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A Literature Review of Knowledge Tracing for Student Modeling: Research Trends, Models, Datasets, and Challenges

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Abstract. Modeling students' knowledge is a fundamental part of online learning platforms. Knowledge tracing is an application of student modeling which renowned for its ability to trace students' knowledge. Knowledge tracing ability can be used in online learning platforms for predicting learning performance and providing adaptive learning. Due to the wide uses of knowledge tracing in student modeling, this study aims to understand the state-of-the-art and future research of knowledge tracing. This study focused on reviewing 24 studies published between 2017 to the third quarter of 2021 in four digital databases. The selected studies have been filtered using inclusion and exclusion criteria. Several previous studies have shown that there are two approaches used in knowledge tracing, including probabilistic and deep learning. Bayesian Knowledge Tracing model is the most widely used in the probabilistic approach, while the Deep Knowledge Tracing model is the most popular model in the deep learning approach. Meanwhile, ASSISTments 2009–2010 is the most frequently tested dataset for probabilistic and deep learning approaches. In the future, additional studies are required to explore several models which have been developed previously. Therefore this study provides direction for future research of each existing approach.

Keywords: knowledge tracing, student modeling, adaptive learning, Bayesian Knowledge Tracing, Deep Knowledge Tracing.

1 Introduction

Online learning platforms such as Massive Open Online Course (MOOC) and Intelligent Tutoring System (ITS) have rapidly grown in recent years because of the flexibility and ease of access. The MOOC currently provides access to online courses but has not been able to model student knowledge hence adaptive learning content is not yet available. Therefore, the ITS was developed as an alternative to address the needs of adaptive learning. However, the ITS is still constrained in its evaluation of student performance.

In order to address this issue, researchers have paid more attention to knowledge tracing on student modeling. Knowledge tracing is aimed to model students'

knowledge state over time based on their previous performance in a series of exercises [1], [2]. The mastery level of skills in the learning process is represented by the knowledge state [1]. Estimation of students' knowledge state can be used to evaluate the learning effectiveness of students, predict students' future performance and support the personalization of adaptive learning content [2], [3].

Corbett et al. [4] first proposed a model that estimated probability using the Bayesian inference scheme named Bayesian Knowledge Tracing (BKT). This model describes the changes in students' cognitive conditions during the knowledge acquisition process. Various improvements have been made to the model, including three learning states BKT (TLS-BKT)[5], cross-skill BKT(CS-BKT)[6], temporal difference BKT (TD-BKT)[7], and the most recent model is Deep Knowledge Tracing (DKT). Piech et al. [8] proposed the DKT model based on deep learning approaches. DKT performs knowledge tracing by applying Recurrent Neural Networks, which can capture complex representations of student knowledge. The aforementioned models then tested using various datasets and evaluation metrics to discover their abilities. According to prior studies, further discussion regarding research trends and future challenges is needed. Unfortunately, there is no literature review that comprehensively discusses related to the knowledge tracing for student modeling in terms of trends, models, and datasets.

This literature review provides thorough information about knowledge tracing for student modeling. The information consists of identified approaches and classified models that have been used in previous studies. This study also followed with an explanation of the evaluation metrics and the most popular datasets. Furthermore, an outline of future research potential is presented.

The rest of this literature review is organized as follows. Section 2 presents the existing studies related to knowledge tracing. Then, it proceeds with section 3, which explains the research methodology. Section 4 discusses the research results and the last section provides the conclusion.

2 Related Works

Along with the continuous improvement in knowledge tracing research, several literature reviews related to this area have emerged. Abyaa et al. [9] systematically reviewing 107 publications related to student modeling from 2013 to 2017. This systematic review mainly discussed the modeled characteristics in the proposed student models, modeling techniques and modeling types. They identified six categories of students' characteristics following with a detailed explanation of each characteristic. The modeling technique then categorized based on the student characteristic. In this section, they introduced the methodologies used in student modeling (BKT, DKT, and their improvements) but did not mention evaluation measures or datasets. Moreover, they also explored how to collect information in student modeling and provided some directions for future research in student modeling.

Pelánek et al. [10] performed an overview from more than 60 papers and only considered the modeling of knowledge and skills. They particularly focuses on Bayesian knowledge tracing and logistic models. This study especially presents a discussion of how the purpose of a model influences choices made in student modeling. They also mentions evaluation metrics that are widely applied in student modeling but do not provide dataset information. In addition, this paper describes future work from developers' and

researchers' perspectives on several aspects. It can support student modeling research such as types of knowledge components, relevant learning processes, data sources that can be used for student modeling, the main purpose of student modeling, and utilization of outputs.

Hernández-Blanco et al. [11] conducted a systematic review from 41 papers including proceedings and articles that applied deep learning. They classified the papers based on the task of educational data mining. The taxonomy comprises thirteen tasks in educational data mining. Knowledge tracing belongs to the task of predicting student performance. Furthermore, they also categorized the datasets, described the technique and discussed future research about deep learning which applied in educational data mining.

Based on several prior literature reviews, it is possible to conclude that knowledge tracing in student modeling plays an important role in the process of developing adaptive learning. Several challenges encountered include the selection of appropriate approaches, models, and datasets. Therefore, this literature review aims to provide a thorough explanation in order to overcome existing problems both in terms of probabilistic model or deep learning model.

3 Research Method

3.1 Research Questions

The main objective of this research is to focus on the state-of-the-art of knowledge tracing models and their performance in student modeling. Hence, the following research questions were used in order to conduct this literature review:

1. RQ1: What are trends in knowledge tracing research from 2017 until the third quarter of 2021?
   Objective: Identify the approaches to address knowledge tracing challenges.

2. RQ2: What are the proposed models to address the issues of knowledge tracing?
   Objective: Identify and classify models that have been used in previous studies. We also intend to review the advantages and disadvantages of the models, as well as the evaluation metrics that are used.

3. RQ3: What kind of datasets are used for knowledge tracing between 2017 and the third quarter of 2021?
   Objective: Identify the most popular dataset for knowledge tracing including a review of the advantages and disadvantages.

4. RQ4: What are the challenges that future knowledge tracing research needs to address?
   Objective: Identify potential further research on knowledge tracing.

3.2 Search Strategy

This study used four digital databases for primary literature sources: SCOPUS, Springer, ScienceDirect, and IEEE Xplore. The search process was carried out using the search query contained in the title, abstract, and keywords. TITLE-ABS-KEY ("knowledge tracing") used as the search query. Afterward, the results were filtered using the inclusion and exclusion criteria.

3.3 Inclusion and Exclusion Criteria

Several inclusion and exclusion criteria are used in this literature review. The following inclusion criteria are used:

- Articles related to knowledge tracing on student modeling.
- Articles were published in journals under the subject area of computer science between 2017 and the third quarter of 2021.
- Articles are publicly accessible and written in English.

While the exclusion criteria used are as follows:

- An overview, a review, or a literature review.
- Articles with insufficient research information, such as evaluation metrics and datasets.

3.4 Selection Process

The selection process is divided into three stages. In the first stage, we conducted a search process on the selected digital databases by applying a predetermined keyword. It resulted in 52 papers. Furthermore, the papers were selected based on inclusion and exclusion criteria. At this stage, the full papers have been read and resulted in 35 papers. In the last stage, we removed the duplicates and obtained 24 papers for further analysis.

4 Research Results

Based on the research method used, 24 papers have been successfully obtained. Table 2 contains detailed information about the papers that were chosen. This section will explain the research findings by responding to each predetermined research question.

Table II. List of Primary Literature Sources in the Field of Knowledge Tracing

Ref.	Year	Publications	Approaches	Models	Datasets
[12]	2017	International Journal of Information and Learning Technology	Probabilistic	Logistic Regression	Assistments Math 2004–2005
[13]	2017	IEEE Transactions on Learning Technologies	Probabilistic	Bayesian Knowledge Tracing	Calcularis, Andes 2011−2012, Dybuster, Bridge to Algebra 2006–2007
[14]	2018	Knowledge-Based Systems	Probabilistic	Bayesian Knowledge Tracing	Assistments Math 2004–2005, Assistments Math 2005–2006, Assistments Math 2006–2007
[3]	2018	Cognitive Computation	Deep Learning	Deep Knowledge Tracing	ASSISTments 2009−2010, Junyi academy

Ref.	Year	Publications	Approaches	Models	Datasets
[7]	2018	IEEE Access	Probabilistic	Bayesian Knowledge Tracing	Junyi academy
[6]	2019	Interactive Learning Environments	Probabilistic	Bayesian Knowledge Tracing	Bridge to Algebra 2006–2007
[15]	2019	Education and Information Technologies	Deep Learning	Deep Knowledge Tracing	STATIC, ASSISTments 2009−2010
[16]	2019	International Journal of Artificial Intelligence in Education	Deep Learning	Deep Knowledge Tracing	ASSISTments 2017
[17]	2020	Knowledge-Based Systems	Deep Learning	Long Short-Term Memory	ASSISTments 2009−2010, Algebra 2005–2006, OLIES 2011
[18]	2020	Applied Intelligence	Deep Learning	Factorization Machine	Algebra 2005−2006, Bridge to Algebra 2006–2007, ASSISTments 2012−2013
[19]	2020	Journal of Educational Data Mining	Probabilistic	Logistic Regression	ASSISTments 2009−2010, ASSISTments 2012−2013, ASSISTments 2015, ASSISTments 2017, Algebra 2005−2006, Bridge to Algebra 2006–2007, Spanish, OLIES 2011, Squirrel
[20]	2020	Neurocomputing	Deep Learning	Deep Neural Network	ASSISTments 2009−2010, ASSISTments 2014−2015, Algebra 2005−2006, Synthetic
[21]	2020	IEEE Transactions on Learning Technologies	Deep Learning	Recurrent Neural Network	HOC4, HOC18
[22]	2020	Information Sciences	Deep Learning	Deep Knowledge Tracing	ASSISTments 2009−2010, ASSISTments 2015, OLIES 2011
[23]	2020	Information Sciences	Deep Learning	Long Short-Term Memory	ASSISTments 2009−2010, Intellilence 2018
[24]	2020	IEEE Access	Deep Learning	Deep Knowledge Tracing	ASSISTments 2009−2010
[25]	2020	Knowledge-Based Systems	Deep Learning	Deep Knowledge Tracing	AiLearn 2019, ASSISTments 2009−2010

Ref.	Year	Publications	Approaches	Models	Datasets
[1]	2021	Expert Systems With Applications	Deep Learning	Long Short-Term Memory	ASSISTments 2009−2010, ASSISTments 2015, ASSISTments 2017, OLIES 2011
[26]	2021	Knowledge-Based Systems	Deep Learning	Recurrent Neural Network	iFLYTEK-SeniorMath2018, Algebra 2006–2007
[2]	2021	IEEE Transactions on Fuzzy Systems	Probabilistic	Bayesian Knowledge Tracing	Algebra 2005–2006, Algebra 2006–2007, Bridge to Algebra 2006–2007, ASSISTments 2009−2010, ASSISTments 2012−2013, ASSISTments 2017
[27]	2021	Interactive Learning Environments	Probabilistic	Performance Factor Analysis	ASSISTments 2009−2010, Andes 2011−2012, Synthetic
[28]	2021	IEEE Access	Probabilistic	Q-matrix	POJ, HDU
[29]	2021	IEEE Transactions on Cybernetics	Deep Learning	Deep Knowledge Tracing	ASSISTments 2009−2010
[30]	2021	IEEE Transactions on Knowledge and Data Engineering	Deep Learning	Recurrent Neural Network	iFLYTEK-SeniorMath2018

4.1 RQ1: What are trends in knowledge tracing research from 2017 until the third quarter of 2021?

According to selected papers, knowledge tracing approaches can be classified into two types: probabilistic and deep learning. Figure 2 shows the use of probabilistic approaches started in 2017, followed by the appearance of deep learning approaches in 2018. The number of studies utilizing deep learning approaches significantly increased by 2020, and the trend began to shift. However, the probabilistic approaches are still being improved to this day.

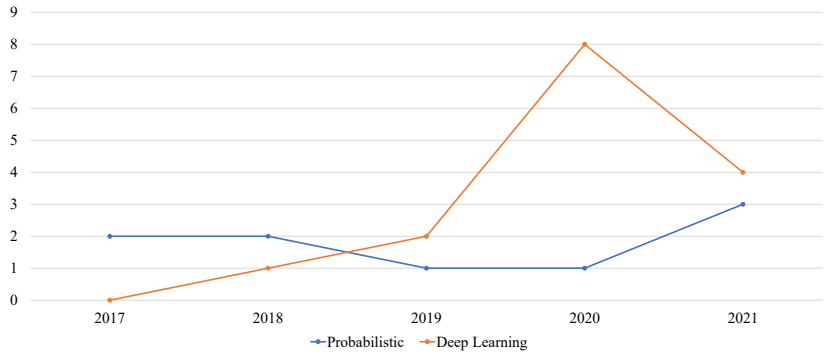

Fig.2 Current Trends In Knowledge Tracing Approaches

The probabilistic approaches have advantages in tracking students' cognition so that they can establish strong interpretation skills, but they have limitations in terms of

accuracy [2]. While the deep learning approaches have advantages in predicting future student performance through a hidden layer that can retain relevant information from the learning logs entered, there are still challenges related to interpretability [18]. The current interpretability cannot explain the change of student's knowledge state based on explicit knowledge components, whereas they can be beneficial for many real-world applications [30].

4.2 RQ2: What are the proposed models to address the issues of knowledge tracing?

RQ1 previously explained that knowledge tracing employs two approaches. Therefore, we categorized the proposed models into two approaches. Bayesian Knowledge Tracing, Logistic Regression, Performance Factor Analysis, and Q-matrix are some of the models developed using a probabilistic approach. Figure 3 illustrates that the models proposed by previous researchers mostly use the Bayesian Knowledge Tracing.

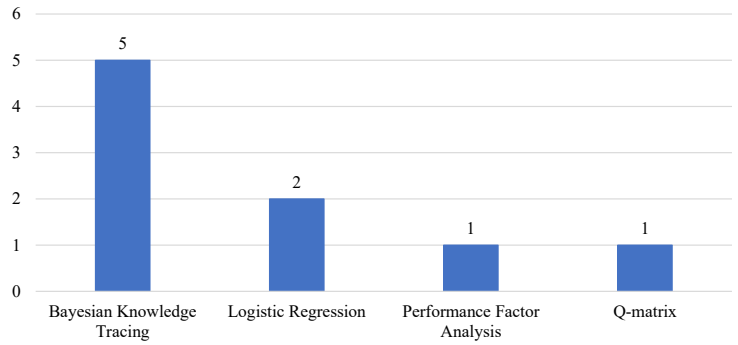

Fig.3 Distribution of Proposed Models Using a Probabilistic Approach

BKT is a Hidden Markov Model (HMM) consisting of latent and observed variables [13]. Latent variables represent students' knowledge related to specific skills that are assumed to be binary (skills mastered by students or not). In contrast, observed variables represent student's answers to specific skills which are assumed to be binary (correct or incorrect) and directly dependent on the latent variables.

In previous studies, proposed models developed using BKT were tested with various datasets and measured using evaluation metrics. Three of the five studies developed with BKT shared the same dataset and evaluation metrics. They all used the Bridge to Algebra 2006–2007 dataset and then evaluated using the Root Mean Squared Error (RMSE). RMSE measures the performance of skill models and has the advantage of showing correlations related to the moment of learning, especially in the BKT model [13]. The lower RMSE score indicates better prediction (0-1).

Liu et al. [2] proposed Fuzzy Bayesian Knowledge Tracing (FBKT) and Type-2 fuzzy Bayesian Knowledge Tracing (T2FBKT). The experiments were conducted with 5-fold cross-validation for more stable results. The results show that the prediction performance of the two proposed models outperforms the other models. The RMSE score obtained by T2FBKT was around 0.1. Furthermore, the study performed by Meng et al. [6] proposed Cross-skill Bayesian Knowledge Tracing (CS-BKT). In this experiment, their proposed model outperforms BKT with an RMSE score of around 0.395. The last study by Klingler et al. [13] proposed Dynamic

Bayesian Networks (DBN). They used 10-fold cross-validation in this experiment. Their proposed model outperforms other models, with an RMSE score of around 0.325. The experimental results of the three studies show that T2FBKT has the lowest RMSE score.

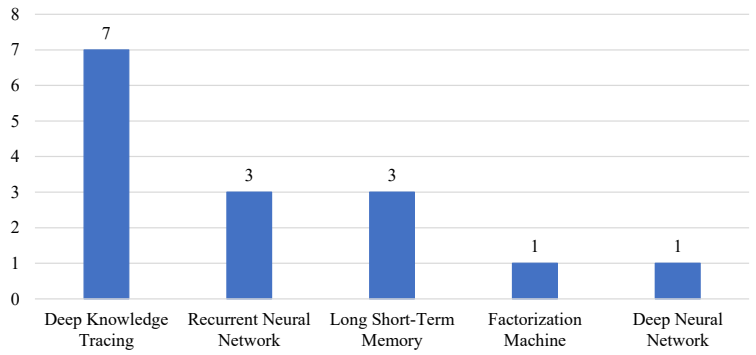

Fig.4 Distribution of the Proposed Models Using a Deep Learning Approach

Deep Knowledge Tracing, Recurrent Neural Network, Long Short-Term Memory, Factorization Machine, Deep Neural Network are classified as deep learning approaches. According to Figure 4, DKT is the most widely proposed model. DKT utilizes a Recurrent Neural Network (RNN) to trace students' knowledge states by finding the hidden structure of each exercise's correlation and analyzing student answers [3], [24]. DKT also captures complex high-dimensional features of items and students [26]. The model's input is the correctness of the problem and the model's output is the probability of each skill being correct [20].

There are four papers on the list of selected papers that use similar datasets and evaluation metrics. The dataset used is ASSISTments 2009−2010 and area under a ROC curve (AUC) as evaluation metric. This evaluation metric's advantages include supporting a summary of performance measurement and robust metrics across all possible thresholds [16]. The higher AUC score indicates that the model applied has a good performance. The score varies from 0.5 (predictive ability is merely as good as a random guess) up to 1 (a perfect predictive score) [12]. A study using experimental data also shows that AUC is naturally insensitive to unbalanced classes [23].

Yang et al. [3] proposed five models based on DKT and using 5-fold cross-validation. Two of the five proposed models, DKT with Random Forest (DKT-RF) and DKT with GBDT (DKT-GBDT), have AUC scores of 74.4% and 74.7%. Meanwhile, Huo et al. [25] proposed a model named heterogeneity mechanism with a maximum entropy regularizer (HeTROPY). The experiment was carried out using 10-fold cross-validation. The AUC score obtained was 87.86%. Whereas Liu et al. [24] proposed the multiple features fusion attention mechanism enhanced deep knowledge tracing (MFA-DKT) model. This model has an AUC score of 96%. Lastly, Sun et al. [29] proposed a dynamic key-value memory network (DKVMN) model. This experiment used 5-fold cross-validation. The experimental results show that the proposed model has the best performance and an AUC score of 91.9%. Based on the results of the four prior studies, MFA-DKT has the highest AUC score.

BKT and DKT have different strengths and weaknesses. BKT excels in simple problem solving and has several extensions with comparable performance to DKT.

However, it still has issues with prediction accuracy, modeling the relationship between different skills, and forecasting performance [13]. Meanwhile, DKT performed well in processing sequential education data but still has several challenges. Some of the challenges faced include the DKT model complexity that raises the tension of psychological interpretation, difficulty in tracing the evolution of student's knowledge state, inconsistent predicted knowledge state across time, predictions that contradict actual student responses, and student's behavior features that are being ignored [3], [15], [24], [26].

4.3 RQ3: What kind of datasets are used for knowledge tracing between 2017 and the third quarter of 2021?

There are 27 datasets that have been used in the studies of knowledge tracing for student modeling. ASSISTments 2009–2010, Algebra 2005–2006, Bridge to Algebra 2006–2007, ASSISTments 2017, and OLIES 2011 are the most widely used datasets. ASSISTments 2009−2010 is the most popular dataset of all and has been used 13 times. This dataset comes from Intelligent Tutoring Systems named ASSISTments, designed to teach topics mostly related to algebra. ASSISTments was originally designed to support state exam preparation and provide automated instruction in the remedial process, which was particularly addressed to middle and high school students [31]. There are 4163 students in this dataset working on 17.751 exercises with 337.990 interactions [23]. ASSISTments 2009–2010 is a public dataset that can be easily accessed via https://sites.google.com/site/assistmentsdata/home/assistment-2009-2010-data. This dataset advantage is the multi-skill approach arranged simultaneously in a time sequence [31]. Many exercises also provided an advantage, especially in generating a list of recommendations [17].

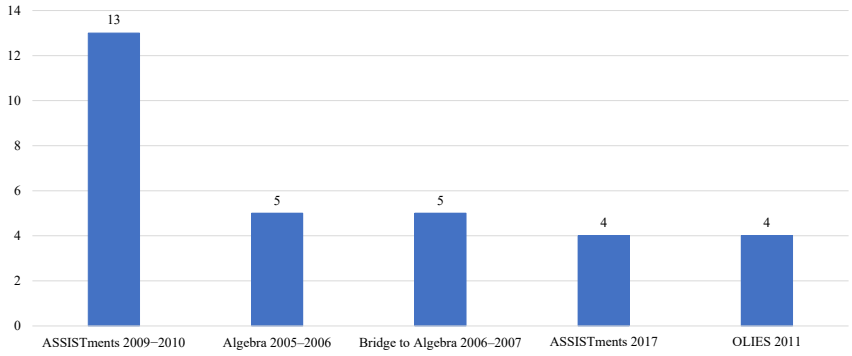

Fig.5 The Most Widely Used Datasets In Knowledge Tracing

4.4 RQ4: What are the challenges that future knowledge tracing research needs to address?

There are several works that can be improved and conducted in the future based on the models that have been previously proposed. On the probabilistic approach, the BKT models have lower accuracy than the DKT models. Several ways can be done to improve accuracy based on prior studies include applying a deep learning approach to improve interpretation ability [2], exploration of the probability matrix to show the relationship between different abilities or knowledge [6], exploring the possibility of learning skill hierarchy from data [13]. Moreover, the implementation of the proposed

model in real-world applications can also be added.

While in the deep learning approach, particularly the DKT models, some research that can be done in the future is the exploration of models to support personalization recommendations so that each student gets the suitable exercises [3], testing the bi-attention architecture to improve accuracy [25], considering the relationship between knowledge concepts to capture the structure of knowledge [24], improve the ability to predict critical events during the student learning process and integrate student psychology as a layer of knowledge when predicting student responses [15].

5 Conclusion

Knowledge tracing for student modeling continues to grow today because of its superiority in predicting student performance. The probabilistic approach was the first approach used in knowledge tracing. Then in 2020, the trend shifted to the deep learning approach. According to the selected paper, DKT is the model with the most often used deep learning approach. The researchers were interested in developing a DKT model because of the high accuracy obtained. One of the proposed models, MFA-DKT has an AUC score of 96%. However, DKT still has gaps related to interpretability. Therefore, future research directions can focus on exploring student learning processes in order to capture the evolution of student knowledge state.

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