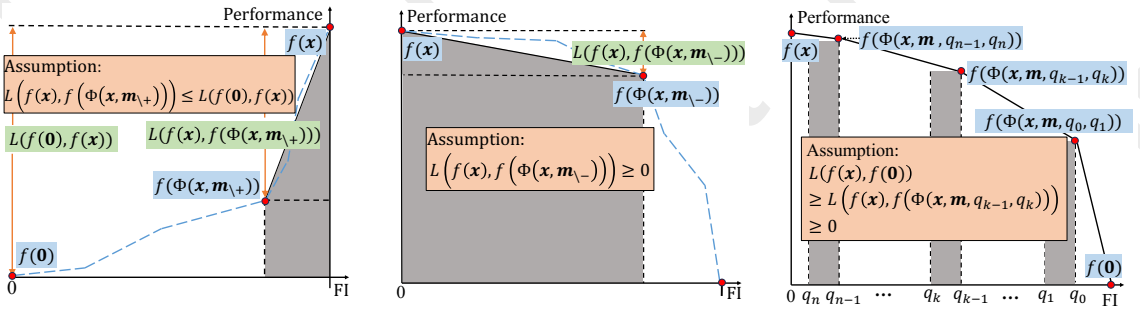

(a) Deletion Game (b) Preservation Game (c) Our method

Figure 2: Figure (a) and (b) illustrate the assumptions of the deletion and preservation games, respectively, while Figure (c) presents our enhanced assumption that encompasses both. The horizontal axis denotes feature importance (FI), the vertical axis denotes model performance, and the shaded region marks the interval of features removed. The blue curve illustrates how model performance may change when different numbers of features are removed. The fluctuating change rate suggests that current methods lack fine-grained explanations.

nations of suboptimal quality [Ismail *et al.*, 2020]. To address these limitations, recent methods have focused on measuring the contribution of features by introducing the temporal relevance between features [Fong and Vedaldi, 2017; Tonekaboni *et al.*, 2020; Crabbé and van der Schaar, 2021; Bento *et al.*, 2021; Leung *et al.*, 2023; Bhalla *et al.*, 2023]. However, these methods typically only distinguish between important and unimportant features and fail to provide fine-grained explanations suitable for knowledge tracing, ignoring the differences in temporal dependencies between knowledge tracing and other temporal domains.

3 Problem Formulation

A student's learning record consists of a sequence of interactions. Each interaction at time step t is denoted as $x_t = (q_t, c_t, a_t)$, where q_t represents the exercise, c_t corresponds to the knowledge concept, and a_t indicates the score. Typically, a_t takes a value of 0 or 1, with 0 indicating an incorrect response to the exercise and 1 indicating a correct response. Given a student's past learning record $\boldsymbol{x} = \{x_1, \cdots, x_t, \cdots, x_T\}$, the goal of knowledge tracing is to predict the learner's score a_{T+1} for exercise q_{T+1} associated with knowledge concept c_{T+1} at the next time step $T+1$. Formally, we define knowledge tracing as $\hat{a}_{T+1} = f(\boldsymbol{x}, q_{T+1}, c_{T+1})$, where f represents the knowledge tracing function we aim to learn from large-scale historical data and $\hat{a}_{T+1}$ is the prediction for time step $T+1$ generated by f.

In addition to predicting $\hat{a}_{T+1}$, we further analyze the impact of each past interaction x_t on $\hat{a}_{T+1}$. Specifically, the explanation of f is defined as a vector $\boldsymbol{m} \in [0,1]^T$, where each m_t quantifies the importance of interaction x_t to prediction $\hat{a}_{T+1}$. For example, $m_t > m_{t'}$ indicates that the interaction x_t has a greater influence on the prediction $\hat{a}_{T+1}$ compared to $x_{t'}$. In this paper, our goal is to propose a novel and model-agnostic explanation method, which can effectively derive $\boldsymbol{m}$ for any knowledge tracing function f.

4 Method

Our explanation method consists of two components: 1) priority-guided explanation and 2) similarity-aware attribution consistency. Each component will be introduced in detail in the following sections.

4.1 Priority Guided Explanation

Assumptions Behind the Mask Optimization Method

We first investigate the underlying assumptions of current mask optimization methods. Based on these insights, we propose enhanced assumptions and leverage them to design our method. Current mask optimization methods can be categorized into the deletion game and preservation game [Dabkowski and Gal, 2017; Enguehard, 2023]. These methods typically adopt one of the two approaches [Crabbé and van der Schaar, 2021] or simply combine them [Dabkowski and Gal, 2017].

In the deletion game, the goal is to use the perturbation function $\Phi(\boldsymbol{x}, \boldsymbol{m})$ to obscure the data as minimally as possible while maximizing the change in the model's predictions. There are two ways to maximize this change: 1) making $f(\Phi(\boldsymbol{x}, \boldsymbol{m}))$ farther from $f(\boldsymbol{x})$, or 2) making $f(\Phi(\boldsymbol{x}, \boldsymbol{m}))$ close to $f(\mathbf{0})$. It has been found that the latter performs better, as it provides a clearer optimization objective. In contrast, the former is challenging to define clearly because there are multiple ways to achieve distance from $f(\boldsymbol{x})$ [Enguehard, 2023]. In the following sections, we refer to the latter as the definition of the deletion game:

$$\underset{\boldsymbol{m}}{\operatorname{argmin}}\, \lambda \|\boldsymbol{m}\|_1 + \mathcal{L}(f(\mathbf{0}), f(\Phi(\boldsymbol{x}, \mathbf{1} - \boldsymbol{m}))),$$

where the perturbation function is typically defined as:

$$\Phi(\boldsymbol{x}, \boldsymbol{s}) = \boldsymbol{x} \odot \boldsymbol{s} + \boldsymbol{b} \odot (\mathbf{1} - \boldsymbol{s}),$$

where $\odot$ denotes element-wise multiplication, and $\boldsymbol{b}$ is a reference vector used to replace the original features in $\boldsymbol{x}$. In our experiment, we set $\boldsymbol{b}$ to the zero embedding $\mathbf{0}$, and define $\mathcal{L}$ as the Jensen–Shannon divergence.

Furthermore, the deletion game is based on the following underlying assumption: a good explanation $\boldsymbol{m}$ satisfies the condition that removing the important features, based on the mask $\boldsymbol{m}$, will significantly reduce the performance of f. This

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assumption is illustrated in Figure 2a. Based on this assumption, we have:

$$\begin{aligned}&\mathcal{L}(f(\boldsymbol{x}), f(\Phi(\boldsymbol{x}, \boldsymbol{m}_{\backslash +})))\\ &\leq \mathcal{L}(f(\boldsymbol{x}), \lim_{\boldsymbol{s}\to\mathbf{0}} f(\Phi(\boldsymbol{x}, \boldsymbol{s}))) = \mathcal{L}(f(\boldsymbol{x}), f(\mathbf{0})),\end{aligned}$$

where $\Phi(\boldsymbol{x}, \boldsymbol{m}_{\backslash +})$ denotes the perturbed input obtained by excluding the most important features from the original input.

In the preservation game, the goal is to obscure as much data as possible while keeping the predictions as close as possible to the original predictions. It is defined as follows:

$$\operatorname*{argmin}_{\boldsymbol{m}} \lambda\|\boldsymbol{m}\|_1 + \mathcal{L}(f(\boldsymbol{x}), f(\Phi(\boldsymbol{x}, \boldsymbol{m}))).$$

The preservation game is based on the following underlying assumption: a good explanation $\boldsymbol{m}$ satisfies the condition that removing the unimportant features, based on $\boldsymbol{m}$, will slightly reduce the performance of f. This assumption is illustrated in Figure 2b. Based on this assumption, we have:

$$\begin{aligned}\mathcal{L}(f(\boldsymbol{x}), f(\Phi(\boldsymbol{x}, \boldsymbol{m}_{\backslash -}))) &\geq \mathcal{L}(f(\boldsymbol{x}), \lim_{\boldsymbol{s}\to\mathbf{1}} f(\Phi(\boldsymbol{x}, \boldsymbol{s})))\\ &= \mathcal{L}(f(\boldsymbol{x}), f(\boldsymbol{x})) = 0,\end{aligned}$$

where $\Phi(\boldsymbol{x}, \boldsymbol{m}_{\backslash -})$ denotes the perturbed input obtained by excluding the least important features from the original input.

Based on the assumptions in deletion game and preservation game, we have:

$$\begin{aligned}&0 \leq \mathcal{L}(f(\boldsymbol{x}), f(\Phi(\boldsymbol{x}, \boldsymbol{m}_{\backslash -})))\\ &\leq \mathcal{L}(f(\boldsymbol{x}), f(\Phi(\boldsymbol{x}, \boldsymbol{m}_{\backslash +}))) \leq \mathcal{L}(f(\boldsymbol{x}), f(\mathbf{0})).\end{aligned} \tag{1}$$

The above equation reflects an ranking assumption regarding the removal of two feature intervals: those containing the least important features and those containing the most important features. We extend this assumption and propose an enhanced version, termed the ranking consistency assumption (Figure 2c). By partitioning features into intervals based on their importance scores (from most to least important) and progressively removing one interval at a time, the model's performance is expected to improve monotonically.

Priority-Guided Explanation Using Ranking Loss

We propose a ranking-based method to provide priority-guided explanation. To achieve this goal, we first define a list of values Q to separate the mask $\boldsymbol{m}$:

$$Q = [q_0, q_1, \cdots, q_k, q_{k+1}, \cdots, q_n],$$

where q_k can be quantiles of $\boldsymbol{m}$ or even any values holds the following constraint:

$$\forall k \in [1, n],\ \max(\boldsymbol{m}) \geq q_k > q_{k+1} \geq \min(\boldsymbol{m}).$$

Subsequently, we define the following binary operation for input perturbation:

$$\mathrm{S}(\boldsymbol{m}, q_{k-1}, q_k) := \begin{cases} s_i = 1 & m_i \geq q_{k-1},\\ s_i = 0 & q_{k-1} > m_i \geq q_k,\\ s_i = 1 & m_i < q_k. \end{cases} \tag{2}$$

where s_i refers to the i-th feature in $\mathrm{S}(\boldsymbol{m}, q_{k-1}, q_k)$. For notation simplicity, we define

$$\begin{aligned}\forall k \in [1, n],\ r_k &= \mathcal{L}(f(\boldsymbol{x}), f(\Phi(\boldsymbol{x}, \mathrm{S}(\boldsymbol{m}, q_{k-1}, q_k)))),\\ \boldsymbol{r} &= [r_1, ..., r_k, ..., r_n].\end{aligned}$$

Recall that, based on deletion game and preservation game, we have the following conclusion:

$$\sup_{k\in[1,n]} r_k = \mathcal{L}(f(\boldsymbol{x}), f(\mathbf{0})),\quad \inf_{k\in[1,n]} r_k = 0.$$

We generalize the order assumption in Equation (1) and obtain the following enhanced assumption:

$$\forall j, k \in [1, n],\ j < k \implies r_j \geq r_k. \tag{3}$$

We implement the order assumption in Equation (3) using ranking loss to provide priority enhanced explanation.

$$\mathcal{L}_{\mathrm{RL}}(\boldsymbol{r}) = \sum_{1\leq i<j\leq n} \max(0, -1\cdot(r_i - r_j) + \gamma), \tag{4}$$

where γ is a hyperparameter that determines the margin.

When a student has a long learning history, the computational cost of this loss function can become substantial. To mitigate this, we apply the ranking loss only to the top-K important features by setting $q_0 = \max(\boldsymbol{m})$, where K is smaller than the length of the original input. This strategy reduces computational overhead and improves the accuracy of prioritizing the top-K features in the most critical explanations.

Directional Ranking Loss for Knowledge Tracing

The above method represents a general formulation designed for multi-class classification tasks. Knowledge tracing, however, is a binary classification task, where the direction of the perturbed prediction's deviation from the original prediction can be further specified.

In knowledge tracing, we aim to identify which features encourage the model to predict a correct response and which lead to an incorrect one. We use c and w to denote the labels for correct and incorrect responses, respectively. Since there are only two classes, the prediction is typically a single value with 1 indicating c and 0 indicating w. When the label is c, the perturbation should shift the prediction away from c and toward w. This will lead to a decrease in $f(\boldsymbol{x})$ after the perturbation is applied. Let $f_k = f(\Phi(\boldsymbol{x}, \mathrm{S}(\boldsymbol{m}, q_{k-1}, q_k)))$, $\boldsymbol{f} = [f_1, ..., f_k, ..., f_n, f_{n+1}]$ and $f_{n+1} = f(\boldsymbol{x})$ [1], we reformulate Equation (3) as

$$\forall j, k \in [1, n+1],\ j < k \implies f_j \leq f_k, \tag{5}$$

and subsequently obtain the directional loss function for class c based on Equation (4) as

$$\mathcal{L}^{c}_{\mathrm{DRLPE}}(\boldsymbol{f}) = \sum_{1\leq i<j\leq n+1} \max(0, f_i - f_j + \gamma).$$

On the other hand, if the label is w, the perturbation should shift the prediction away from w and toward c, which will lead to an increase in $f(\boldsymbol{x})$ after the perturbation is applied. Again, we reformulate Equation (3) as

$$\forall j, k \in [1, n+1],\ j < k \implies f_j \geq f_k, \tag{6}$$

and subsequently obtain the directional loss function for class w based on Equation (4) as

$$\mathcal{L}^{w}_{\mathrm{DRLPE}}(\boldsymbol{f}) = \sum_{1\leq i<j\leq n+1} \max(0, -1\cdot(f_i - f_j) + \gamma).$$

[1] Through experiments, We observe that adding an additional item $f_{n+1} = f(\boldsymbol{x})$ to $\boldsymbol{f}$ without perturbation improves performance.

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By combining the above two cases, we define the Directional Ranking Loss for Priority-Guided Explanation (DRLPE) as:

$$\mathcal{L}_{\text{DRLPE}}(\boldsymbol{f}) = \begin{cases} \mathcal{L}^{c}_{\text{DRLPE}}(\boldsymbol{f}), \text{if the true label is } c, \\ \mathcal{L}^{w}_{\text{DRLPE}}(\boldsymbol{f}), \text{if the true label is } w. \end{cases} \tag{7}$$

One last important point is that the binary mask operation in Equation (2) is not differentiable. To solve this issue, we adopt the straight-through trick from Gumbel-Softmax [Jang *et al.*, 2017]:

$$\mathrm{S}(\boldsymbol{m}, q_{k-1}, q_k) = \mathrm{S}(\boldsymbol{m}, q_{k-1}, q_k) + \boldsymbol{m} - sg[\boldsymbol{m}],$$

where $sg[\cdot]$ represents the stop-gradient operator, which acts as the identity operator during the forward pass and has a zero partial derivative during the backward pass.

4.2 Similarity-Aware Attribution Consistency

Since a student's performance on a specific exercise is influenced by their performance on other exercises involving similar knowledge concepts [Piech *et al.*, 2015; Pandey and Karypis, 2019], we introduce the similarity-aware attribution consistency regularization. This regularization ensures that interactions with similar knowledge concepts have comparable importance scores for the model's predictions. Inspired by previous work [Ghosh *et al.*, 2020], the similarity between interactions is defined as follows:

$$\forall t' < t, w(t,t') = \sum_{\tau=t'+1}^{t} \frac{\exp(\frac{1}{\sqrt{d}}\boldsymbol{e}(x_t)\boldsymbol{e}(x_\tau)^T)}{\sum_{1\le\tau'\le t}\exp(\frac{1}{\sqrt{d}}\boldsymbol{e}(x_t)\boldsymbol{e}(x_{\tau'})^T)},$$

where $\boldsymbol{e}(x)$ is a fixed, non-trainable embedding of x, extracted from the pretrained target model, d is the dimension of $\boldsymbol{e}(x)$, and $w_{t,t'}$ is the cumulative similarity between interactions at t and t'. We enforce consistency in the importance scores of different interactions based on their similarity. This is defined as follows:

$$\mathcal{L}_{\text{consis}}(\boldsymbol{m}) = \sum_{t=0}^{T}\sum_{\tau=t+1}^{T} w(t,\tau)\|m_t - m_\tau\|^2,$$

where m_t is importance score of interaction at t.

4.3 Loss Function

We formally define the overall loss function as follows:

$$\underset{\boldsymbol{m}}{\operatorname{argmin}}\, \mathcal{L}_{\text{DRLPE}}(\boldsymbol{r}^f) + \lambda_1\mathcal{L}_{\text{consis}}(\boldsymbol{m}) + \lambda_2\mathcal{L}_1(\boldsymbol{m}),$$

where λ_1, λ_2 are hyperparameters balancing the loss terms and $\mathcal{L}_1(\boldsymbol{m})$ represents the Lasso regularization applied to $\boldsymbol{m}$.

5 Experiment

5.1 Experimental Setup

Dataset. We evaluate the explanation methods on two public datasets, ASSISTment 2009[2] and ASSISTment 2017[3]. These datasets, collected from an online tutoring platform, are used to train the knowledge tracing models to be explained. For the ASSISTment 2009 dataset, we remove records without corresponding knowledge concepts, resulting in a dataset containing 4,151 students, 16,891 exercises, and 110 associated concepts, with a total of 325,637 records. The ASSISTment 2017 dataset includes 1,709 students, 3,162 exercises, and 102 associated concepts, comprising 942,816 interaction records.

Knowledge tracing models. To comprehensively evaluate our proposed method, we select representative knowledge tracing models from various deep learning frameworks as explanation targets. The selected models include **DKT** [Piech *et al.*, 2015], **DKVMN** [Zhang *et al.*, 2017], **SAKT** [Pandey and Karypis, 2019], and **AKT** [Ghosh *et al.*, 2020].

Metrics. Due to the absence of ground-truth explanations for knowledge tracing, we adopt the following two metrics in our experiments, inspired by the evaluation methods proposed in previous studies [Kim *et al.*, 2020; Tonekaboni *et al.*, 2020; Leung *et al.*, 2023].

Comprehensiveness (Comp). We remove the most important features and compute the average change of Area Under the ROC Curve (AUC) compared with the original inputs. Higher is better with this metric, as it indicates that the explanation methods have identified the important features that significantly impact model performance.

$$\text{Comprehensiveness} = \text{AUC}(f(\boldsymbol{x})) - \text{AUC}(f(\boldsymbol{x}_{\setminus +})),$$

where $\boldsymbol{x}_{\setminus +}$ represents the perturbed input obtained by removing the important features from the original input.

Sufficiency (Suff). Instead of removing the important features, we remove the unimportant features and compute the change in the AUC compared to the original input. A lower score indicates better performance, as it signifies that the explanation methods have identified unimportant features with little or no impact on model performance.

$$\text{Sufficiency} = \text{AUC}(f(\boldsymbol{x})) - \text{AUC}(f(\boldsymbol{x}_{\setminus -})),$$

where $\boldsymbol{x}_{\setminus -}$ represents the perturbed input obtained by removing the unimportant features from the original input.

5.2 Experiment Result

Comparison to Existing Methods

We compare our method against three static methods, including **FO** [Zeiler and Fergus, 2014], **LIME** [Ribeiro *et al.*, 2016], and **KernelSHAP** [Lundberg and Lee, 2017], as well as four temporal methods, including **FIT** [Tonekaboni *et al.*, 2020], **TimeSHAP** [Bento *et al.*, 2021], **DynaMask** [Crabbé and van der Schaar, 2021], and **WinIT** [Leung *et al.*, 2023]. The results are presented in Table 1. Ours method outperforms others across all four models and both datasets. We also found that temporal explanation methods, such as DynaMask and FIT, generally outperform static explanation methods, likely due to their incorporation of temporal dependencies. For the AKT model, attention-based explanations show better performance compared to other baseline methods. However, this advantage is not observed in SAKT, suggesting that attention-based explanations do not always provide superior performance, despite the success of attention-based methods in various domains.

[2]https://sites.google.com/site/assistmentsdata/home/2009-2010-assistment-data/skill-builder-data-2009-2010

[3]https://sites.google.com/view/assistmentsdatamining/dataset

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Type	Methods	ASSISTment 2009		ASSISTment 2017		ASSISTment 2009		ASSISTment 2017	
		Comp ↑	Suff ↓	Comp ↑	Suff ↓	Comp ↑	Suff ↓	Comp ↑	Suff ↓
		DKT				DKVMN			
	Random	0.0192	0.0183	0.0044	0.0025	0.0184	0.0160	0.0041	0.0079
Static	FO	0.0682	0.0138	0.0889	0.0012	0.0740	0.0188	0.0994	0.0013
	LIME	0.0792	0.0118	0.0845	0.0014	0.0787	0.0132	0.0981	0.0010
	KernelSHAP	0.0745	0.0127	0.0745	0.0011	0.0785	0.0148	0.0973	0.0013
Temporal	TimeSHAP	0.0344	0.0402	0.0624	0.0158	0.0513	0.0507	0.0807	0.0445
	FIT	0.0465	0.0155	0.0425	-0.0019	0.0538	0.0123	0.0287	0.0024
	WinIT	0.0305	0.0271	0.0357	0.0008	0.0376	0.0217	0.0540	0.0014
	DynaMask	0.0915	0.0103	0.0999	0.0006	0.0507	0.0231	0.0899	0.0014
	Ours	**0.1470**	**-0.0980**	**0.2379**	**-0.0499**	**0.1498**	**-0.0886**	**0.1088**	**-0.1058**
		SAKT				AKT			
	Random	0.0574	0.0347	0.0007	0.0047	0.0261	0.0317	0.0040	0.0019
	Attention	0.0790	0.0282	0.0243	0.0001	0.0719	0.0426	0.0636	0.0082
Static	FO	0.1147	0.0186	0.0009	-0.0012	0.0417	0.0294	0.0630	0.0004
	LIME	0.1046	0.0184	-0.0002	-0.0005	0.0535	0.0210	0.0588	-0.0003
	KernelSHAP	0.1065	0.0226	0.0022	-0.0014	0.0590	0.0211	0.0608	-0.0017
Temporal	TimeSHAP	0.0893	0.1005	0.0396	-0.0060	0.0419	0.0597	0.0504	0.0160
	FIT	0.0249	0.0656	0.0019	0.0075	0.0467	0.0265	0.0315	0.0022
	WinIT	0.0695	0.0426	0.0226	-0.0026	0.0476	0.0258	0.0139	-0.0001
	DynaMask	0.1294	0.0241	0.0222	-0.0016	0.0374	0.0355	0.0540	0.0019
	Ours	**0.3228**	**-0.0666**	**0.2777**	**-0.0609**	**0.0886**	**-0.0323**	**0.1304**	**-0.0188**

Table 1: Performance of explanation methods on the knowledge tracing model. The best method is highlighted in bold, and the second-best method is underlined. For ↑ metrics, the higher the better, while for ↓ ones, the lower the better.

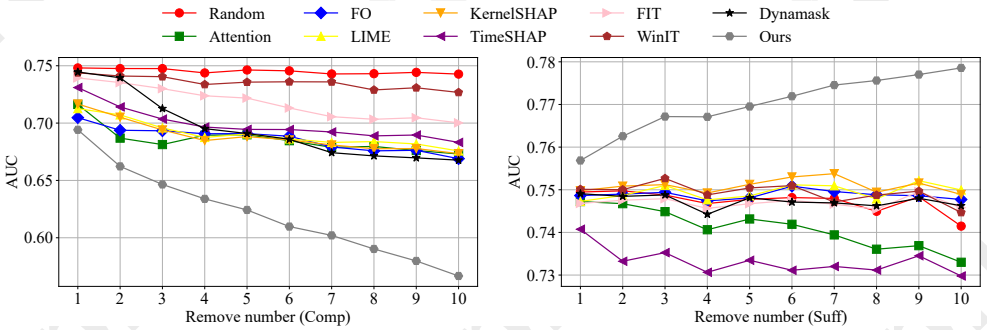

Figure 3: Removement experiments on ASSISTment 2017. A lower AUC indicates better performance in Comp, while a higher AUC indicates better performance in Suff.

Ablation Experiment for Different Components

To evaluate the contribution of each component in our method, we conducted ablation studies on two datasets and four knowledge tracing models. Specifically, we tested three variants of our method:

- **w/o Ranking**. We eliminate the ranking loss to examine its impact on the explanation. Formally, we redefine the ranking loss in Equation (5) and Equation (6) as follows:

$$\forall k \in [1, n],\ f_k \leq f_{n+1}, \quad \text{if the true label is } c,$$
$$\forall k \in [1, n],\ f_k \geq f_{n+1}, \quad \text{if the true label is } w.$$

- **w/o AC**. We remove the attribution consistency regularization on the mask.
- **w/o Direction**. We replace the directional ranking loss defined in Equation (7) with the ranking loss defined in Equation (4).

As shown in Table 2, removing the ranking loss component significantly degrades performance in most models and datasets, highlighting its importance. We also observe that removing the directional ranking loss component has a greater impact on performance than removing the attribution consistency component. These results indicate that both components are crucial for the performance of our method and for providing fine-grained explanations. Additionally, we found that the attribution consistency component has a significantly greater influence on performance than other components, but only in specific cases, such as the DKVMN model on the ASSISTment 2017 dataset. We believe this is because this regularization imposes a strong assumption on the model's internal decision process, which may not be suitable for all models. Nevertheless, the regularization still positively impacts the explanation quality, as demonstrated by the results.

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Methods	ASSISTment 2009		ASSISTment 2017		ASSISTment 2009		ASSISTment 2017	
	Comp (-%)	Suff (+%)	Comp (-%)	Suff (+%)	Comp (-%)	Suff (+%)	Comp (-%)	Suff(+%)
	DKT				DKVMN			
Ours	0.1470 (0%)	-0.0980 (0%)	0.2379 (0%)	-0.0499 (0%)	0.1498 (0%)	-0.0886 (0%)	0.1088 (0%)	-0.1058 (0%)
w/o Ranking	**0.0186** (**87**%)	**0.0191** (**120**%)	**0.0257** (**89**%)	-0.0051 (90%)	**0.0186** (**88**%)	**0.0500** (**156**%)	0.0209 (81%)	0.0389 (137%)
w/o AC	0.1264 (14%)	-0.0710 (27%)	0.2346 (1%)	-0.0482 (3%)	0.0724 (52%)	-0.0560 (37%)	**0.0074 (93%)**	-0.0573 (46%)
w/o Direction	0.0575 (61%)	-0.0028 (97%)	0.0560 (76%)	**0.0123** (**125**%)	0.0449 (70%)	0.0295 (133%)	0.0618 (43%)	**0.0568** (**154**%)
	SAKT				AKT			
Ours	0.3228 (0%)	-0.0666 (0%)	0.2777(0%)	-0.0609 (0%)	0.0886 (0%)	-0.0323 (0%)	0.1304 (0%)	-0.0188 (0%)
w/o Ranking	**0.0355** (**89**%)	**0.0508** (**176**%)	0.0129 (95%)	-0.0074 (88%)	**0.0116** (**87**%)	**0.0242** (**175**%)	0.0232 (82%)	**0.0181** (**196**%)
w/o AC	0.2458 (24%)	-0.0152 (77%)	0.1814 (35%)	**0.0078** (**113**%)	0.0836 (6%)	-0.0169 (48%)	0.0619 (53%)	-0.0103 (45%)
w/o Direction	0.1069 (67%)	0.0189 (128%)	**0.0036** (**99**%)	0.0023 (104%)	0.0159 (82%)	0.0126 (139%)	**0.0060** (**95**%)	0.0033 (117%)

Table 2: Ablation study. The values in the format X (Y%) represent the absolute performance difference (X) and the relative performance change (Y%) when removing the corresponding module from the method. A positive Y% indicates a performance degradation. The most important components are highlighted in bold, and the second most important components are underlined.

Methods	ASSISTment 2009		ASSISTment 2017	
	$\Delta_{\text{Comp}} \uparrow$	$\Delta_{\text{Suff}} \downarrow$	$\Delta_{\text{Comp}} \uparrow$	$\Delta_{\text{Suff}} \downarrow$
Attention	**0.0489**	0.0075	0.0273	0.0012
FO	0.0077	0.0005	0.0233	-0.0001
LIME	0.0166	0.0016	0.0278	0.0005
KernelShap	0.0186	-0.0006	0.0263	-0.0015
TimeShap	0.0141	0.0141	0.0229	0.0104
FIT	0.0152	0.0031	0.0101	-0.0007
WinIT	0.0173	0.0022	0.0040	**-0.0046**
DynaMask	0.0086	0.0019	0.0252	-0.0006
Ours	0.0408	**-0.0094**	**0.0308**	-0.0025

Table 3: Sensitivity to the ranking of feature importance on the AKT model. The best methods are highlighted in bold, and the second-best method is underlined. For $\uparrow$ metrics, the higher the better, while for $\downarrow$ ones, the lower the better.

Ranking Sensitivity in Explanation Methods

To evaluate different methods from this perspective, we propose an intuitive method to assess whether explanations from different methods preserve the ranking of important features.

The process is as follows: first, we permutate the ranking of explanations for the top-K important features so that m_i does not match with x_i for $i \leq K$. Then, we evaluate the performance of the explanation on the top-$\lfloor K/2 \rfloor$ features. In other words, the permutation operation will replace some features with importance rankings in the range $[1, \lfloor K/2 \rfloor]$ with features having importance rankings in the range $[\lfloor K/2 \rfloor + 1, K]$ or shuffle the features ranking in $[1, \lfloor K/2 \rfloor]$. We define the ranking sensitivity of explanations as the expected change in explanation performance after a single permutation.

$$\Delta H = \mathbb{E}_{\boldsymbol{m} \sim \mathcal{E}(\mathcal{D}), \tilde{\boldsymbol{m}} \sim \mathcal{P}_K(\boldsymbol{m})}(H(\boldsymbol{m}) - H(\tilde{\boldsymbol{m}})),$$

where $H(\cdot)$ represents a metric for evaluating an explanation, such as Comp. $\mathcal{E}(\mathcal{D})$ represents the explanations for the dataset $\mathcal{D}$, and $\mathcal{P}_K(\boldsymbol{m})$ is the permutation set of $\boldsymbol{m}$ with the top-K features permuted. Direct computation of ΔH is computationally expensive. Therefore, in practice, we use some sampled instances from $\mathcal{P}_K(\boldsymbol{m})$ to approximate it. A higher Δ_{Comp} or lower Δ_{Suff} indicates that the explanation is more sensitive to the ranking of important features within $[1, \lfloor K/2 \rfloor]$ and effectively differentiates features ranked in $[1, \lfloor K/2 \rfloor]$ from those in $[\lfloor K/2 \rfloor + 1, K]$.

The results are presented in Table 3, where we evaluate ΔH for all methods on the AKT model across two datasets. Our method consistently outperforms others in almost all metrics, except for a slight disadvantage compared to WinIT on ASSISTment 2017 and Attention on ASSISTment 2009, though it still surpasses the remaining methods. In most cases, we observe that $\Delta_{\text{Comp}} > 0$ and $\Delta_{\text{Suff}} < 0$, indicating that the shuffled explanations are inferior to the original ones and that these explanations successfully capture the priority among important features. However, we also notice that, in the ASSISTment 2009 dataset, $\Delta_{\text{Suff}} > 0$ for most baseline methods, which suggests that these explanations fail to capture the priority among important features.

Impact Study on the Number of Removed Interactions

We evaluate our methods by removing different numbers of interactions and observing performance changes in the AKT model on ASSISTment 2017, as shown in Figure 3. To study whether the explanation methods can provide fine-grained explanations, we evaluate the performance on the top 10 features. The figure demonstrates that our method consistently outperforms others by a considerable margin. Additionally, the performance of our methods continuously decreases in Comp and increases in Suff as the number of masked interactions increases, while the performance of other methods fluctuates. This suggests that our method not only excels in identifying the most important interactions but also outperforms in ranking the top 10 interaction importance, while other methods exhibit mediocre performance when assigning importance scores to a small number of interactions.

6 Conclusion

In this work, we introduce a fine-grained feature-attribution method tailored to knowledge tracing that supports improved learning outcomes. Our approach outperforms existing techniques in uncovering key interactions across diverse models and real-world datasets, underscoring the value of task-specific explanations. While current evaluation relies on model performance, future work will explore more objective and comprehensive metrics to assess explanation quality and their educational value.

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