KNOWLEDGE TRACING: A BRIEF OVERVIEW OF THE ADVANCES DONE SINCE 2021 USING DEEP LEARNING TECHNIQUES

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Abstract: This paper aims to describe briefly the direction followed by the models based on deep learning techniques attempting to solve the Knowledge Tracing (KT) task since 2021. The goal of the KT task is to model a student's knowledge level based on their responses to a series of activities (known as interactions) provided by a learning platform. A summary of the advances made during the last year within the research area will be presented in this manuscript, with a unique focus on those models that use neural networks to provide a solution. The interest in that segment of models stems from the fact that they have achieved the highest performance over solutions based on probabilistic or logistic models. This theoretical analysis facilitates the understanding of the current state of the art for new researchers of this area. Furthermore, a brief analysis of the classification will be made accompanied with a description of relevant models. The contribution includes the timeline chart followed by the KT models, a short comparison between recently proposed taxonomies for the models within the research area, a brief description of relevant models published since 2021 falling outside any category included in the taxonomies. Lastly a short discussion of findings, possible new applications of the research area and conceivable future directions are discussed.

Key words: Knowledge Tracing, Deep Learning, Intelligent Education, Educational Data Mining.

1 Introduction

Knowledge tracing in fact is not a new research area, however the interest in this particular research task started to grow up significantly in the year 2015, when

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the first deep learning based model called Deep Knowledge Tracing (DKT)(Piech et al., 2015) was introduced. The DKT model was the first attempt to solve the task without using traditional (probabilistic or logistic) techniques, the model overwhelmingly outperformed previous models and therefore caught significant attention from the research community. Later, in 2017 a new model named Dynamic Key-Value Memory Network (DKVMN)(Jiani Zhang et al., 2017) introduced significant improvements in the task, including the way that knowledge concepts (KC) were addressed to simplify the interpretability of the knowledge abstraction; in the same way (Abdelrahman & Wang, 2019) proposed another models based in memory extension to solve the task .

Soon after, other solutions incorporated additional characteristics as for instance attention mechanisms (Pandey & Karypis, 2019) trying to generalize the complex representation of acquired knowledge from spare data which is the case of real world data, their approach identifies relevant KC to give them more importance. Subsequently some other authors (Pandey & Srivastava, 2020)(N. Zhang et al., 2020)(Zhu et al., 2020) (Ghosh et al., 2020) proposed later additional attention based solutions.

New solutions incorporate graph based techniques (Nakagawa et al., 2021) (Tong et al., 2020), forgetting mechanisms (Y. Chen et al., 2017) (Nagatani et al., 2019) or inclusive some text awake solutions (Q. Liu, Huang, et al., 2021).

Recently some other models (Abdelrahman & Wang, 2021) combines various of the characteristics at the same time.

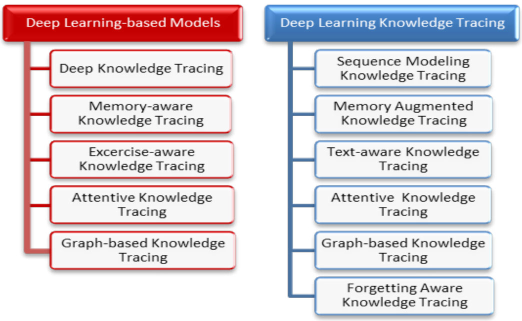

Image no. 1: A taxonomy of deep learning knowledge tracing models (a)(Q. Liu, Shen, et al., 2021) , (b) (Abdelrahman et al., 2022).

All these previously mentioned models are solutions based in deep learning technics however that do not mean that models based on machine learning have also been constantly evolving and producing additional solutions, however those solutions land out of this work scope, for those who are interested on them is highly recommended to check them out.

Although the solutions proposed in the task have been growing vastly, scare literature reviews and standardization of the terms used have appeared in the field which makes quite complicated to advance in a strong based research direction. Recently, (Q. Liu, Shen, et al., 2021) published a survey related to KT, their main contribution was to propose a new taxonomy of existing basic KT models from a technical perspective and provide a comprehensive overview of these models in a systematic manner. Their analysis covers probabilistic, logistic, and deep learning-based model, in Image no. 1 (a) can be found the segment of the taxonomy proposed for deep learning models.

Due to the wideness of their approach their analysis is general and shallow in depth, therefore in this paper a more concrete analysis focused exclusively on deep learning-based models is offered. They summarized the models that were published until the second quarter of 2021, here is extended their work by analyzing the models that appeared after that date until the first trimester of 2022.

This year, (Abdelrahman et al., 2022), published another survey covering a broad range of methods starting from the early attempts to the recent state-of-the-art methods, they highlighted the theoretical aspects of models and the characteristics of benchmark datasets, herein neither a review of datasets, assessment methods not methods that are not based on deep learning are contemplated, however it is contrasted the taxonomy proposed for deep knowledge tracing with the one proposed by (Q. Liu, Shen, et al., 2021) we shed light on key taxonomizing differences between closely related methods and summarize them. This work diverges in depth and time extension covered. It includes an extensive report of the obtained results which help to clarify their differences.

In the following sections, will be discussed each of the given research questions on detail as illustrated in Table no. 1, in the section II is discussed the method used, the strategy followed in the research, the inclusion and exclusion criteria and it will be described the data collected following the given strategy. Section III contains the problem definition and the outcomes of the research (will be studied in detail), that includes the description of the studies and the development of each one of the research questions involving an analysis to answer them. This section also includes a chronological timeline to introduce the development of the KT techniques, thus it will be clear how the most popular and core techniques have acquired their current importance, especially the state-of-the-art models, In Section IV, is posed a discussion of additional application and possible future directions. Finally, Section V includes the conclusions rides on this overview.

Table no. 1: Define research questions for the overview.

RQID	Research Question	Objective
RQ-1	How fast has the KT task been developed in the last year?	Provide a view of the number of solutions published in the last years
RQ-2	What is the development timeline followed by models based in deep learning?	Present the timeline followed by models based on deep leaning.
RQ-3	What are the core techniques that have contributed for the KT task development?	Analise what techniques are providing a higher enhancement to solve the task
RQ-4	What are the actual and future research tasks?	Foresee a feasible research direction in the field.

2 Method Used

For this manuscript it was adapted a landmark literature survey protocol (Stapić et al., 2012) which categorize the review process into three main stages as shown in Image no. 2 in order to identify, evaluate, and understand a particular research direction:

Planning the Review: The purposes of this stage are to identify the need of the review and develop a review protocol.

Conducting the Review: Involves identifying the research, selecting the primary studies to extract, asses, monitor and synthetize information.

Reporting the Review: It is important to communicate the results of a systematic review effectively.

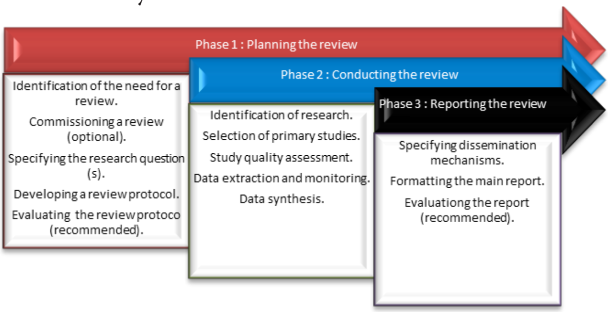

Image no. 2: General steps of the methodology of a systematic literature review

The identified phase from Image no. 2, are applied along the paper as following:

Phase 1: In the chapter I (introduction) was clearly stated the motivation of this review, as well as the goals that are striving to be reached formulated throw the research questions. In chapter II, the introduction of both, the problem and the method used in this work provides the ground to clarify the structure followed to develop the review protocol used in the research.

Phase 2: The core part was done in Section III and IV, where it was executed the research strategy, the data collection the analysis and there were summarized the outcomes of the overview presented.

Phase 3: The dissemination of the work was done through the publication of two papers; this document which contains the results of research done in the topic restricted in time to the advances done since 2021 and other general document which free the time constraint but is focused mostly on the time breakthroughs during the last 7-year period in contrast.

Research Strategy: Establishes an unbiased search while being relevant for the research questions, the key idea was use Boolean terminology to include the documents that contains "Knowledge Tracing" in the title and "Deep Learning" in any part of the document as a mandatory criterion. There were selected 3 popular repositories for the search: Web of Science, IEEE Xplore Digital Library and Google Scholars. The search was first limited to articles published since 2015 to extract a timeline of the evolution and later to articles published since 2021 for the purpose of this report and include journals and conferences only.

Study Selection Criteria: It was established the following inclusion criteria in this search procedure:

- The search phrases are part of the title or abstract(optional).
- Some works mainly dealt with Knowledge Tracing without mentioning related keywords in the title, abstract, or keywords. In such a case, we look for the desired keywords in other parts of the literature. We include those works if we find any.

Besides, a series of exclusion criteria are also established to skip studies that may not be relevant from this review:

- Studies that are not written in English.
- Eliminate duplicates.
- Filter all those documents that are not based on deep learning techniques.

Quality Assessment Criteria: A cross-checking approach has been used for assessing these selected studies to ensure consistency among different findings.

Data Synthesis: Following the data collection, we analyze it for additional information extraction and visualize it using various data visualization tools and techniques, such as histograms, pie maps, tables, and so on, which are discussed in the following chapter.

3 Problem Definition and Outcomes

Here in is introduced the formal definition of the KT task as well as the introduction of relevant preliminary knowledge.

In smart education, each learner interacts with a system which provides questions related to a particular topic, each question can include one or more knowledge concepts (KC, sometimes is presumed to be one KC for each question but not always). It is assumed that the learner completes the exercise independently and the register of the whole answers given by the learner until certain time t are represented as vector X_t The interaction at a time t, is modeled as tuple (q_t, a_t) representing de question and the answer given at that moment, in general the answer is binary variable. If the user answers the question q_t correctly at the time t, then $a_t = 1$ otherwise $a_t = 0$.

The knowledge tracking task can be modeled as a supervised sequence learning task. Knowing the user's answering interactive records $X_t = \{x_1, x_2, \ldots, x_t\}$, by modeling their answering situation, from the interaction the user's implicit knowledge state is extracted from the history, and the change of the knowledge state over time is tracked. Since the evaluation of the knowledge state cannot be explicitly quantified, the existing knowledge tracing task predicts the probability P of the user answering the exercises correctly at the next time step. $(a_{t+1} \mid q_{t+1}, X_t)$ thus, indirectly reflecting the evaluation of the user's knowledge state.

RQ-1: How fast has the KT task been developed in the last year?
The KT related research primarily emerged in 2015. Therefore, we considered the publication period from the beginning of 2015 until the first trimester of 2022. As presented in Image no. 3, in the given span, the number of publications has been increasing consistently.

Image no. 3: Number of publications containing "Knowledge Tracing" in the title of articles from 2015 to 2022 indexed by (a) IEEE explore (b) Web of Science

It also can be seen that 2021 have the highest number of publications, but as its shown, there are 2 and 9 publications respectively in the first trimester of 2022, which suggest that during this year the number of publications might also keep growing. Note that this trend is from the selected databases only but can be considered enough to see that this is the general trend in the research direction.

RQ-2: What is the development timeline followed by models based in deep learning that solve the KT task?

To answer this question is important to consider the taxonomies of the deep learning models presented in *Image no. 1*, which contains two taxonomies; (a) (Q. Liu, Shen, et al., 2021), and (b) (Abdelrahman et al., 2022). To trace the timeline of the development is introduced a representative publication of each category, thus firstly notice that both, taxonomies (a) and (b), are very similar, lets analyse the categories on more detail:

Deep Knowledge Tracing

On the taxonomy presented in (a) the category named Deep Knowledge Tracing is exclusively for the DKT model (Piech et al., 2015), however on (b) apart from considering DKT they also consider extensions of the model (Yeung & Yeung, 2018), (Minn et al., 2018), etc.

Memory Knowledge Tracing

The category Memory-aware KT from taxonomy (a) and Memory augmented KT from taxonomy (b), are the same. The main feature is the use of an external memory to enhance the model. The most representative model for this category is the work known as Dynamik key-value memory network (Jiani Zhang et al., 2017).

Textual Knowledge Tracing

Equally, the model Exercise-aware KT from taxonomy (a) and Text-aware KT from taxonomy (b), have the same focus, which is give more importance to the textual questions as they claim that understanding well the question is the first step towards a correct answer, the first model introducing this characteristic was Exercise-Enhanced Recurrent Neural Network (EERNN) (Su et al., 2018).

Attentive Knowledge Tracing

Both taxonomies (a) and (b) include the same categories names, they attempt to incorporate any kind of attention mechanism into KT models, the first model in to add this characteristic was Self-attentive knowledge tracing (Pandey & Karypis, 2019).

Graphed Knowledge Tracing

This is a solution based in Graph Neural Networks (GNN), casting the knowledge structure as a graph, the knowledge tracing task is reformulated as a time series node-level classification problem in GNN. Since the knowledge graph structure is not explicitly given in many cases, various implementations of the graph structure are proposed in the first model introducing this approach (Nakagawa et al., 2019).

Forgetting Knowledge Tracing

Additionally, the (b) includes, and extra category named Forgetting-aware KT, which is reduced in the taxonomy (a) to an additional characteristic that can be incorporated in a representative model (Nagatani et al., 2019).

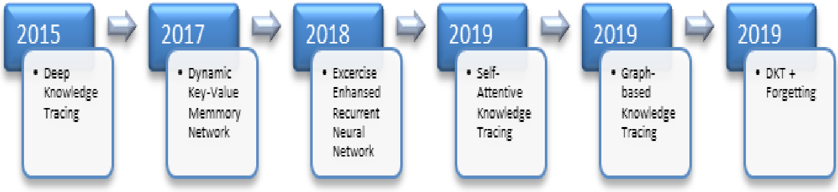

Image no. 4: Knowledge tracing development in the Deep Learning direction since 2015

The evolution follow by the research is shown on Image no. 4, which also includes a representative model. A deeper analysis of each of these models can be found in the other general document aimed to be published simultaneal.

RQ-3: What are the core techniques that have contributed for the KT task development?

During the years 2021 and the first trimester of 2022, various publications have appeared, table no.2 contains examples of the proposed models classified according to the taxonomies introduced earlier, the list contains the results published in both IEEE Xplore and Web of Science, the included files have been manually reviewed to be classified using the taxonomy presented before.

From this same table we can observe that there is not a tendency clearly stablished, and enhancement models have been proposed for all the categories, Attention-based model have received slightly more consideration, and forgetting mechanisms have been included in different models as a complementary (somehow must-have) characteristic of the model since it depicts a more realistic situation.

Table no. 2: Emerged publications solving the Knowledge Tracing task during 2021 and the first trimester of 2022.

Category	Publications
Sequential	(Tian et al., 2021), (Mandlazi et al., 2021), (Vaisakh et al., 2021), (Lai et al., 2021)
Memory	(Sun et al., 2021), (Wan et al., 2021), (Qin et al., 2021), (S. Liu, Zou, et al., 2021)
Textual	(Q. Liu, Huang, et al., 2021)
Attention	(Wang et al., 2021), (Zeng et al., 2021), (C. Liu, 2021), (Wu et al., 2021), (Y. Liu, Zhou, et al., 2021), (Gan et al., n.d.)
Graph	(Yang et al., 2021), (Junrui Zhang et al., 2021), (Nakagawa et al., 2021)
Other	(He, 2021), (Ma et al., 2021), (Song et al., 2021), (Yin Wong et al., 2022), (Song et al., 2022)

The table also contains an additional category at the end, this incorporates proposed models that either missed or novel perspectives, some of them are briefly explained:

(He, 2021) proposed an extensible embedding framework to synthesize skill, exercise, performance factors and side factors.

(Ma et al., 2021) introduced Time Convolution Network into the field of knowledge tracking for the first time, which is expert in processing time series prediction tasks.

(Yin Wong et al., 2022) propose a task agnostic incremental context aware attentive knowledge tracing (iAKT) approach to learn incrementally. The iAKT regularizes representations to learn from diverse learner performance distributions.

(Song et al., 2022) propose a Bi-Graph Contrastive Learning based Knowledge Tracing (Bi-CLKT) model. Specifically, they design a two-layer comparative learning scheme based on an "exercise-to-exercise" (E2E) relational subgraph. It involves node-level contrastive learning of subgraphs to obtain discriminative representations of exercises, and graph-level contrastive learning to obtain discriminative representations of concepts.

(Song et al., 2021) propose a Joint graph convolutional network based deep learning named Joint Knowledge Tracing (JKT) framework to address two major shortcomings in KT: 1) they only consider "exercise-to-concept" relationships; 2) the multi-hot embeddings lack interpretability. With the framework it is not only possible to establish connections between exercises under cross-concepts, but also to help capture high-level semantic information and increase the model's interpretability.

4 Discussion and Future Directions

This overview has reviewed current developments in the field of knowledge tracing, specifically the advances done since 2021, including works that introduce possible applications and trends in the fields.

RQ-4: What are the actual and future research tasks?

The number of publications of table no.2, suggest that a sharp directions in the research field is not well stablished, innovative solutions have plenty of room to be posted on the table as well as new applications, as for instance, (T. Chen et al., 2022) propose a knowledge graph-based framework for fusing multi-source data from public transportation systems to construct contact networks, design algorithms to model epidemic spread, and verify the validity of an effective digital contact tracing method. They take advantage of the trip chaining model to integrate multi-source public transportation data to construct a knowledge graph. A contact network is then extracted from the constructed knowledge graph, and a breadth first search algorithm is developed to efficiently trace infected passengers in the contact network.

Some authors also suggest that KT models that can handle real-time responses need to be developed and further measure students' knowledge states from both past interactions and real-time response.

Additionally, incorporating student feedback in the models is a promising avenue that may yield better results.

5 Conclusion

In this overview, was conducted a comprehensive outline of knowledge tracing. More specifically, it was analyzed proposed taxonomies from the technical perspective, which split the basic KT models into five and six categories respectable as shown in Image no.1 Based on those taxonomy, it was presented a timeline of the evolution of the research area in the last few years.

Later was introduced several variants of KT models specifically those that were published from 2021 to the end of the first trimester of 2022. An additional and more general review that dive deeper in the whole panorama instead of focusing exclusively on the latest advances is concurrently being published, it is recommended for the reader.

Finally, we outlined some potential future directions for this young but promising research field including new applications.

This overview of knowledge tracing can serve as a basic understanding of the current state of the research for both researchers and practitioners.

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6 Bibliography

Abdelrahman, G., & Wang, Q. (2019). Knowledge tracing with sequential key-value memory networks. *SIGIR 2019 – Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 175–184. https://doi.org/10.1145/3331184.3331195

Abdelrahman, G., & Wang, Q. (2021). *Deep Graph Memory Networks for Forgetting-Robust Knowledge Tracing*. 1–11. http://arxiv.org/abs/2108.08105

Abdelrahman, G., Wang, Q., & Nunes, B. P. (2022). *Knowledge Tracing: A Survey*. *1*(1), 1–36. http://arxiv.org/abs/2201.06953

Chen, T., Zhang, Y., Qian, X., & Li, J. (2022). A knowledge graph-based method for epidemic contact tracing in public transportation. *TRANSPORTATION RESEARCH PART C-EMERGING TECHNOLOGIES*, *137*. https://doi.org/10.1016/j.trc.2022.103587

Chen, Y., Liu, Q., Huang, Z., Wu, L., Chen, E., Wu, R., Su, Y., & Hu, G. (2017). Tracking knowledge proficiency of students with educational priors. *International Conference on Information and Knowledge Management, Proceedings*, *Part F1318*, 989–998. https://doi.org/10.1145/3132847.3132929

Gan, W., Sun, Y., & Sun, Y. (n.d.). Knowledge structure enhanced graph representation learning model for attentive knowledge tracing. *INTERNATIONAL JOURNAL OF INTELLIGENT SYSTEMS*. https://doi.org/10.1002/int.22763

Ghosh, A., Heffernan, N., & Lan, A. S. (2020). Context-Aware Attentive Knowledge Tracing. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2330–2339. https://doi.org/10.1145/3394486.3403282

He, L. (2021). Integrating Performance and Side Factors into Embeddings for Deep Learning-Based Knowledge Tracing. *2021 IEEE International Conference on Multimedia and Expo (ICME)*, 1–6. https://doi.org/10.1109/ICME51207.2021.9428154

Lai, Z., Wang, L., & Ling, Q. (2021). Recurrent knowledge tracing machine based on the knowledge state of students. *Expert Systems*, *38*(8). https://doi.org/10.1111/exsy.12782

Liu, C. (2021). *Multi-factor Memory Attentive Model for Knowledge Tracing*. *2019*. https://proceedings.mlr.press/v157/liu21c.html

Liu, Q., Huang, Z., Yin, Y., Chen, E., Xiong, H., Su, Y., & Hu, G. (2021). EKT: Exercise-aware knowledge tracing for student performance prediction. *IEEE Transactions on Knowledge and Data Engineering*, *33*(1), 100–115. https://doi.org/10.1109/TKDE.2019.2924374

Liu, Q., Shen, S., Huang, Z., Chen, E., & Zheng, Y. (2021). *A Survey of Knowledge Tracing*. 1–20. http://arxiv.org/abs/2105.15106

Liu, S., Zou, R., Sun, J., Zhang, K., Jiang, L., Zhou, D., & Yang, J. (2021). A Hierarchical Memory Network for Knowledge Tracing. *EXPERT SYSTEMS WITH APPLICATIONS*, *177*. https://doi.org/10.1016/j.eswa.2021.114935

Liu, Y., Zhou, J., & Lin, W. (2021). Efficient Attentive Knowledge Tracing for Long-Tail Distributed Records. *2021 IEEE/ACIS 6th International Conference on Big Data, Cloud Computing, and Data Science (BCD)*, 104–109. https://doi.org/10.1109/BCD51206.2021.9582084

Ma, R., Zhang, L., Li, J., Mei, B., Ma, Y., & Zhang, H. (2021). DTKT:An Improved Deep Temporal Convolutional Network for Knowledge Tracing. *2021 16th International*

Conference on Computer Science Education (ICCSE), 794–799. https://doi.org/10.1109/ICCSE51940.2021.9569258

Mandlazi, J., Jadhav, A., & Ajoodha, R. (2021). Evaluating Deep Sequential Knowledge Tracing Models for Predicting Student Performance. *2021 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, 1–6. https://doi.org/10.1109/CSDE53843.2021.9718405

Minn, S., Yu, Y., Desmarais, M. C., Zhu, F., & Vie, J. J. (2018). Deep Knowledge Tracing and Dynamic Student Classification for Knowledge Tracing. *Proceedings – IEEE International Conference on Data Mining, ICDM*, *2018-Novem*, 1182–1187. https://doi.org/10.1109/ICDM.2018.00156

Nagatani, K., Zhang, Q., Sato, M., Chen, Y.-Y., Chen, F., & Ohkuma, T. (2019). Augmenting knowledge tracing by considering forgetting behavior. *The World Wide Web Conference*, 3101–3107.

Nakagawa, H., Iwasawa, Y., & Matsuo, Y. (2019). Graph-based knowledge tracing: Modeling student proficiency using graph neural networks. *Web Intelligence*, *19*(1–2), 87–102. https://doi.org/10.3233/WEB-210458

Nakagawa, H., Iwasawa, Y., & Matsuo, Y. (2021). Graph-based knowledge tracing: Modeling student proficiency using graph neural networks. *Web Intelligence*, *19*(1–2), 87–102. https://doi.org/10.3233/WEB-210458

Pandey, S., & Karypis, G. (2019). A self-attentive model for knowledge tracing. *EDM 2019 – Proceedings of the 12th International Conference on Educational Data Mining*, 384–389.

Pandey, S., & Srivastava, J. (2020). RKT: Relation-Aware Self-Attention for Knowledge Tracing. *International Conference on Information and Knowledge Management, Proceedings*, 1205–1214. https://doi.org/10.1145/3340531.3411994

Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L., & Sohl-Dickstein, J. (2015). Deep knowledge tracing. *Advances in Neural Information Processing Systems*, *2015-Janua*, 505–513.

Qin, X., Li, Z., Gao, Y., & Xue, T. (2021). Knowledge Tracing With Learning Memory and Sequence Dependence. *2021 IEEE International Conference on Engineering, Technology Education (TALE)*, 1–6. https://doi.org/10.1109/TALE52509.2021.9678654

Song, X., Li, J., Lei, Q., Zhao, W., Chen, Y., & Mian, A. (2022). Bi-CLKT: Bi-Graph Contrastive Learning based Knowledge Tracing. *KNOWLEDGE-BASED SYSTEMS*, *241*. https://doi.org/10.1016/j.knosys.2022.108274

Song, X., Li, J., Tang, Y., Zhao, T., Chen, Y., & Guan, Z. (2021). JKT: A joint graph convolutional network based Deep Knowledge Tracing. *INFORMATION SCIENCES*, *580*, 510–523. https://doi.org/10.1016/j.ins.2021.08.100

Stapić, Z., García López, E., Cabot, A. G., De, L., Ortega, M., & Strahonja, V. (2012). Performing systematic literature review in software engineering. *Proc.23rd Central Eur. Conf. Inf. Intell. Syst. (CECIIS),* 441–447.

Su, Y., Liu, Q., Liu, Q., Huang, Z., Yin, Y., Chen, E., Ding, C., Wei, S., & Hu, G. (2018). Exercise-enhanced sequential modeling for student performance prediction. *32nd AAAI Conference on Artificial Intelligence, AAAI 2018.*

Sun, X., Zhao, X., Li, B., Ma, Y., Sutcliffe, R., & Feng, J. (2021). Dynamic Key-Value Memory Networks With Rich Features for Knowledge Tracing. *IEEE TRANSACTIONS ON CYBERNETICS*. https://doi.org/10.1109/TCYB.2021.3051028

Tian, Y., Niu, Z., & Liu, D. (2021). Learning Strategy Based on Deep Knowledge Tracing. *2021 3rd International Conference on Computer Science and Technologies in Education (CSTE)*, 75–79. https://doi.org/10.1109/CSTE53634.2021.00022

Tong, S., Liu, Q., Huang, W., Huang, Z., Chen, E., Liu, C., Ma, H., & Wang, S. (2020). Structure-based knowledge tracing: An influence propagation view. *Proceedings – IEEE International Conference on Data Mining, ICDM*, *2020-Novem*(Icdm), 541–550. https://doi.org/10.1109/ICDM50108.2020.00063

Vaisakh, K. V, Ravi, A., O, A. K., Sai, A., & Bhaskar, J. (2021). SkillCrest: A Skill Assessment System Using Deep Knowledge Tracing and User Feedback Sentiment Analysis. *2021 2nd Global Conference for Advancement in Technology (GCAT)*, 1–7. https://doi.org/10.1109/GCAT52182.2021.9587697

Wan, H., Tang, L., Zhong, Z., & Liu, K. (2021). Improving Online Teaching Based on Knowledge Tracing Model. *2021 IEEE International Conference on Engineering, Technology Education (TALE)*, 1–5. https://doi.org/10.1109/TALE52509.2021.9678661

Wang, X., Mei, X., Huang, Q., Han, Z., & Huang, C. (2021). Fine-grained learning performance prediction via adaptive sparse self-attention networks. *Information Sciences*, *545*, 223–240. https://doi.org/10.1016/J.INS.2020.08.017

Wu, H., Xu, B., & Cai, Y. (2021). Exponent-Enhanced Attentive Knowledge Tracing based Online Learning Reinforcing. *2021 2nd International Conference on Big Data and Informatization Education (ICBDIE)*, 147–150. https://doi.org/10.1109/ICBDIE52740.2021.00041

Yang, Y., Shen, J., Qu, Y., Liu, Y., Wang, K., Zhu, Y., Zhang, W., & Yu, Y. (2021). GIKT: A Graph-Based Interaction Model for Knowledge Tracing. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *12457 LNAI*, 299–315. https://doi.org/10.1007/978-3-030-67658-2_18

Yeung, C. K., & Yeung, D. Y. (2018). Addressing two problems in deep knowledge tracing via prediction-consistent regularization. *Proceedings of the 5th Annual ACM Conference on Learning at Scale, L at S 2018*. https://doi.org/10.1145/3231644.3231647

Yin Wong, C. S., Yang, G., Chen, N. F., & Savitha, R. (2022). Incremental Context Aware Attentive Knowledge Tracing. *ICASSP 2022 – 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 3993–3997. https://doi.org/10.1109/ICASSP43922.2022.9746810

Zeng, J., Zhang, Q., Xie, N., & Yang, B. (2021). *Application of Deep Self-Attention in Knowledge Tracing*. 1–6. http://arxiv.org/abs/2105.07909

Zhang, Jiani, Shi, X., King, I., & Yeung, D. Y. (2017). Dynamic key-value memory networks for knowledge tracing. *26th International World Wide Web Conference, WWW 2017*. https://doi.org/10.1145/3038912.3052580

Zhang, Junrui, Mo, Y., Chen, C., & He, X. (2021). GKT-CD: Make Cognitive Diagnosis Model Enhanced by Graph-based Knowledge Tracing. *2021 International Joint Conference on Neural Networks (IJCNN)*, 1–8. https://doi.org/10.1109/IJCNN52387.2021.9533298

Zhang, N., Du, Y., Deng, K., Li, L., Shen, J., & Sun, G. (2020). Attention-Based Knowledge Tracing with Heterogeneous Information Network Embedding. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 12274 LNAI* (pp. 95–103). https://doi.org/10.1007/978-3-030-55130-8_9

Zhu, J., Yu, W., Zheng, Z., Huang, C., Tang, Y., & Fung, G. P. C. (2020). Learning from Interpretable Analysis: Attention-Based Knowledge Tracing. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 12164 LNAI* (Issue 61772211). Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_66