Programming Knowledge Tracing: A Comprehensive Dataset and A New Model

Renyu Zhu¹, Dongxiang Zhang², Chengcheng Han¹, Ming Gao¹, Xuesong Lu^{1*}, Weining Qian¹, Aoying Zhou¹

¹East China Normal University, ²Zhejiang University

52175100003@stu.ecnu.edu.cn, zhangdongxiang@zju.edu.cn, 51195100009@stu.ecnu.edu.cn, {mgao, xslu, wnqian,

ayzhou}@dase.ecnu.edu.cn

Abstract

In this paper, we study knowledge tracing in the domain of programming education and make two important contributions. First, we harvest and publish so far the most comprehensive dataset, namely BePKT, which covers various online behaviors in an OJ system, including programming text problems, knowledge annotations, user-submitted code and system-logged events. Second, we propose a new model PDKT to exploit the enriched context for accurate student behavior prediction. More specifically, we construct a bipartite graph for programming problem embedding, and design an improved pre-training model PLCodeBERT for code embedding, as well as a double-sequence RNN model with exponential decay attention for effective feature fusion. Experimental results on the new dataset BePKT show that our proposed model establishes state-of-the-art performance in programming knowledge tracing. In addition, we verify that our code embedding strategy based on PLCodeBERT is complementary to existing knowledge tracing models to further enhance their accuracy. As a side product, PLCodeBERT also results in better performance in other programming-related tasks such as code clone detection.

1 Introduction

Massive open online course (MOOC) has reshaped user learning experience and become more and more prevalent, especially in the period of pandemic. For instance, Coursera has received 35 million new enrollments between mid-March and end of July in 2020¹. For these online learning platforms, knowledge tracing (Corbett and Anderson 1994) plays the key role in providing a customized experience according to each user's unique background, ability and status. Hence, there have been significant research efforts devoted to knowledge tracing and various models have been proposed, including DKT (Piech et al. 2015), DKT+ (Yeung and Yeung 2018), DKVMN (Zhang et al. 2017), SAKT (Pandey and Karypis 2019), CKT (Shen et al. 2020), AKT (Ghosh, Heffernan, and Lan 2020), PEBG (Liu et al. 2020), and HGKT (Tong et al. 2020). Details of these works will be reviewed in the subsequent section.

Despite the success of knowledge tracing in MOOC systems, we find that negligible attention has been paid to online programming platforms, which also have attracted a massive user base. The White House's 2016 announcement about the CS4All² has driven more and more students to learn computer science and be equipped with the computational thinking skills to embrace the era of digital economy. In the concept of CS4ALL (Barnes 2017), programming is a core CS skill. In this paper, we are motivated to study programming knowledge tracing so as to provide a personalized learning experience for online students. In particular, we make two important contributions to the research domain.

First, we observe that existing programming datasets, such as BlackBox (Brown et al. 2014), Code Hunt (Bishop et al. 2015), Code.org (Kalelioğlu 2015), Cloud-Coder (Spacco et al. 2015), and CodeBench (Pereira et al. 2020), are not suitable for the task of programming knowledge tracing. The reason is that these datasets lack sufficient context information to provide reliable performance. Furthermore, none of them contains knowledge concept annotations to facilitate the tracing of learning status, rendering it unable to derive the degree of mastering for each concept in the knowledge graph. To bridge the gap, we harvest a comprehensive dataset from our OJ system, which naturally contains all the online user behaviors. We also annotate the programming problems with labels of knowledge concepts and difficulty levels. Finally, we obtained a dataset, namely BePKT, for Behavior-based **P**rogramming **K**nowledge **T**racing, which will be published to benefit the research community.

Second, compared with MOOC, online programming platforms are preferably focused on skill practice instead of knowledge absorption, which makes a unique feature of programming knowledge tracing. Since user-submitted code is a very important clue to understanding users learning status, we need to develop an effective code embedding strategy and integrate it into the programming knowledge tracing framework. Although code representation learning has attracted attention from the domain of software engineering, the syntax-tree based strategies (Zhang et al. 2019; Zügner et al. 2021) are not suitable for programming knowledge tracing. The reason is that most of the user-submitted codes

^{*}Corresponding author

¹https://www.classcentral.com/report/mooc-stats-pandemic/

²https://obamawhitehouse.archives.gov/blog/2016/01/30/ computer-science-all

in our OJ system are written by beginners and full of various compilation errors. Thus, it is challenging to leverage the syntax structure for code embedding and we need to resort to token-based embedding. CodeBERT (Feng et al. 2020) is a pre-training model leveraging the power of RoBERTa (Liu et al. 2019) to learn code features from a large corpus in Github. Nevertheless, the discrepancy between the code with possible errors from beginners and the high-quality code in Github repository prevents these models working well in the task of programming knowledge tracing. To address the gap, we propose a two-stage pre-training model PLCode-BERT (Programming Learning CodeBERT) to first finetune CodeBERT with a mass amount of student codes from codeforces³. After that, we propose a supervised classification pre-training to further enhance code embedding. The derived code embedding, together with the semantic features of problems and concepts learned from bipartite graph embedding, are fused by a double-sequence model with exponential decay attention to predict user learning behavior.

In the experimental study, we compare our proposed framework with state-of-the-art knowledge tracing models. To make a fair comparison, we also enhance them with our proposed code embedding strategy, as a side product to verify the effect of our code pre-training model. Experimental results on BePKT show that our method outperforms its competitors in the task of programming knowledge tracing. Additionally, we introduce another programming-related dataset POJ (Mou et al. 2016) with the task of code clone detection, to verify the effectiveness of PLCodeBERT. The results both on BePKT and POJ demonstrate the ability of PLCodeBERT to represent codes in programming education.

To sum up, the major contributions of the paper include:

- We harvest and publish a comprehensive dataset BePKT⁴ for programming knowledge tracing.
- We propose an improved two-stage pre-training framework PLCodeBERT for effective code embedding. It works well not only in programming knowledge tracing but also in other programming-related tasks such as code clone detection.
- We propose a new double-sequence architecture with enhanced context embedding for programming knowledge tracing. Experimental results verified its superiority.

2 Related Works

2.1 Knowledge Tracing

Early solutions rely on traditional machine learning models and representative works include BKT (Corbett and Anderson 1994) and KTM (Vie and Kashima 2019). BKT uses binary variables to represent latent concepts and adopts hidden Markov models (HMM) and Bayes rules for model learning. KTM applies factorization machines to integrate problemrelated information and user behavior.

⁴Download:https://drive.google.com/drive/folders/ 1Jt6f0MV1paGLlctJqxHtdF1Vh2mUnsoV?usp=sharing

Recent trend on knowledge tracing has been shifted to devising deep learning models. DKT (Piech et al. 2015) is a pioneering DL model that uses RNN to model students' learning status in the temporal dimension. DKT+ (Yeung and Yeung 2018) improves DKT with a regularization component for more consistent prediction. DKVMN (Zhang et al. 2017) introduces a dynamic key-value memory network to store the knowledge and update the corresponding knowledge state. Its output is the mastery level of each concept. CKT (Shen et al. 2020) uses hierarchical convolutional layers to extract individualized learning rates based on continuous learning interactions. SAKT (Pandey and Karypis 2019) adopts Transformer to deal with data sparsity issue. AKT (Ghosh, Heffernan, and Lan 2020) combines the attention mechanism and Rasch model (Rasch 1993) to fully exploit the context information. PEBG (Liu et al. 2020) improves knowledge tracing by pre-training question embedding. There have also emerged works, such as GIKT (Yang et al. 2020) and HGKT (Tong et al. 2020), trying to solve knowledge tracing with graph neural networks.

In the domain of programming knowledge tracing, there exist very few research works. (Wang et al. 2017) is focused on code representation learning so as to infer a student's knowledge state. Each code submission is represented as an abstract syntax tree (AST) and fed into a recurrent neural network. As mentioned, our OJ system contains syntactically incorrect codes. They are unable to be converted to AST representation and call for a new code embedding strategy.

2.2 Code Embedding

Existing works on code embedding can be classified into structured-based and context-based strategies. Structuredbased methods represent code based on parse trees. Code2vec (Alon et al. 2018), ASTNN (Zhang et al. 2019), CODE TRANSFORMER (Zügner et al. 2021), Graph-CodeBERT (Guo et al. 2021), and CLSEBERT (Wang et al. 2021) fall into this category. Early context-based studies adopt basic text representation models, such as RNN (Zaremba and Sutskever 2014; Dam, Tran, and Pham 2016) or attention-based model (Iyer et al. 2016). Recently, researchers directly apply NLP pre-training strategies in code embedding, such as CodeBERT (Feng et al. 2020), GPT-C (Svyatkovskiy et al. 2020), and PLBART (Ahmad et al. 2021). These models are pre-trained on a large code corpus that is collected from mature software engineering projects.

3 BePKT Dataset

In this section, we present the collection of BePKT dataset and compare it with existing programming datasets.

3.1 Data Collection

BePKT is collected from our OJ system with thousands of registered students in the university. There are two types of information that are useful for knowledge tracing. One is the knowledge base with programming problems and their

³https://codeforces.com/

semantic annotations. For each problem, we manually annotate its associated knowledge concept and difficulty level. The other type is users' online behavior, which we extract from system logs and organize the data according to the event types. There are 5 types of such online events, including viewing problems, viewing concepts, viewing submissions, viewing ranking and submitting codes. Figure 1 illustrates an example of learning behavior trajectory for the courses of "The Beginning of C Programming" and "Data Structure" from the same student. The number of user events ranges from 0 to 222. In the peak days, the user was mainly involved in the events of viewing problems. In total, we col-



Figure 1: An example of a complete timeline for the collection of student behaviors in BePKT. From September 11, 2019, to July 10, 2020, the student has been using our OJ system, with the number of user events fluctuating daily.

lected learning behavior data from 906 users for nearly two years (From September, 2019, to July, 2021) of programming learning history. The knowledge base contains 1054 problems and 106 concepts. Each problem is associated with a difficulty level, as well as one or multiple concepts. There are 1054 annotated problem-concept pairs.

For the knowledge tracing task, we make two refinements:

- Remove all non-student data.
- Remove student data with less than 20 code submission records.

Finally, we obtained 422 students' programming learning trajectories with an average submission length of nearly 161.

3.2 Comparison with Existing Datasets

In Table 1, we summarize the comparison of our BePKT with existing programming datasets. We can see that BePKT is the most comprehensive – it is the only dataset that contains user code, online events, problem text and knowledge concepts. Most datasets only contain user behavior data, but lack an informative knowledge base, which we think plays a vital role in programming knowledge tracing. We believe the publication of BePKT can benefit the community and attract more research attention to the topic.

4 Programming Knowledge Tracing

In this section, we give the formal definition of programming knowledge tracing, and introduce the detailed architecture design of our method.

4.1 **Problem Definition**

We formulate a student's historical programming behavior as a sequence of coding events in our OJ system. Each coding event at time step t is represented by tuple $\langle p_t, c_{p_t}, d_t, r_t \rangle$, where p_t is the coding problem, c_{p_t} contains a set of knowledge concepts associated with p_t, d_t is the code submitted by the student and r_t is a binary signal from the system indicating whether the student has correctly solved the problem. Given a sequence of historical coding events { $\langle p_1, c_{p_1}, d_1, r_1 \rangle, \ldots, \langle p_{t-1}, c_{p_{t-1}}, d_{t-1}, r_{t-1} \rangle$ }, programming knowledge tracing aims to predict the value of r_t for input $\langle p_t, c_{p_t} \rangle$. Note that at time step t, user code d_t is not required so that the model can be used to predict for any programming problems. To facilitate understanding, an example of data model for programming knowledge tracing is shown in Figure 2.



Figure 2: Data model for programming knowledge tracing.

4.2 Overall Architecture

We propose a deep learning framework, namely PDKT, to solve programming knowledge tracing. As shown in Figure 3, the architecture of PDKT is mainly composed of two functional modules. The first is context representation learning, including bipartite graph embedding to learn problem embedding and a two-stage code pre-training framework PLCodeBERT. PLCodeBERT obtains code embedding by fine-tuning pre-trained CodeBERT from an external programming corpus and supervised classification pre-training from BePKT. The second part is a double-sequence model. It uses two RNNs to effectively capture sequential features in the problem and code embedding sequences, which are weighted by exponential decay attention inspired by Ebbinghaus' Forgetting Curve (Ebbinghaus 2013) and then fused with the new problem embedding for final prediction. Details of the sub-modules are introduced in the following.

4.3 Context Representation Learning

Bipartite Problem Embedding since both problems and concept annotations are available in our dataset, we are motivated to build a bipartite graph for these two types of information and adopt existing graph embedding approaches to fully exploit the relations between problems and concepts and obtain their semantic representations. In our implementation, we select GAT (Velickovic et al. 2018) as the underlying graph embedding model because it can learn vertex representations from the explicit relations and implicit relations concurrently in bipartite networks. In other words, the

Table 1: Comparison between BePKT and existing public programming datasets.

Data	Lang	Level	Source	#User	Code	Click Event	Problem	Concept
PLAGIARISM(Ljubovic 2020)	C/C++	CS1	ide	N/A	\checkmark	Х	Х	X
BlackBox(Brown et al. 2014)	Java	N/A	ide	1M	N/A	N/A	N/A	N/A
CloudCoder(Spacco et al. 2015)	Python/C	CS1	online ide	646	N/A	N/A	N/A	N/A
Code.org(Kalelioğlu 2015)	Scratch	CS0	N/A	500k	N/A	N/A	\checkmark	N/A
POJ(Mou et al. 2016)	C/C++	CS1	online judge	104	\times	×	×	X
CodeHunt(Bishop et al. 2015)	Java/C#	N/A	online ide	258	\checkmark	\checkmark	X	X
CodeBench(Pereira et al. 2020)	Python	CS1	online judge	2714	\checkmark	\checkmark	X	X
BePKT	C/C++	CS1	online judge	906	~	~	~	1



Figure 3: The PDKT architecture overview.

implicit relationship between problems or concepts (as illustrated by dot lines in Figure 3) can also be effectively learned by GAT.

Furthermore, in our dataset, problem descriptions and concept names are provided with plentiful text based on Chinese. In order to capture the semantics, we adopt BERT-wwm (Cui et al. 2020), a Chinese pre-training model to initialize the node embeddings in the GAT.

Code Embedding via Pre-training Framework As aforementioned in Section 2.2, the structured-based code embedding strategies proposed in the community of software engineering cannot be directly transplanted for code analysis in OJ systems, where a large portion of codes are associated with compilation errors. In fact, these errors are useful clues to capture a student's learning status in our application of programming knowledge tracing. In this paper, instead of relying on syntax trees, we propose an improved pre-training framework PLCodeBERT based on CodeBERT (Feng et al. 2020) that learn features from raw code text. PLCodeBERT is composed of two stages: 1) unsupervised pre-training in a mass amount of student codes to fine-tune CodeBERT and 2) code embedding inspired by supervised visual feature pre-training via image classifica-

tion in ImageNet.

In the first stage, we perform a further pre-training to finetune CodeBERT inspired by (Gururangan et al. 2020). In the beginning, we harness an external data source with abundant codes⁵, which contains 1, 262, 910 user-submitted codes in multiple programming languages. Then we use the tokenizer that comes with the model to tokenize the corpus of all languages and adopt the MLM (Masked Language Modeling) task to make further pre-training. Finally, we obtain a new pre-training model PLCodeBERT.

In the second stage, we propose a supervised learning strategy to derive more effective code embedding. The idea is inspired by the common practice in computer vision where the features pre-trained by image classification in ImageNet can be directly used as visual embedding to support more advanced applications. In our setting of code classification, we construct the target space with 9 distinct labels. If the code is error-free, we annotate it with the label "correct". Otherwise, we define 8 types of submission errors in our OJ system, such as "Compile Error", "Wrong Answer", "Time Limit Exceeded", "Memory Limit Exceeded", and so on.

⁵https://www.kaggle.com/agrigorev/codeforces-code

In addition to pre-training models, such as CodeBERT and PLCodeBERT, we also investigate the performance of basic text representation models on two-stage code embedding. Different from pre-training models, we tokenize⁶ the corpus by language and use Word2Vec⁷ to obtain code token embedding. Then we apply the same classification task to derive effective code embedding with different text classification models. As to text classification model selection, we offline tried TextCNN (Kim 2014), TextRNN (Liu, Qiu, and Huang 2016), TextRNN_Att (Zhou et al. 2016), as well as a recent text representation model DRCN (Kim, Kang, and Kwak 2019). Results show that PLCodeBERT is more suitable for code classification and final prediction in all basic text representation models and pre-training models. The detailed analysis will be presented in Section 5.5.

4.4 Double-Sequence Modeling

Given the derived embeddings for problems and codes, denoted by $p_t \in \mathcal{R}^{d_1}$ and $d_t \in \mathcal{R}^{d_0}$, respectively, we are now ready to present our double-sequence modeling (DSM) with exponential decay attention to tackle programming knowledge tracing. Initially, the two sequences p_1, \cdots, p_{t-1} and d_1, \cdots, d_{t-1} are sent to two separate RNNs, which start forward propagation from an initial states $(g^{(0)} \text{ for problems})$ and $h^{(0)}$ for codes). In our implementation, $h^{(0)}$ and $g^{(0)}$ are initialized as zero tensors, because these students with no coding activity are considered to be newbies in programming. For each time step from k = 1 to t, we apply the following equations to update hidden states $q^{(k)}$ and $h^{(k)}$:

$$g^{(k)} = tanh(b_g + W_g h^{(k-1)} + U_g q^{(k)}),$$

$$h^{(k)} = tanh(b_h + W_h h^{(k-1)} + U_h d^{(k)}),$$

where W_g, U_g, W_h, U_h are the weight coefficients, and b_g, b_h are the bias terms. To predict the performance at time step k = t, we use attention to assign higher weight to the previous problems and codes which are more similar to the current problem p_t . The similarity function is computed by:

$$\mathbf{S}_{\mathbf{g}} = FC(p_t)\mathbf{G}^T, \quad \mathbf{S}_{\mathbf{h}} = FC(p_t)\mathbf{H}^T,$$

where \mathbf{G}^T and \mathbf{H}^T denote the transposes of concatenation of $g^{(k)}$ and $h^{(k)}$ from time step k = 1 to t - 1, respectively, and FC represents fully connected networks. Furthermore, inspired by The Ebbinghaus Forgetting Curve (Ebbinghaus 2013), we add an exponential decay to the similarity matrix before applying softmax to get normalized attention weights:

$$\begin{aligned} \mathbf{A}_{\mathbf{h}} = softmax(\exp(-\lambda \mathbf{D}) \odot \mathbf{S}_{\mathbf{h}}), \\ \mathbf{A}_{\mathbf{g}} = softmax(\exp(-\lambda \mathbf{D}) \odot \mathbf{S}_{\mathbf{g}}), \end{aligned}$$

where λ is the exponential decay hyperparameter, \odot is the elementwise multiplication, and $\mathbf{D} = [t - 2, t - 3, \dots, 1, 0]$ is the time step difference vector. The underlying motivation for applying exponential decay attention is that recent programming events are much more important to measure a student's current learning status.

Using weighted sum, we obtain the students' programming knowledge mastery $O_g^{(k)}$ and coding capability $O_h^{(k)}$ at k = t - 1:

$$O_g^{(t-1)} = \sum_k (\mathbf{A_g})_k g^{(k)}, k \in \{1, 2, \cdots, t-1\},$$
$$O_h^{(t-1)} = \sum_k (\mathbf{A_h})_k h^{(k)}, k \in \{1, 2, \cdots, t-1\}.$$

To calculate the similarity of knowledge mastery $O_g^{(t-1)}$ and programming ability $O_h^{(t-1)}$ with problem p_t , we concatenate the corresponding vectors and use two fully connected networks. Finally, we concatenate the two similarities and use another fully connected network, through the sigmoid function to get the final prediction probability $\hat{r}_t \in [0, 1]$:

$$\hat{r}_t = SIG(FC(FC(O_h^{(t-1)} \oplus p_t) \oplus FC(O_g^{(t-1)} \oplus p_t))),$$

where FC represents fully connected networks, SIG denotes sigmoid function, and \oplus denotes concatenation.

For parameter training, we compute the binary crossentropy loss between predictions and ground truths to update all parameters θ in the proposed model:

$$L(\theta) = \sum_{k} -(r_k \log \hat{r}_k + (1 - r_k) \log(1 - \hat{r}_k)).$$

5 Experiment

In this section, we first compare the proposed PDKT model with other knowledge tracing approaches in our crafted BePKT dataset, whose details have been presented in Section 3. Then ablation studies are provided to justify the effectiveness of three major components in PDKT. Finally, we take a deep insight into the design of later components, which are the influence of code embedding strategy, the effectiveness of PLCodeBERT, and the detailed analysis of exponential decay attention.

5.1 Comparison Models

The baselines include classic methods proposed for knowledge tracing, as well as two hybrid variants that extend stateof-the-art models to incorporate our proposed code embedding.

- DKT (Piech et al. 2015) is the first work to apply RNN to model student's learning sequence.
- DKVMN (Zhang et al. 2017) introduces a memoryaugmented neural network (MANN) to capture the mastery level of each knowledge concept.
- DKTP (Yeung and Yeung 2018) improves DKT with enhanced regularization.
- AKT (Ghosh, Heffernan, and Lan 2020) uses a novel monotonic attention mechanism based on Transformer and is considered as state-of-the-art.
- DKTP+PLCodeBERT and AKT+PLCodeBERT are extended versions of DKTP and AKT, respectively, to incorporate our code pre-training model PLCodeBERT.

⁶https://github.com/dspinellis/tokenizer

⁷https://radimrehurek.com/gensim/models/word2vec.html

The implementations of DKMVN, DKTP, and AKT are generously provided by the authors. For DKT, we use the reproduced code in Github⁸.

5.2 Parameter Setting and Performance Metric

In bipartite problem embedding, we set problem embedding size to 256. In pre-training code embedding, for basic text presentation models, we use 100, 512, 5×10^{-4} , and 768 as the values for code token embedding size, batch size, learning rate, and code embedding size, respectively. For pre-training models, we use 768, 16, 5×10^{-5} , and 768 as the values for code token embedding size, batch size, learning rate, and code embedding size, respectively. In doublesequence modeling, we set batch size, learning rate, and exponential decay λ , to 8, 10^{-5} , and 0.6, respectively. Following (Ghosh, Heffernan, and Lan 2020), we set sequence length to 200. We use Adam as the default optimizer.

Following previous knowledge tracing works, we also use AUC as the performance metric. For each method, we repeat the training process five times and report the average AUC.

5.3 Performance on BePKT

Table 2 shows the AUC performance of all methods on BePKT, from which we derive the following observations. 1) PDKT outperforms its competitors with a noticeable margin, verifying the effectiveness of our embedding strategy and model design. 2) When code embedding is incorporated, the AUC of DKTP and AKT is boosted by an additional 2.03% and 3.65%, respectively, implying that our code embedding is complementary to existing models and can further improve their performances. 3) RNN based methods (e.g., DKT and DKT+) outperform DKVMN and AKT. It means RNN is more suitable to capture sequential programming behavior. This observation also motivated us to adopt RNN in our proposed PDKT model.

Table 2: The AUC results of different methods on BePKT.

Methods	AUC
DKT	0.7197
DKVMN	0.7089
DKTP	0.7369
AKT	0.7128
DKTP+PLCodeBERT	0.7572
AKT+PLCodeBERT	0.7493
PDKT	0.7745

5.4 Ablation Studies

To justify the three key components in the proposed PDKT architecture, including bipartite problem embedding, code embedding, and attended double-sequence modeling, we perform ablation studies to evaluate the effect of each component. As shown in Table 3, we implement four variants of PDKT by removing or replacing function modules in our model.

Table 3: The AUC results of different variants of PDKT.

Methods	AUC
Remove code embedding and its RNN encoding	0.7163
Remove problem embedding and its RNN encoding	0.7546
Remove classification for code embedding	0.7050
Replace GAT with Node2 vec	0.7643
PDKT	0.7745

In the first ablation experiment, we remove code embedding and its associated sequential modeling. The model is reduced to only leverage the features from input problems and knowledge concepts. The double-sequence modeling becomes single-sequence and the attention module is removed as it plays no effect in this scenario. We can see that without integrating code features, the performance degrades dramatically, verifying the effectiveness of our strategies of code embedding and its fusion with problem features.

The second ablation experiment is similar to the first one, except that we remove problem features and their sequential modeling this time. The AUC drops, but not significantly as in the first ablation study. This shows that coding embedding plays a more important role than problem embedding in the input sources. The user-submitted code contains a more informative context to leverage.

In the third ablation experiment, our goal is to evaluate the effect of supervised code classification to generate pretrained code features for programming knowledge tracing. It is interesting to observe that without this component, the AUC is even worse than that in the first ablation study (i.e., without using code embedding). It means we cannot simply rely on unsupervised embedding from corpus pre-training. The derived features are not discriminative for the task of programming knowledge tracing and bring negative effects.

In the last ablation experiment, we replace GAT with Node2Vec (Grover and Leskovec 2016) as an alternative graph embedding approach. We observe a slight decrease of the AUC, which means GAT is superior to Node2Vec. This is because GAT can better learn the vertex representations from the explicit relations and implicit relations concurrently in the bipartite graph.

5.5 Selection of Code Embedding Strategies

As mentioned in Section 4.3, we design a supervised classification task to derived pre-trained code features and use them to support programming knowledge tracing. In this experiment, we evaluate how code classification strategies can affect the performance on final prediction. The design space is set with two knobs on the number of target classes and text classification models. In the first knob, we set two classification tasks, namely 2-classification and 9-classification. The former uses binary labels to indicate the correctness of user-submitted code. The latter provides more detailed error labels (details are presented in Section 4.3). The second knob includes six types of classification models, including

⁸https://github.com/chsong513/DeepKnowledgeTracing-DKT-Pytorch

four basic text representation models and two pre-trained models. In Table 4, we report both classification accuracy as well as AUC on the final task of PKT for each model instance. From the results, we can see that 1) PLCodeBERT outperforms the other models in all cases. 2) Code features trained by 9-classification are more helpful to the task of programming knowledge tracing than 2-classification features. These are the reasons for selecting PLCodeBERT and 9-classification in our PDKT model. 3) There is a positive correlation between the results of classification accuracy and AUC, implying that features learned from classification are also effective for programming knowledge tracing. 4) In all cases, PLCodeBERT outperforms CodeBERT, demonstrating the importance of pre-training for effective code embedding.

Table 4: The classification accuracy and final predict AUC results of different strategy in supervised code classification.

Madala	2-classifi	cation	9-classification		
widdels	Accuracy	AUC	Accuracy	AUC	
TextCNN	70.06%	0.7420	46.38%	0.7519	
TextRNN	68.99%	0.7301	35.17%	0.7406	
DRCN	69.58%	0.7318	35.62%	0.7442	
TextRNN_Att	70.25%	0.7432	46.81%	0.7561	
CodeBERT	73.61%	0.7501	63.45%	0.7682	
PLCodeBERT	73.95%	0.7543	65.79%	0.7745	

5.6 Effectiveness of PLCodeBERT

To further verify the effectiveness of PLCodeBERT in code embedding, we introduce an extra task called code clone detection, using POJ dataset (Mou et al. 2016) provided by CodeXGLUE (Lu et al. 2021). POJ is a classic programming learning dataset collected from an online judge system that supports several programming-related tasks, including code clone detection, as shown in Table 1. Since the target is to retrieve the TOP-K codes with the same semantic, we choose MAP@R score, the mean of average precision scores, as the evaluation metric. We use the same experimental setting as CodeBERT and only reserve the first stage of PLCodeBERT. We compare PLCodeBERT to several existing representative pre-training models, and report the performance in Table 5. From the results, we can see that PLCodeBERT achieves state-of-the-art performance on the task of code clone detection. In particular, PLCodeBERT improves the result by nearly 6% compared to CodeBERT. The results both in Table 4 and Table 5 demonstrate the effectiveness of PLCodeBERT and the importance of further pre-training in programming codes.

5.7 Analysis of Exponential Decay Attention

We present a further investigation of exponential decay attention in double-sequence modeling in this experiment. Figure 4 shows the fitting curves of AUC results on varying exponential decay values λ with or without attention. When adding exponential decay with attention (yellow line with square dots), as λ increases, the performance increases first

Table 5: The MAP@R scores of different methods on POJ dataset.

Method	MAP@R
RoberTa (Liu et al. 2019)	76.67
CodeBERT (Feng et al. 2020)	82.67
GraphCodeBERT (Guo et al. 2021)	85.16
CLSEBERT (Wang et al. 2021)	88.24
PLCodeBERT	88.63

and reaches the maximum value of 0.7745 when $\lambda = 0.6$, then decreases and finally stabilizes. When $\lambda = 0$, it is equivalent to the typical attention, and the performance is deplorable, which shows the importance of exponential decay. When adding exponential decay without attention (red line with circle dots), the model ignores the vectors correlation and prediction results are much worse. It is noticed that the two curves converge to the same value gradually because when the exponential decay value is too large, the model only depends on the output of the previous step, and attention will not work.



Figure 4: The influence of exponential decay value with-/without attention.

6 Conclusion and Future Work

In this paper, we public a behavior-based programming knowledge tracing dataset BePKT, with the most comprehensive contexts. And we propose a state-of-the-art model in programming knowledge tracing, namely PDKT. PDKT employs a double-sequence model with exponential decay attention to model problem and code sequences. In particular, we construct a bipartite graph and design a two-stage pre-training framework PLCodeBERT to strengthen problem and code embedding, respectively. Extensive experiment results show that our method design is reasonable, and PLCodeBERT can complement existing knowledge tracing models and improve the ability of code representation in programming learning. Avenues of future work include i) collecting more student data to enrich BePKT, and ii) exploring the influence of clicking events on programming knowledge tracing.

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