The 7th International Conference on Interdisciplinary Research
on Computer Science, Psychology, and Education (2023)

Exploring Prefix-Tuning-Based Models for Open-Ended Knowledge Tracing

Suhyune Son, Myunghoon Kang, Jaechoon Jo°
Korea University, Jeju National University
{ssh5131, chaos038527}@korea.ac.kr, jaechoon.jo@gmail.com

Abstract

Knowledge tracing (KT) aims to predict the correctness of a learner's responses to target questions by assessing the extent of knowledge acquisition based on their past problem-solving records. Previous research in this domain employed binary classification models that solely predicted correctness, thereby failing to leverage the information embedded in a learner's responses. Recent studies have transformed this task into a generative one, leading to the emergence of open-ended knowledge tracing (OKT), specifically tailored to estimate knowledge in the field of computer science, particularly concerning programming inquiries. Nevertheless, research addressing the optimal OKT model remains largely unexplored. Consequently, this paper introduces a novel OKT method, which adjusts response generation based on the evolving knowledge state of the learner over time. We empirically demonstrate the superiority and efficiency of the proposed method in experiments conducted in this paper.

Keywords: Knowledge Tracing, Educational AI, Prefix-tuning

1. Introduction

Knowledge Tracing (KT) is a task that involves tracking the learning progress of individuals and predicting the correctness of answers to target questions based on their past problem-solving records. Leveraging KT technology, personalized feedback and recommendations for learners have been recognized as effective tools in the field of AI-based education [1].

Typically, KT consists of two main modules: Knowledge Estimation and Response Prediction. In the Knowledge Estimation module, the model calculates a representation of the learner's current knowledge state based on their past problem-solving activities. Subsequently, in the Response Prediction module, the model predicts the learner's correctness on the target question based on the knowledge state estimated in the previous module.

Existing KT research has predominantly utilized binary classification techniques to predict whether a learner's response to a target question is correct or not [2, 3]. While these binary classification-based methodologies have demonstrated strong performance in KT, they have limitations. These models only predict binary values indicating whether the learner answers the target question correctly or not, disregarding the content of the learner's responses, especially in open-ended questions[4]. Consequently, they fail to leverage essential information embedded in the learner's responses to measure their current knowledge state accurately.

To overcome these limitations, an open-ended knowledge tracing (OKT) task has been proposed, which simultaneously predicts responses to open-ended questions and tracks the learner's knowledge acquisition [4].

Therefore, this paper introduces a method for an efficient open-ended knowledge tracing (OKT) framework. The proposed method consists of three main modules: The Knowledge Representation module is responsible for transforming textual problem prompts and code into continuous representations. In the Knowledge Estimation module, the current knowledge state of the learner is predicted, and to enhance prediction accuracy, a Transformer encoder [5] is employed. In the Response Generation module, the learner's response is adjusted based on the estimated knowledge state, utilizing the prefix-tuning [6] controllable generation method.

In this paper, we demonstrate the superiority and efficiency of the proposed method through performance eval-

[0]°Corresponding author.

uation and comparative analysis.

2. Method

In the Knowledge Estimation module, the current learner's knowledge state, denoted as h, is predicted based on representations of past questions and code generated by the learner. Departing from the traditional Deep Knowledge Tracing (DKT) approach that uses LSTM [7], this paper employs a Transformer [5] encoder to gain a more fine-grained understanding of the learner's knowledge state. The objective is to enhance comprehension of the evolving learner's knowledge state by utilizing the Transformer, which is effective at capturing long-range dependencies and modeling sequential data.

In this paper, the objective is to generate learner code controlled by the learner's knowledge state using the prefix-tuning method [6]. To apply prefix-tuning, the parameters of the fine-tuned GPT-2 model are kept fixed, and only the parameters corresponding to the prefix are optimized. The embedding value for the first token in the prefix, representing knowledge state h, is initialized based on the prediction made by the Knowledge Estimation module. Furthermore, to investigate the impact of prefix parameters on performance, the paper evaluates code generation performance based on the length of the prefix, denoted as p.

Table 1. The results of the performance comparison of the OKT model's response generation based on different prefix lengths

	Prefix length	CodeBLEU	Dist-1
Previous OKT	x	0.681	0.423
ours	5	0.5378	0.3463
	50	0.6825	0.3748
	70	0.7155	0.4124
	100	**0.7190**	**0.4411**
	300	0.7067	0.4297

3. Result

The comparison of response generation performance of the OKT model based on different prefix lengths is presented in Table 1. It is observed that as the length of the prefix increases, there is an improvement in code generation performance. This trend is attributed to the fact that, with the model parameters fixed, a longer prefix results in an increased number of parameters being learned for learner code generation.

However, when the prefix length reaches 300, performance degrades in all metrics. This is due to the nature of the prefix-tuning approach, which exhibits optimal performance when only a very small percentage (0.1%) of all parameters is fine-tuned [6]. Consequently, the best performance is achieved when the prefix length is set to 100, and performance deteriorates when exceeding this value, as the maximum sequence length is capped at 1024.

4. Conclusion

In this paper, a novel method for enhancing open-ended knowledge tracing (OKT) has been proposed. The proposed method comprises three modules: Knowledge Representation, Knowledge Estimation, and Response Generation. Through these modules, effective tracking of a learner's knowledge in programming can be achieved. Experimental results demonstrate that the proposed method excels in handling diverse knowledge states and responses, thereby advancing the field of OKT research.

Acknowledgements

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2022-2018-0-01405) supervised by the IITP(Institute for Information Communications Technology Planning Evaluation). This work was supported by Institute of Information communications Technology Planning Evaluation(IITP) grant funded by the Korea government(MSIT) (No. 2020-0-00368, A Neural-Symbolic Model for Knowledge Acquisition and Inference Techniques). This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(NRF-2021R1A6A1A03045425).

Reference

[1] S. Ritter, J. R. Anderson, K. R. Koedinger, and A. Corbett, "Cognitive tutor: Applied research in mathematics education," *Psychonomic bulletin & review*, Vol. 14, pp. 249–255, 2007.

[2] C. Piech, J. Bassen, J. Huang, S. Ganguli, M. Sahami, L. J. Guibas, and J. Sohl-Dickstein, “Deep knowledge tracing,” *Advances in neural information processing systems*, Vol. 28, 2015.

[3] A. Ghosh, N. Heffernan, and A. S. Lan, “Context-aware attentive knowledge tracing,” *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*, pp. 2330–2339, 2020.

[4] N. Liu, Z. Wang, R. Baraniuk, and A. Lan, “Open-ended knowledge tracing for computer science education,” *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 3849–3862, 2022.

[5] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, “Attention is all you need,” *Advances in neural information processing systems*, Vol. 30, 2017.

[6] X. L. Li and P. Liang, “Prefix-tuning: Optimizing continuous prompts for generation,” *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 4582–4597, Aug. 2021. [Online]. Available: https://aclanthology.org/2021.acl-long.353

[7] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural computation*, Vol. 9, No. 8, pp. 1735–1780, 1997.