

LANA: Towards Personalized Deep Knowledge Tracing Through Distinguishable Interactive Sequences *

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ABSTRACT

In educational applications, *Knowledge Tracing* (KT) has been widely studied for decades as it is considered a fundamental task towards adaptive online learning. Among proposed KT methods, Deep Knowledge Tracing (DKT) and its variants are by far the most effective ones due to the high flexibility of the neural network. However, DKT often ignores the inherent differences between students (e.g. memory skills, reasoning skills, ...), averaging the performances of all students, leading to the lack of personalization, and therefore was considered insufficient for adaptive learning. To alleviate this problem, in this paper, we proposed Leveled Attentive KNowledge TrAcing (LANA), which firstly uses a novel student-related features extractor (SRFE) and pivot modules to distill and distinguish students' unique inherent properties from their respective interactive sequences. Moreover, inspired by Item Response Theory (IRT), the interpretable Rasch model was used to cluster students by their ability levels, and thereby utilizing leveled learning to assign different encoders to different groups of students. With pivot module reconstructed the decoder for individual students and leveled learning specialized encoders for groups, personalized DKT was achieved. Extensive experiments conducted on two real-world large-scale datasets demonstrated that our proposed LANA improves the AUC score by at least 1.00% (i.e. EdNet \uparrow 1.46% and RAIED2020 \uparrow 1.00%), substantially surpassing the other State-Of-The-Art KT methods.

Keywords

Education, Personalized Learning, Adaptive Learning, Knowledge Tracing, Machine Learning, Deep Learning

*A full version of this paper is available at https://github.com/sooptq/LANA-pytorch/raw/main/LANA_EDM2021.pdf

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1. INTRODUCTION

Knowledge Tracing (KT) aims to accurately retrieve students' knowledge states at a certain time by his past sequential exercising interactions. To evaluate KT's performance, it is asked to predict the correctness of students' future exercises with the retrieved knowledge states as Equation 1 represented.

$$P(r_{t+1}^{s_i} | I_1^{s_i}, I_2^{s_i}, I_3^{s_i}, \dots, I_t^{s_i}, \{I_{t+1}^{s_i} - r_{t+1}^{s_i}\}), I_t^{s_i} = (e_t^{s_i, q_j}, c^{q_j}, r_t^{s_i}) \quad (1)$$

Where $e_t^{s_i, q_j}$ is referred as student $s_i \in \mathbb{N}^+$ answering question $q_j \in \mathbb{N}^+$ at discrete time step $t \in \mathbb{N}^+$, c^{q_j} represents the contextual information of question q_j (e.g. related concepts, part, etc.) [23, 14, 10, 4], and $r_t^{s_i} \in \{0, 1\}$ represents the correctness of student s_i 's answer to q_j at time t . Additionally, the student's interaction sequence is defined as $S_{t_0, t_1}^{s_i} = \{I_t^{s_i} | t_0 < t < t_1\}$ and κ is defined as $\kappa_t^{s_i} = \{s_i, q_j, c^{q_j}, r_t^{s_i}\}$, referring to all features that participated in one interaction $I_t^{s_i}$ for latter explanation.

Traditionally, KT was regarded as a sequential behavior mining task [8, 17], and therefore various methods established models with the theory of bayesian probability (BKT [3]) and psycho-statistics (IRT [5]), providing excellent interpretability and good performance. Nevertheless, recently proposed Deep Knowledge Tracing (DKT) [16] and its variants [13, 4, 14, 1, 18] significantly outperform other KT methods in metrics using Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM [6]). However, DKT distinctly lacks personalization for students compared to BKT and IRT [15, 25], which are capable of separately training unique models for each student, while DKT only trains a unified model for all students due to massive training data and abundant computing resources required by deep learning. Hence, DKT weakly reflects the large inherent property (i.e. memory skills, reasoning skills, or even guessing skills) gaps between students.

ASSUMPTION 1. For any interactive sequences satisfying $\|S_{t_0, t_1}^{s_i}\| > \Theta \gg 1$, $\|\kappa\| > \Psi$ and $t_2 - t_1 > \mathcal{E}$, $S_{t_0, t_1}^{s_i}$ can be distinguished from $S_{t_0, t_1}^{s_j}$ and $S_{t_2, t_3}^{s_i}$ respectively.

Is it possible to bring personalization back to DKT? To answer this question, we observed that the proactive behavior

sequence (i.e. interactive sequences) of each individual is unique and changeable over time. Hence, we argue that the minimal personalized unit in KT is “a student at a certain time t_i ” instead of just “a student”, and **student’s inherent properties at time t_i can be represented by his interactive sequences around time t_i (Assumption 1)**. In such a way, these student-related features could tremendously help personalize the KT process since they could be used to identify different students at different stages. Consequently, in our proposed Leveled Attentive Knowledge Tracing (LANA), unique student-related features are distilled from students’ interactive sequence by a Student-Related Features Extractor (SRFE). Moreover, inspired by BKT and IRT that assign completely different models to different students, LANA, as a DKT model, successfully achieves the same goal in a different manner. Detailedly, instead of separately training each student a model like BKT and IRT, **LANA learns to learn correlations between inputs and outputs on attention of the extracted student-related features**, and thus becomes transformable for different students at different stages. More specifically, the transformation was accomplished using pivot module and leveled learning, where the former one is a model component that seriously relies on the SRFE, and the latter one is a training mechanism that specializes encoders for groups with interpretable Rasch model defined ability levels. Formally, the LANA can be represented by:

$$\underbrace{r_t^{s_i} \sim (f(p_t^{s_i}))(h_t^{s_i})}_{\text{Adaptive by Pivot Module}}, \quad \underbrace{p_t^{s_i} \sim k(h_t^{s_i}), \quad h_t^{s_i} \sim g(h_{<t}^{s_i}, S_{0,t}^{s_i})}_{\text{Adaptive by Leveled Learning}}, \quad (2)$$

where $h_t^{s_i}$ is referred as student s_i ’s knowledge state at time t respectively, $f(\cdot)$ (decoder), $g(\cdot)$ (encoder) and $k(\cdot)$ (SRFE) are three main modules that LANA seeks to learn.

2. METHODOLOGY

2.1 Base Modifications

There are mainly two base modifications in the LANA model (Figure 1) that were made to the basic transformer. Firstly, in the LANA model, the positional information (e.g. positional encoding, positional embedding) was directly fed into the attention module with a private linear projection, instead of being added to the input embedding and shared the same linear projection matrix with other features in the input layer. Although experiments in [22] suggested that blending input embedding with positional information is effective, recently some work [19] debated that when the model becomes deeper, it tends to “forget” the positional information fed into the first layer. Moreover, some other work [9] believed that adding positional information to the input embedding and offering them to the attention module, is essentially making them share the same linear projection matrix, which is not reasonable since the effects of the input embedding and the positional information are clearly distinctive. For exactly the same reason, in the LANA model, multiple input embeddings (i.e. question ID embedding, student ID embedding, etc.) are concatenated instead of added, leading to the second base modification. Specifically, assumes there are m input embeddings in total, each with a dimension of D^f . Then after concatenating, the input embedding would have a total dimension of D^{mf} . Hence, a $D^{mf} \rightarrow D^f$ linear projection layer was used to map the con-

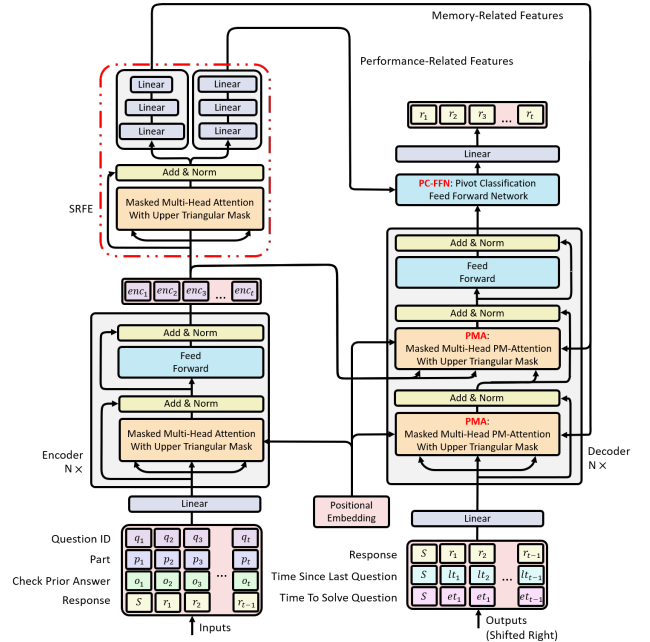


Figure 1: The overall model architecture of LANA. There are mainly three differences compared to vanilla transformer-based KT method [1, 18]: I. Modifications to the basic transformer model. II. Introduced SRFE and III. Introduced PMA Module and PC-FFN Module, which collectively referred to as pivot module.

catenated input embedding of dimension D^{mf} to dimension D^f .

2.2 Student-Related Features Extractor (SRFE)

Student-Related Features Extractor (SRFE) summaries students’ inherent properties from their interactive sequences with Assumption 1 for the pivot module to personalize the parameters of the decoder. Specifically, SRFE contains an attention layer and several linear layers, where the attention layer was used to distill student-related features from the provided information by the encoder, and the linear layers were leveraged to refine and reshape these features. It is notable that in the LANA model there were primarily two SRFEs: memory-SRFE and performance-SRFE, where the former one was utilized to derive students’ memory-related features for the PMA module (be introduced later) and the latter one was dedicated to distill students’ performance-related features (i.e. Logical thinking skill, Reasoning skill, Integration skill, etc.) for PC-FFN module (introduced later either). The reshaping process was drawn in Figure 3 for better illustration, where bs , n_{heads} , seq and d_{piv} are referred to as the model’s batch size, the number of attention heads [22], the length of the input sequence and the dimension of performance-related features. The intuition that memory-related features have a second dimension of n_{head} comes from the theory that each attention head only pays attention to one perspective of the features. Thus it is reasonable that each student has different memory skills for different attention heads (e.g. for different concepts).

2.3 Pivot Module

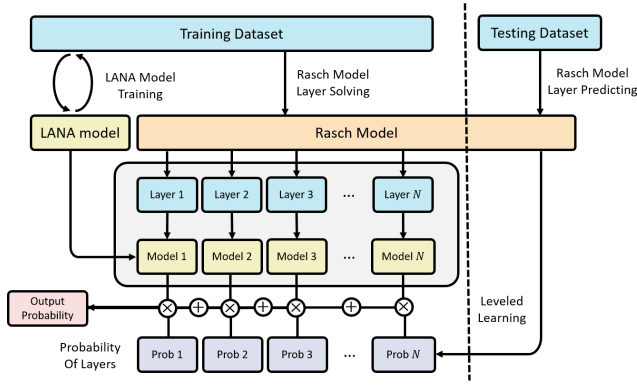


Figure 2: The workflow of leveled learning: interpretable Rasch model was leveraged to analyze students' overall ability levels, and then cluster students into multiple layers, where each layer would respectively fine-tune the LANA model by its own training data.

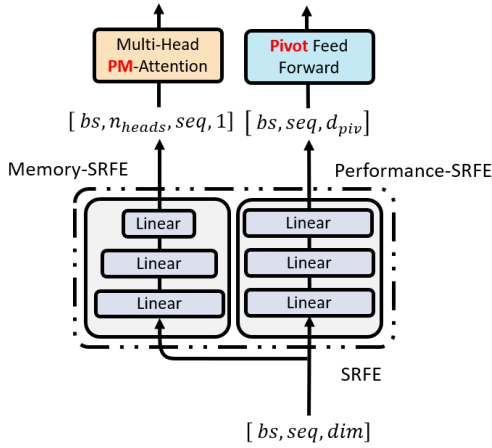


Figure 3: The data shape transformation of two SRFE: Memory-SRFE and Performance-SRFE.

Provided an ordinary input x , a student-related features p and a target output y , pivot module learns the process of learning how to project x to y based on p , instead of simply learning to project x to y (i.e. Pivot module learns to learn) as Equation 3 shown.

$$y = (f(p))(x), \quad (3)$$

where $f(\cdot)$ here is the function that pivot module learns to learn. That is, the projection matrix of x is adapted to p instead of being fixed. To accomplish this dynamic mapping, the weight and bias of x need to be a projection from p . Assumes $p \in \mathbb{R}^{D_p}$, $x \in \mathbb{R}^{D_x}$ and $y \in \mathbb{R}^{D_y}$, Equation 3 could be formally presented in Equation 4:

$$y = W^x x + b^x, \quad (4)$$

where $W^x \in \mathbb{R}^{D_y \times D_x}$ and $b^x \in \mathbb{R}^{D_y}$. Since W^x and b^x is derived from p , the detailed transformation could be revealed in Equation 5, which was also depicted in Figure 4 for better illustration.

$$W^x = W_1^p p + b_1^p, \quad b^x = W_2^p p + b_2^p, \quad (5)$$

where $W_1^p \in \mathbb{R}^{(D_y \times D_x) \times D_p}$, $b_1^p \in \mathbb{R}^{(D_y \times D_x)}$, $W_2^p \in \mathbb{R}^{D_y \times D_p}$ and $b_2^p \in \mathbb{R}^{D_y}$.

By simplification, Equation 3 can be defined as Equation 6, being named as *PivotLinear*(x, p).

$$y = (Wp)x + b = \text{PivotLinear}(x, p), \quad (6)$$

where $W \in \mathbb{R}^{D_y \times D_x \times D_p}$ and $b \in \mathbb{R}^{D_y}$.

In the LANA model, there are primarily two modules that pertain to the pivot module: Pivot Memory Attention (PMA) Module and Pivot Classification Feed Forward Network (PC-FFN) Module. In many methods [4, 14], Vanilla Memory Attention (VMA) Module was employed to consider the “forgetting” behavior of students, which is pivotal in KT’s context since students are very likely to have done similar exercises to the one he is going to do, and if the student could remember the answers to previous similar exercises, the probability of him correctly answering the future related exercises will be increased greatly. Inspired by the Ebbinghaus Forgetting Curve [12] and much previous work [14, 4], “forgetting” behavior of students are defined as exponentially decaying weights of corresponding interactions in the timeline. Detailedly, in the original attention module, the weight of item j on item k , i.e. $\alpha_{j,k}$, is determined by the sigmoid result of the similarity between item j and item k :

$$\alpha_{j,k} = \frac{\text{sim}(j, k)}{\sum_{k'} \text{sim}(j, k')}, \quad (7)$$

where $\text{sim}(\cdot)$ is a function to calculate the similarity between item i and item j by dot production. In order to take “forgetting” behavior into $\alpha_{j,k}$ ’s account (e.g. The further away from j , the lower the weight $\alpha_{j,k}$ would be), we replaced Equation 7 with Equation 8:

$$\alpha_{j,k,m} = \frac{e^{-(\theta+m) \cdot \text{dis}(j,k)} \cdot \text{sim}(j, k)}{\sum_{k'} \text{sim}(j, k')}, \quad (8)$$

where m is the student’s memory-related features extracted in memory-SRFE, θ is a private learnable constant that describes all students’ average memory skill in the PMA module, and $\text{dis}(\cdot)$ calculates the time distance between item j and item k (e.g. item j is done $\text{dis}(j, k)$ minutes after item k is done). The reason for representing the memory skill with two learnable parameters is to reduce the difficulty for model converging since m has a much longer back-propagation path compared to θ . When θ is introduced to fit

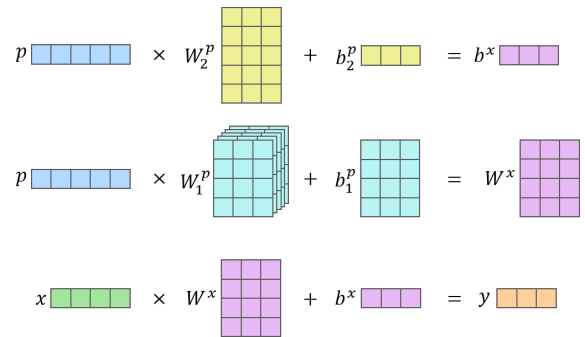


Figure 4: An illustration of the data transformation in the pivot module.

the average memory skill of all students, the distribution of m becomes a Gaussian distribution, which makes the model much easier to learn.

On the other hand, PC-FFN was utilized to make the final prediction in reference to the performance-related features, which essentially is a PivotLinear module with a dropout and activation. The idea of this module comes from many investigations that the early layers in a deep neural network are often used as a feature extractor while the latter layers are often used as a decision-maker to decide which feature is useful to the output of the model. As a result, these investigations point out that many models are actually having similar early layers, and it is the latter layers that make these models distinctive in usage. Consequently, PC-FFN in the LANA model was utilized as a personalized decision-maker to adaptively make the final prediction based on students' distinctive inherent properties:

$$PC-FFN(x, p) = x + PivotLinear(PivotLinear(x, p), p), \quad (9)$$

where p is the students' performance-related features extracted in the performance-SRFE.

2.4 Leveled Learning

While the pivot module enables the decoder to be transformable for different students, the encoder and the SRFE of the LANA model that provides necessary information for the pivot module remains the same for all students. This is not problematic if the length of the input sequence is large enough since Assumption 1 assures long sequences are always distinguishable, unless they both belong to the same student at the same time period. However, DKT, especially transformer-based DKT, can only be inputted with the latest n (commonly $n = 100$) interactions at once due to the limited memory size and high computational complexity. Consequently, it is possible for the encoder and SRFE to output similar results for two different students, resulting in a failure for the decoder to adapt. To alleviate this problem, it is natural to think of assigning different students with different encoders and SRFEs that are highly specialized (sensitive) to their assigned students' patterns. However, in practice, it is not feasible to train a unique encoder for each individual student considering both the limited training time and the limited training data. As a result, a novel leveled learning (Figure 2) method was proposed to address this problem, which was initially inspired by the fine-tuning mechanism in transfer learning [20], where we consider each student a unique task, and we want to transfer a model that fits well on all students to one student s_i efficiently.

Leveled learning holds the view that the earlier layers of a model are similar for similar tasks. Thus, to save training time and enlarge the training set, instead of training each student a unique encoder and SRFE by his private training data, students with similar ability levels are considered to be grouped together, sharing their private training data and having the same encoder and SRFE. Therefore, LANA firstly utilizes an interpretable Rasch model to analyze the ability level a^{s_i} for each student s_i , then groups students into different independent layers l_i . Assuming the ability distribution of all students and students at the level l_i are Gaussian distribution $N(\mu_a, \sigma_a^2)$ and $N(\mu_i, \sigma_i^2)$ respectively,

we have the Equation 10:

$$\mu_a = \frac{\sum_i \mu_i}{L}, \quad \sigma_a^2 = \sum_i \sigma_i^2. \quad (10)$$

In LANA, for simplicity, we consider all layers share the same variance σ^2 ¹, and the difference of mean μ_i between consecutive layers is a constant τ . Hence, μ_i and σ_i^2 are given by:

$$\mu_i = \mu_a - \frac{L-1}{2} \times \tau + i \times \tau, \quad \sigma_i^2 = \frac{\sigma_a^2}{L}. \quad (11)$$

where $L = ||l_i||$ is the number of layers. With both μ_i and σ_i^2 retrieved for every layer l_i , given a student's ability constant a^{s_i} , we can now calculate the probability of s_i been grouped into different layers by Equation 12:

$$p_i^{s_i} = \frac{\phi_i(a^{s_i})}{\sum_{i'} \phi_{i'}(a^{s_{i'}})}, \quad \phi_i(a^{s_i}) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{(a^{s_i} - \mu_i)^2}{2\sigma_i^2}} \quad (12)$$

where $p_i^{s_i}$ is referred as the probability of student s_i being grouped into layer l_i . As it can be seen from Equation 12, students that have high ability levels are not necessarily grouped into layers with high expected ability levels μ_i . Contrarily, these high ability students only have a higher probability of been grouped into high ability layers in comparison with those low ability students, which obeys rules in reality (e.g. high ability students may also come from normal schools).

Then, the LANA model that has been pre-trained on all students was duplicated L times, each cloned model m_i would be assigned to a layer l_i to be dedicatedly fine-tuned with l_i 's private training data by weighted back-propagation:

$$loss_i = p_i \times loss(predict_i, target), \quad (13)$$

where $predict_i$ is the prediction of the model m_i .

While the training phase of leveled learning seems promising, the inference phase of it suffers problems. The first problem is how to make the prediction using multiple specialized models. In LANA, the prediction was made by $top-k$ models fusion. Detailedly, when student s_i 's future responses are needed to be predicted, LANA firstly computes p_i , then feed s_i 's interactive sequence to all models m_i that satisfies $p_i \in top-k(p)$, where k needs to be manually set up to control the predicting time. Then, the outputs of these models would be multiplied by $sigmoid(p_i)$ to form the final prediction. The workflow of leveled learning's inference step could be described in Equation 14:

$$r_i = \sum_{i'} (m_{i'}(x) \times \frac{p_{h'}}{\sum_{h'} p_{h'}}), \quad i' \in \{i \mid p_i \in top-k(p)\}, \quad (14)$$

where r_i is the leveled learning's final prediction and x is the input of the model. This workflow seems similar to the ensemble where multiple models are unitized to generate the final answer. Nonetheless, weights of models in LANA are probabilities that come from an interpretable Rasch model

¹In practice, if the number of layers is small, their variances then need to be manually measured and tuned based on the targets. If the number of layers is large, then multiple layers can be regarded as one layer and therefore sharing the same variance for all layers should be fine.

so that it is clear which model is dominant to x . Moreover, unlike in ensemble, where the role of each model is ambiguous, in LANA, every model has its explainable effect (e.g. l_L is committed to high ability students, and therefore a student with large p_L indicates he must be similar to those high ability students in l_L), suggesting that leveled learning significantly outperforms ensemble in interpretability. Detailed comparison was shown in Table 1. On the other hand, the

Table 1:
COMPARISON BETWEEN LEVELED LEARNING AND ENSEMBLE

	Leveled Learning	Ensemble
Sub-set Select	Psycho-statistics	Random
Interpretability	Good	Bad
Predicting Time	Controllable (top-k)	Uncontrollable

second problem of the leveled learning is how to compute p_i for students that LANA has never met in training, namely the “cold start” problem [24]. In vanilla KT context, we can only initiate newly arrived students’ ability levels to the average ability level of all students. However, in practice, we can estimate their ability levels more accurately by asking them to do a couple of sample exercises or using ranking at school.

3. EXPERIMENTS

3.1 Experimental Setup

In order to evaluate the effectiveness of the proposed LANA², we applied it to two real-world large-scale datasets in comparison with many other State-Of-The-Art (SOTA) KT methods. Specifically, EdNet [2] and RAIEd2020 [7] are employed in our experiments, where EdNet is currently the largest publicly available benchmark dataset in education domain, consisting of over 90,000,000 interactions and nearly 800,000 students. On the other hand, RAIEd2020 is a recently published real-world dataset that has approximately the same size as EdNet with nearly 100,000,000 interactions and 400,000 students. Particularly, the average number of exercising interactions per student in RAIEd2020 is double to EdNet’s. Moreover, 6 KT methods that had previously achieved SOTA performance have participated in the comparison: DKT [16], DKVMN [26], SAKT [13], SAINT [1], SAINT+ [18], AKT [4]. In terms of the basic experimental environment, all experiments were conducted with Pytorch³ 1.6 on a Linux server that is equipped with an Nvidia V100 GPU. For hyper-parameters setup, the learning rate was set to $5e - 4$ with *AdamW* [11] optimizer, the length of the input sequence was set to 100, the batch size was set to 256, and other detailed configurations were listed in our source code. The input features κ in EdNet contains *Question ID*, *Question part*, *Students’ responses*, *Time interval between two consecutive interactions* and *Elapsed time of an interaction*, whereas in RAIEd2020, a new feature is additionally added to κ , which indicates *Whether or not the student check the correct answer to the previous question*. Finally, The Area Under the receiver operating characteristic Curve (AUC) was leveraged in our experiments as the

²<https://github.com/Soptq/LANA-pytorch>

³<https://pytorch.org/>

Table 2:
THE AUC COMPARISON OF DIFFERENT METHODS TESTED ON EDNET AND RAIEd2020 DATASETS

Dataset	Model	AUC
EdNet	DKT	0.7638 ^r
EdNet	DKVMN	0.7668 ^r
EdNet	SAKT	0.7663 ^r
EdNet	SAINT	0.7816
EdNet	SAINT+	0.7913
EdNet	SAINT+ & BM	0.7935
EdNet	LANA	0.8059
RAIEd2020	SAKT	0.7832
RAIEd2020	AKT	0.7901
RAIEd2020	SAINT+	0.7956
RAIEd2020	SAINT+ & BM	0.7991
RAIEd2020	LANA	0.8056

Table 3:
INVESTIGATION OF THE EFFECTIVENESS OF DIFFERENT IMPROVEMENTS IN LANA

Dataset	BM	Pivot Module		LL	AUC	Boost
		PMA	PC-FFN			
EdNet					0.7913	-
EdNet	✓				0.7935	↑ 0.0022
EdNet		✓			0.7997	↑ 0.0084
EdNet			✓		0.7923	↑ 0.0010
EdNet				✓	0.7933	↑ 0.0020
EdNet	✓	✓			0.8029	↑ 0.0116
EdNet		✓	✓		0.8015	↑ 0.0102
EdNet	✓	✓	✓		0.8038	↑ 0.0125
EdNet	✓	✓		✓	0.8050	↑ 0.0137
EdNet	✓	✓	✓	✓	0.8059	↑ 0.0146
RAIEd2020					0.7956	-
RAIEd2020	✓				0.7991	↑ 0.0035
RAIEd2020		✓			0.8020	↑ 0.0064
RAIEd2020			✓		0.7965	↑ 0.0009
RAIEd2020				✓	0.7977	↑ 0.0021
RAIEd2020	✓	✓			0.8031	↑ 0.0075
RAIEd2020		✓	✓		0.8027	↑ 0.0071
RAIEd2020	✓	✓	✓		0.8035	↑ 0.0079
RAIEd2020	✓	✓		✓	0.8051	↑ 0.0095
RAIEd2020	✓	✓	✓	✓	0.8056	↑ 0.0100

performance metric, which has been widely used in many other KT-related proposals.

For the ease of explanation, hereinafter Base Modification (Section 2.1), Pivot Module (Section 2.3) and Leveled Learning (Section 2.4) would be abbreviated as *BM*, *PM* and *LL* respectively.

3.2 Results And Analysis

The overall experimental results of different KT methods on different datasets were illustrated in Table 2. Because we had successfully reproduced the performance of SAINT and SAINT+ that was previously reported in SAINT+’s paper [18] (with considerable precision), AUCs of other models are therefore directly cited from the paper (labeled with subscript r).

From the comparison table, it can be seen that in both Ed-

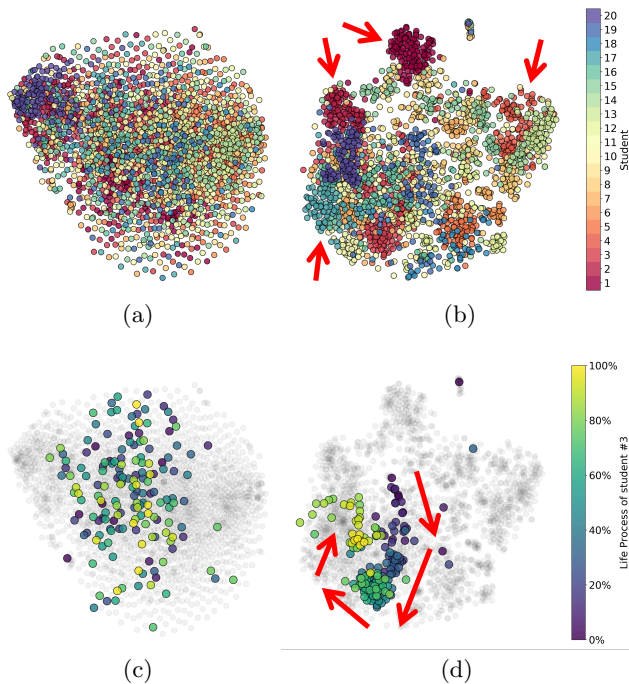


Figure 5: The visualization of intermediate features in SAINT+ (a) and in LANA (b). Compared to (a), students in (b) (different colors) are notably clustered (marked arrows). The learning process of student #3 overtime in SAINT+ (c) and in LANA (d). compared to (c), a clear learning path appeared in (d).

Net and RAIED2020 datasets, LANA (marked bold) outperforms the previous SOTA method (marked italic) by 1.46% and 1.00% respectively, readily verifying the effectiveness of our proposed improvements. Moreover, LANA also surpasses SAINT+ & *BM* by 1.24% and 0.65% respectively, suggesting adaptability contributes most to LANA’s AUC increment. Considering experimented datasets are by far the two largest knowledge tracing datasets in the world, these results undoubtedly provide strong evidence of the validity of the proposed LANA method.

3.3 Ablation Studies

In this section, we investigated the effectiveness of each of our proposed improvements: *BM* that customizes the basic transformer architecture, *PM* that enables the decoder to be adaptive to the students’ personal characteristics, and *LL* that interpretably specializes encoders and SRFEs for better predicting performance. The results of the ablation study were shown in Table 3.

The table shows in EdNet, applying *BM* alone was already capable of improving the predicting AUC by approximately 0.2% averagely, verifying the importance of both the action of positional embedding and the personalized linear projection for each input feature in KT’s context. Meanwhile, applying *LL* solely can benefit the model performance as well, by generally 0.2% compared to 0.1% with the vanilla ensemble. Considering without *PM*, *LL* would just perform fitting on students with different ability levels, the

performance gain from sole *LL* could be interpreted as reductions in students’ inherent properties gaps. Moreover, *BM + PM* drastically boosts the model performance by nearly 1.25%, suggesting *PM* makes proper use of extracted student-related features from SRFE to adaptively reparameterize the model’s decoder for different students at different stages, and therefore contributes most to the final performance gain. Finally, by combining all improvements together, *BM + PM + LL* (i.e. LANA) achieves a final AUC of 0.8059, substantially outperforms previous SOTA by at least 1.46%.

3.4 Features Visualization

For vividly illustrating the validity of student-related features distilling in LANA, 20 students’ intermediate features from PC-FFN module was sampled to generate Figure 5 by t-SNE[21]. In figure 5 (a) and (b), each sample represents intermediate features of different students with different colors in SAINT+ and LANA respectively. It can be seen that in SAINT+, samples are almost randomly distributed, indicating the correlation between samples of the same student is not more significant compared to samples of the others due to the ignorance of students’ personalities. On the other hand, in LANA, clusters (marked arrows) of samples have notably appeared in comparison to (a). Thus, we concluded that LANA is capable of successfully extracting student-related features from their interactive sequences, summarizing the similarities and differences, which eventually results in more distinguishable features for the final classifier.

Furthermore, we individually visualized student #3’s (randomly picked) samples along the time axis to investigate the transitioning pattern of features in Figure 5 (c)(SAINT) and (d)(LANA). In (c), there is no clear pattern in the change of features over time, while in (d), a clear transitioning path could be noticed. Since many other students are sharing the same pattern in LANA, we argue that it represents the trajectory of the student’s ability changes with more and more exercising. Namely, it is the learning path of the student. Consequently, we contended that it is potentially helpful for other applications, such as learning stages transfer and learning path recommendation.

4. CONCLUSION

In this paper, we proposed a novel **L**eveled **A**ttentive **K**nowledge **T**racing (LANA) method that was committed to bringing adaptability back to DKT. Instead of directly learning the model parameters of different students, LANA distills students’ inherent properties from their respective interactive sequences by a novel SRFE, and learns the function to reparameterize the model with these extracted student-related features. Consequently, innovative pivot module was proposed to produce an adaptive decoder. Besides, a novel leveled learning training mechanism was introduced to cluster students by interpretable Rasch model defined ability level, which not only specializes the encoder and therefore enhances the significance of students’ latent features, but also saves much training time. Extensive experiments on the two largest public benchmark datasets in the education domain strongly evaluate the feasibility and effectiveness of the proposed LANA, features visualization also suggests extra impacts of LANA, be it learning stages transfer or learning path recommendation.

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