FDKT: Towards an interpretable deep knowledge tracing via fuzzy reasoning

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In educational data mining, knowledge tracing (KT) aims to model learning performance based on student knowledge mastery. Deep-learning-based KT models perform remarkably better than traditional KT and have attracted considerable attention. However, most of them lack interpretability, making it challenging to explain why the model performed well in the prediction. In this paper, we propose an interpretable deep KT model, referred to as fuzzy deep knowledge tracing (FDKT) via fuzzy reasoning. Specifically, we formalize continuous scores into several fuzzy scores using the fuzzification module. Then, we input the fuzzy scores into the fuzzy reasoning module (FRM). FRM is designed to deduce the current cognitive ability, based on which the future performance was predicted. FDKT greatly enhanced the intrinsic interpretability of deep-learning-based KT through the interpretation of the deduction of student cognition. Furthermore, it broadened the application of KT to continuous scores. Improved performance with regard to both the advantages of FDKT was demonstrated through comparisons with the state-of-the-art models.

CCS Concepts: • **Applied computing** → **Education**; • **Information systems** → *Information systems applications.*

Additional Key Words and Phrases: educational data mining, knowledge tracing, model interpretability, fuzzy reasoning, deep learning

1 INTRODUCTION

Online education systems such as MOOC, ASSISTments, and Khan Academy are being increasingly used, producing large amounts of student learning data [1–7]. Knowledge tracing (KT) [8–10] focuses on predicting future performance based on estimating the over-time knowledge mastery of students from the learning logs, as shown in Fig. 1. KT is one of the important tasks of educational data mining [11, 12] and can be applied to various scenarios, such as facilitating better personalized learning resource recommendations [13, 14].

Model interpretability recently has attracted increasing attention in the field of educational data mining, including the KT task. **Interpretability** is defined as *the ability to provide explanations in understandable terms to a human* [15, 16]. Being able to explain the reasons why the model was able to achieve good prediction performance in an interpretable KT model is as crucial as achieving desirable performance [17]. To obtain this understanding, interpretability can be improved from both intrinsic and post hoc aspects, as shown in Fig. 2. **Intrinsic** interpretability explains *how the model works*, the interpretability comes from the model-specific constraints based on the domain knowledge [18]. The way to construct an intrinsically interpretable model, for example, is by using interpretable models such as linear regression, decision tree, and decision rules. **Post**

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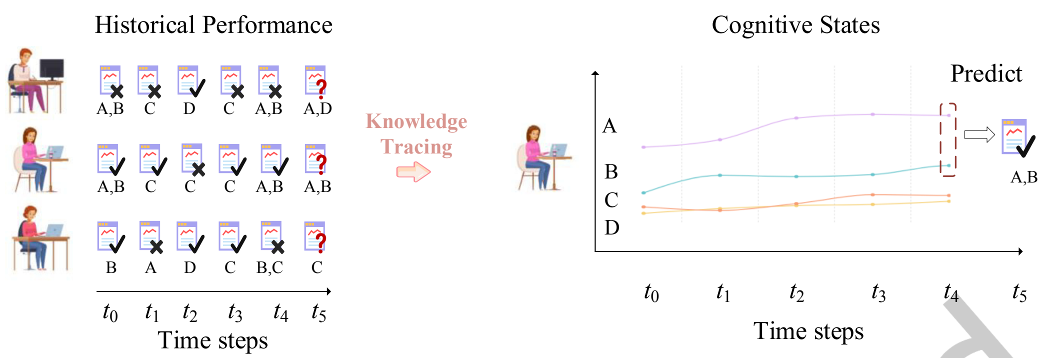

Fig. 1. Schematic of knowledge tracing. A, B, C, and D represent four knowledge components, examined by various exercises. Knowledge tracing estimates the over-time cognitive states of students and predicts future performance based on their cognitive states.

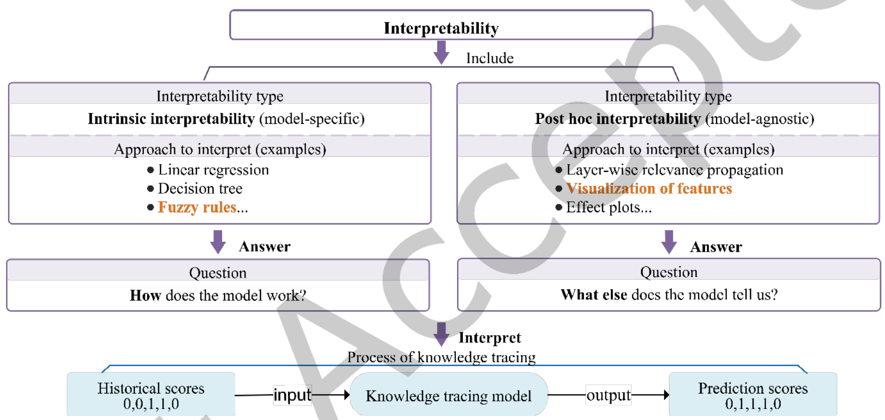

Fig. 2. Schematic of model interpretability, using knowledge tracing as an example. Models with interpretability better reason the obtained prediction than models lacking interpretability, in terms of both intrinsic and post-hoc aspects. The former usually explains the working of the model; the latter usually interprets further workability of the model.

hoc interpretability provides answers to the question *what else can the model tell us*. It refers to improving interpretability using model-agnostic methods [18], such as visualization of the features and effects. KT is more concerned with the cognitive state of the student, and the accuracy of its assessment cannot be directly measured. Instead, the accuracy of performance predictions is measured. Therefore, interpretability is significant in KT to explain the process of obtaining the predicted results and the relationship between the predicted results and the cognitive state.

Since it is difficult to measure students' knowledge mastery, most existing KT models use end-to-end learning to measure the accuracy of prediction performance [19]. Therefore, interpretability is typically not the major focus of most existing models, especially for those deep-learning-based KT models from the intrinsic aspect [19, 20]. This can be analyzed from the following three aspects. 1) The first deep-learning-based KT model, the deep knowledge tracing (DKT) [21], applied recurrent neural networks to KT. Estimating student cognition is difficult for DKT, since there is no interpretable parameter to inspect [22]. It has achieved excellent prediction

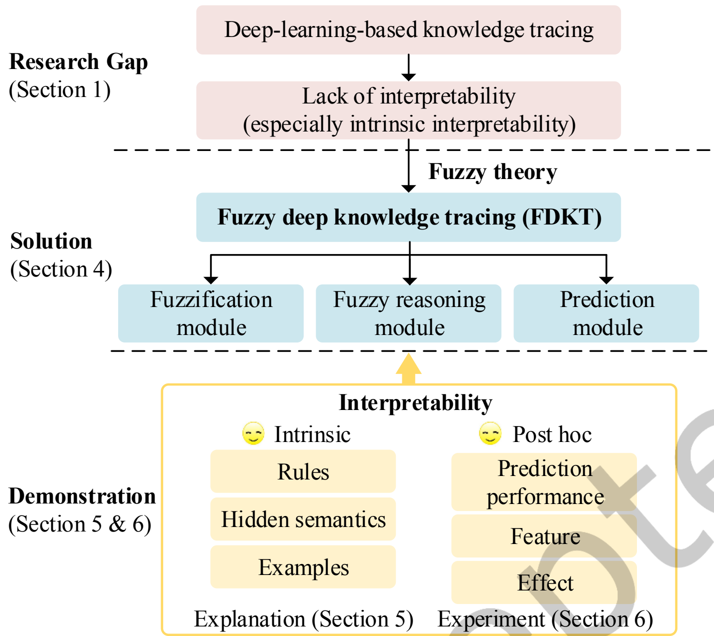

Fig. 3. Schematic of the limitations and contributions

accuracy owing to its large vectors of 'neurons' which are hard to interpret. 2) With an increasing amount of attention being paid to interpretable machine learning approaches, some studies have attempted to improve the interpretability of DKT using post hoc methods such as layer-wise relevance propagation [20] and visual methods [23]. They have attempted to answer the question of what else the DKT can tell but have not been able to explain the intrinsic process. 3) Some deep-learning-based KT models have denoted hidden layers as student cognition to enhance the interpretability to some extent [24–27]. However, the lack of intrinsic interpretability can also be attributed to how the model is constructed, its parameters, non-linear activation functions, and so on. In other words, such models cannot be explained as the interpretable ones, such as decision trees or rules.

Fuzzy theory is a powerful tool to represent human knowledge and mimic human reasoning capabilities, which is demonstrated as successful applications in education data mining [28, 29]. FuzzyCDF [28] is a typical cognitive diagnosis framework that leveraged fuzzy theory to model students' abilities to continuous score scenarios. The temporal characteristics of the learning logs were not considered in cognitive diagnosis (in other words, KT can be regarded as a dynamic cognitive diagnosis task). In our previous work, FBKT [29] reported effective performance fuzzifing the continuous scores into the type-1 and type-2 fuzzy sets in Bayesian KT. However, as is the case with the traditional Bayesian KT [30], they must classify students' learning logs by the knowledge components related to the exercises [31]. For example, $(A_1, A_2, B_1, A_3, C_1, B_2)$ is the original exercising sequence of a student, where A_1 denotes the first exercise related to the knowledge component A. FBKT cannot directly deal with them, and instead, it preprocessed the sequence into three portions: (A_1, A_2, A_3), (B_1, B_2), and (C_1). As a result, it changed the temporal information in the original sequence. Furthermore, fuzzy reasoning offers a better framework for interpretability considerations owing to its rules [32]. Based on fuzzy reasoning, the above applications have not utilized fuzzy rules to reason such that they owned inadequate intrinsic interpretability.

Contributions. The major contributions of this study are as follows, shown in Fig. 3. In this paper, we propose fuzzy deep knowledge tracing (FDKT), which introduces fuzzy neural networks (FNNs) [33] to enhance the interpretability of existing deep-learning-based KT models. Specifically, FDKT contains three main modules, i.e., the fuzzification, fuzzy reasoning, and prediction modules. First, the continuous scores on the historical exercises are fuzzified into several fuzzy scores, rather than hard encoding similar to a black box. Subsequently, the current fuzzy cognition is deduced according to the fuzzy reasoning module, which is the core of the proposed model improving intrinsic interpretability. Finally, the performance is predicted. It is remarkable that the proposed model has demonstrated interpretability in terms of both the intrinsic and post hoc aspects.

- To improve the interpretability (especially in the intrinsic aspect) of the traditional deep-learning-based KT models, we explored the utility of fuzzy reasoning in the field of KT. The proposed model combines the advantages of both fuzzy theory and neural networks, i.e., the ability to combine language-based knowledge (e.g., expert experience) and the ease of training the model parameters (e.g., backpropagation).
- To deal with the uncertainty in the KT task, i.e., uncertainty regarding the levels of continuous scores of students and their cognitive states, we extend the application of the most deep-learning-based KT models in continuous scenarios.
- The above-mentioned two benefits are demonstrated as follows. a) Its intrinsic interpretability is explained through the rules and hidden semantics (Section 5), and post hoc interpretability is experimentally visualized (Section 6.3). b) Better prediction performance, in the continuous-score application, is achieved when compared to 14 state-of-the-art models using 4 real-world datasets (Section 6.2).

This paper is organized as follows. Related work is reviewed in the next section. In Section 3, background material is presented, including the deep knowledge tracing and fuzzy neural networks. In Section 4, the framework of FDKT is detailed. In Section 5, the intrinsic interpretability of FDKT is presented. In Section 6, the experiments are discussed. Finally, Section 7 concludes the paper.

2 RELATED WORK

The related work is introduced including the KT models and the interpretability in educational data mining. Several representative models mentioned in this section are compared with the proposed FDKT in Table 1.

2.1 Knowledge Tracing

With regard to the two mainstream types, that is, Bayesian and deep-learning-based KT models, the former rely on intrinsic interpretable first-order Markov models [30]. However, their prediction performance is not satisfactory as they are less representative in terms of the complexity of the human brain and human knowledge. The latter have shown remarkable improvement in terms of prediction accuracy using deep learning methods, with the strong characterization capabilities. Therefore, they have attracted a significant amounts of attention [21, 24–27, 37].

In the type of deep-learning-based KT models, DKT uses recurrent neural networks (RNNs) to model student learning and achieves an excellent AUC in prediction performance [21]. Using a memory-augmented neural network, DKVMN exploits the relationships between concepts [24]. [38] proposed three distributed memory networks to model student performance, i.e., DMN, ADMN, IADMN. To enhance the predictive consistency in DKT, [39] introduced regularization terms to propose DKT+. DKT_DSC assigns students to a distinct classification to improve the accuracy of DKT [40]. Deep-IRT is a synthesis of the item response theory (IRT) model and DKVMN. Thus, it retains the prediction performance of the DKVMN and interpretability of IRT [25]. The self-attention-based approach SAKT captures a complex representation of human learning [34]. KQN introduces the probabilistic skill similarity of the knowledge components [27]. AKT uses a novel monotonic attention mechanism and the Rasch model to regularize the concept and question embeddings [35]. CKT models individualization in KT

Table 1. Comparison between FDKT and some representative models [1]

Models	BKT [30]	DKT [21]	FuzzyCDF [28]	FBKT [29]
Fuzzy sets	✗	✗	✔	✔
Fuzzy reasoning	✗	✗	✗	✗
Dynamic data	✔	✔	✗	✔
Continuous scores	✗	–	✔	✔
Mixing KCs	✗	✔	✔	✗
Interpretability	–	–	Visualization	Example
Models	**DKVMN [24]**	**DeepIRT [25]**	**SAKT [34]**	**KQN [27]**
Fuzzy sets	✗	✗	✗	✗
Fuzzy reasoning	✗	✗	✗	✗
Dynamic data	✔	✔	✔	✔
Continuous scores	–	–	–	–
Mixing KCs	✔	✔	✔	✔
Interpretability	Attention & Visualization	Combination [2] & Example	Attention & Visualization	Visualization
Models	**AKT [35]**	**CKT [36]**	**FDKT**	
Fuzzy sets	✗	✗	✔	
Fuzzy reasoning	✗	✗	✔	
Dynamic data	✔	✔	✔	
Continuous scores	–	–	✔	
Mixing KCs	✔	✔	✔	
Interpretability	Attention & Visualization	Visualization	Rules & Hidden semantics & Example & Visualization	

[1] – refers that the item has not been demonstrated in the paper.
[2] *Combination* refers to a combination of the KT model and the traditional model in education.

[36]. The federated DKT collectively trains high-quality DKT models for multiple silos using federated learning method [37]. Based on the dual-attentional mechanism, MF-DAKT [41] enriches question representations and utilizes multiple factors to model the knowledge tracing process. CL4KT [42] uses four data enhancement methods and hard negatives to reveal the learning history of similar and dissimilar semantics. With the evolution of graph neural networks [43–46], researchers have begun delving into the graph structural relationships within KT tasks. GIKT [47] employs the graph convolutional network to effectively integrate the problem-skill correlation.

2.2 Interpretability in Educational Data Mining

In recent years, model interpretability has attracted more attention by researchers in the field of educational data mining, including student models. A model is expected to be easy to understand with satisfactory prediction performance [20]. In this subsection, the existing studies towards interpretable student models are introduced (KT is considered as a type of student model).

For the traditional student models like DINA [48], IRT [49], LFA [50], PFA [50], and BKT [30], they provide better understanding based on interpretable probabilistic statistics or Markov models, etc. To improve the prediction performance of the traditional models, deep-learning-based models spring up. However, it is an open problem of model interpretability because there are large vectors of artificial 'neurons' [21, 31].

To alleviate this problem, we classify the subsequent work into the following categories. 1) Some introduced the educational theory into the models. For example, NeuralCD [51] placed a monotonicity assumption taking from

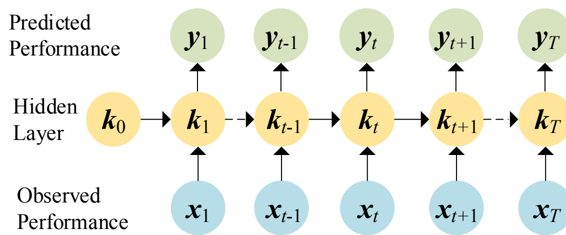

Fig. 4. Framework of the DKT models [21]. In the model, there are input, hidden, and output layers, where input and output layers corresponding to the observed performance and predicted performance, respectively. $\boldsymbol{x}_t$, $\boldsymbol{k}_t$, and $\boldsymbol{y}_t$ are the representation vectors of observed performance, hidden variable, and predicted performance at time step t , respectively.

an educational property on the framework to enhance its interpretability, where the monotonicity assumption is described as follows: the probability of correct response to the exercise is monotonically increasing at any dimension of the student's knowledge proficiency. DIRT [52] and Deep-IRT [25] combined deep learning with IRT to make the model more explainable. 2) Attention-based methods also offer some interpretability to student models. For example, Refs. [24, 35, 53, 54] utilized attention mechanism to makes the models more interpretable. 3) Many studies also take advantage of visualization towards interpretability. Such as RCD [55], GKT [56], HGKT [57], FuzzyCDF [28], DKVMN [24], SAKT [34], KQN [27], AKT [35], CKT [36]. They vividly demonstrated part of the results of the models via visualization.

The above studies have made a certain effort towards interpretable KT models, owing to the methods like visualization and attention. However, the KT models with intrinsic interpretability still need to be further explored.

3 BACKGROUND

The backgrounds in DKT, fuzzy theory, and fuzzy neural networks (FNN) are introduced.

3.1 Deep Knowledge Tracing

KT models the students' performance on exercises in a time-varying prediction task, where each exercise is related to a knowledge component.

We use the DKT model as an example to explain the KT process. As shown in Fig. 4, the student answers an exercise at each time step. $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_T$ denotes the input vector at each time step, where $\boldsymbol{x}_t$ contains the following two aspects of information: 1) the knowledge components of the exercise that the student answers at time step t; and 2) the score of the exercise that the student achieves at time step t. In particular, the scores of exercises in the traditional DKT model were only taken in $\{0, 1\}$. $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T$ denotes the output vector at each time step, where $\boldsymbol{y}_t$ represents the predicted probability vector that the student would respond with correct answers to the exercises, related to each knowledge component at time step t. $\boldsymbol{k}_1, \boldsymbol{k}_2, \ldots, \boldsymbol{k}_T$ denotes the hidden vector in the network that temporarily stores information. The objective of the DKT model is to minimize the negative log-likelihood of the observed sequence of the students' scores.

3.2 Fuzzy Theory

Fuzzy logic [58] is an expansion of binary logic. It was developed to address ambiguities that exist in the real world, such as hot and cold, fast and slow, and large and small. In classical two-valued logic, all objects are assumed explicit [59]. For example, in a classification task, an object may or may not belong to this class. Fuzzy logic solves many problems in reality that cannot be clearly described.

Fuzzy Sets and Membership Functions. Fuzzy sets [60] are a fundamental concept in fuzzy logic theory. Fuzzy sets allow for the representation of uncertainty and vagueness by assigning degrees of membership to elements. In a fuzzy set, each element of the universe of discourse can have a membership value ranging from 0 to 1, indicating the degree to which the element belongs to the set. The membership function defines this mapping of elements to membership degrees. Various types of membership functions can be used, such as triangular, trapezoidal, Gaussian, or sigmoidal functions, depending on the nature of the problem and the desired representation. A formal description of the fuzzy sets and their operations is as follows: Suppose there exist fuzzy sets $\tilde{M}_i$ and $\tilde{S}_j$. The membership functions $mf_i^{(k)}$ and $mf_j^{(k)}$ denote the degrees to which element k belongs to $\tilde{M}_i$ and $\tilde{S}_j$, respectively.

T-norm Fuzzy Logics. The main objective of t-norm fuzzy logics [61] is to extend classical two-valued logic by introducing intermediary truth values between 1 (representing truth) and 0 (representing falsity). These intermediary truth values serve to quantify the degrees of truth associated with propositions. The degrees of truth in t-norm fuzzy logics are considered to be real numbers within the range of the unit interval [0, 1]. Prominent examples include the minimum t-norm, product t-norm, and Lukasiewicz t-norm, among others. For example, the fuzzy intersected set of $\tilde{M}_i$ and $\tilde{S}_j$ is denoted by $\tilde{M}_i \sqcap \tilde{S}_j$. When using minimum t-norm logics, the membership function $mf_{i,j}^{(k)}$ is defined as $mf_{i,j}^{(k)} = \min\{mf_i^{(k)}, mf_j^{(k)}\}$. When using product t-norm logics, $mf_{i,j}^{(k)} = mf_i^{(k)} \cdot mf_j^{(k)}$. Due to the widespread application of the minimum t-norm in fuzzy logic, this calculation method will be used in the subsequent sections.

Fuzzy Rules. A fuzzy system is essentially a rule-based expert system consisting of a set of linguistic rules and one of the most commonly used fuzzy rules in the form of IF-THEN [62]. A formal description of the fuzzy rules is as follows: R: IF x_1 is $\tilde{M}_1$, and ..., x_i is $\tilde{M}_i$, THEN y_1 is $\tilde{S}_1$, and ..., and y_j is $\tilde{S}_j$, where $\tilde{M}_1, \ldots, \tilde{M}_i$ and $\tilde{S}_1, \ldots, \tilde{S}_j$ are fuzzy sets.

3.3 Fuzzy Neural Networks

FNN is gradually turning into a research hotpot, because it combines the powerful calculation and representation capabilities of the neural networks with the heuristic expert knowledge of the fuzzy system. For example, IF-THEN [62] (introduced in Section 3.2) expresses the output preferences under the specified conditions, which is a kind of knowledge.

The traditional FNN is limited to static problems due to its feedforward network structure [33]. To address this shortcoming, Lee and Teng [63] proposed the recurrent FNN (RFNN) by capturing the dynamic response of the system through its internal feedback loop, which is more suitable for describing dynamic systems as compared to the FNN.

In the RFNN, there are four layers: input, membership, rule, and output layers. The input nodes are fuzzified into the membership layers that contain the memory terms storing the past information of the network. The membership nodes enter the rule layer through the application of fuzzy intersection operation (detailed in Section 3.2). Finally, the output nodes are obtained through a linear combination of each rule node. The RFNN can be shown to be a universal uniform approximator for continuous functions over compact sets if it satisfies a certain condition [63].

4 FRAMEWORK OF FDKT

FDKT is proposed to enhance the interpretability of the deep-learning-based KT models, owing to the reasoning of the fuzzy rule-based module. In this section, we first formulate the task and then present the model of the FDKT containing the fuzzification, fuzzy reasoning, and prediction modules. Subsequently, the rules of fuzzy reasoning and the layered operation of FDKT are detailed. Finally, the time complexity is analyzed.

The notation used in this paper is listed in Table 2.

Table 2. Notations

Notation	Description
I	Number of the fuzzy cognition sets
J	Number of the fuzzy score sets
K	Number of the knowledge components
T	Total time steps
$x_t^{(k)}$	Observed score on the knowledge components k at time step t, $k \in \{1, 2, ..., K\}$, $t \in \{1, 2, ..., T\}$
$y_t^{(k)}$	Target score of the knowledge components k at time step t, $k \in \{1, 2, ..., K\}$, $t \in \{1, 2, ..., T\}$
$\hat{y}_t^{(k)}$	Predicted score of the knowledge components k at time step t, $k \in \{1, 2, ..., K\}$, $t \in \{1, 2, ..., T\}$
$m_t^{(k)}$	Student's cognition of the knowledge components k at time step t, $k \in \{1, 2, ..., K\}$, $t \in \{1, 2, ..., T\}$
$\tilde{M}_i$	The i-th fuzzy cognition set, $i \in \{1, 2, ..., I\}$
$\tilde{S}_j$	The j-th fuzzy score set, $j \in \{1, 2, ..., J\}$
$mc_{t,i}^{(k)}$	Membership value (probability) of $m_t^{(k)} \in \tilde{M}_i$
$ms_{t,j}^{(k)}$	Membership value (probability) of $x_t^{(k)} \in \tilde{S}_j$
$RN_{i,j}$	Fuzzy rule node when $m_{t-1}^{(k)} \in \tilde{M}_i$ and $x_t^{(k)} \in \tilde{S}_j$
$r_{i,j}$	Output of the fuzzy rule node $RN_{i,j}$
μ_j	Mean value in the Gaussian membership function of $\tilde{S}_j$
σ_j	Standard deviation value in the Gaussian membership function of $\tilde{S}_j$
$\boldsymbol{w}_1$	Weight vector in the prediction module
$\boldsymbol{w}_2$	Weight vector in the fuzzy reasoning module

4.1 Formulation

FDKT aims to estimate student cognition of the knowledge components and predict their future performance on exercises based on previous performance. Notably, the input is the performance which is continuous; however the input has been bisected in most existing studies. We denote I, J, K as the numbers of fuzzy cognition sets, fuzzy score sets, and knowledge components, respectively. Further, T is the total time step. The input consists of the input continuous score x_t and knowledge component $k, k \in \{1, 2, ..., K\}$. FDKT estimates the current cognition $(m_t^{(1)}, ..., m_t^{(K)})$ and predicts the next-time-step performance $y_t^{(k')}, k' \in (1, 2, ..., K)$ on k' based on $m_t^{(k')}$. For the current cognition of k, $m_t^{(k)} \in \tilde{M}_1, ..., m_t^{(k)} \in \tilde{M}_I$ with probabilities of $mc_{t,1}^{(k)}, ..., mc_{t,I}^{(k)}$, respectively, where $\{\tilde{M}_1, \tilde{M}_2, ..., \tilde{M}_I\}$ denotes I fuzzy cognition sets. For clarity, the notation used is listed in Table 2, in order of appearance in this paper.

Optimization. The objective of FDKT is to minimize the loss $\mathcal{L}_f = l(\boldsymbol{y}, \hat{\boldsymbol{y}})$ between the ground truth and prediction scores, optimized through gradient descent on batches. $l(\cdot)$ denotes the mean absolute error.

4.2 Model

The framework of FDKT is shown in Fig. 5 (a). In the framework, the fuzzy score sets and fuzzy cognition sets are defined as follows. **Fuzzy score sets** are the fuzzy sets defined for the continuous scores obtained by students answering the exercises. Different fuzzy score sets represent different score levels and continuous scores belong to fuzzy score sets with a certain probability. **Fuzzy cognition sets** are the fuzzy sets defined for the students' cognitive states of knowledge components. Different fuzzy cognition sets represent different levels of cognition. As shown in Fig. 5 (a), FDKT contains three main modules: the fuzzification, fuzzy reasoning, and prediction modules.

Specifically, the network structure of FDKT at time step t is shown in Fig. 5 (b). The **fuzzification module** addresses the input of the continuous score $x_t^{(k)}$ into the fuzzy scores (denoted as $\tilde{\boldsymbol{S}} = \{\tilde{S}_1, \tilde{S}_2, ..., \tilde{S}_J\}$). The **fuzzy**

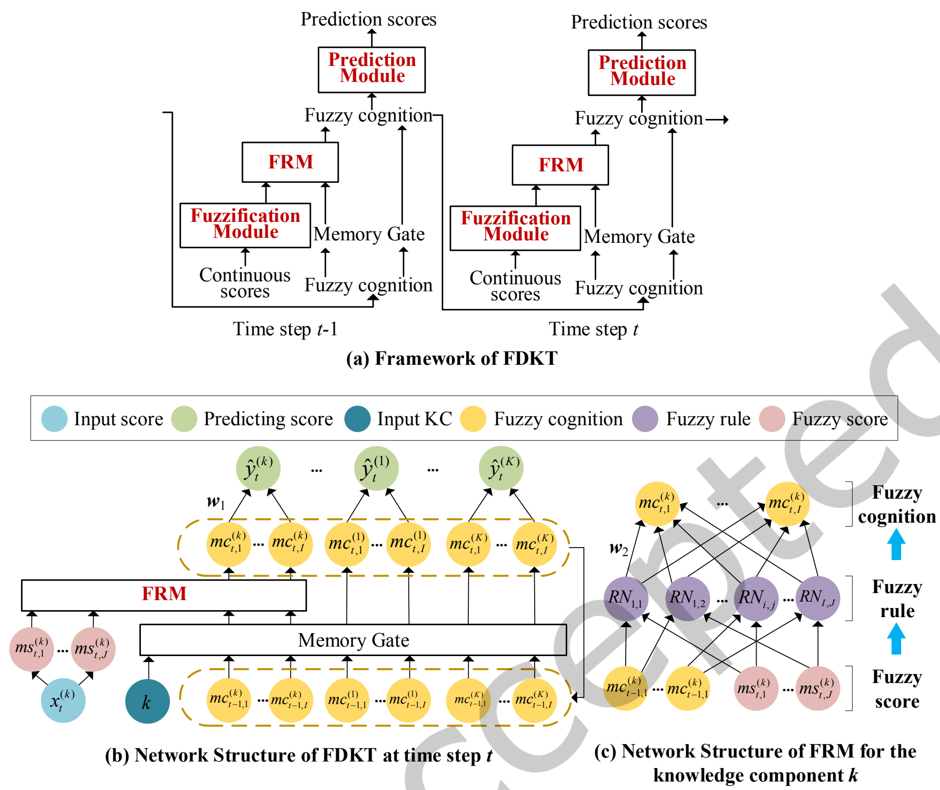

Fig. 5. Schematic of the FDKT. (a) is the framework of FDKT, which includes three main modules: fuzzification, fuzzy reasoning, and prediction. (b) and (c) depict the network structures of FDKT and FRM at time step t, respectively.

reasoning module (FRM) determines the current fuzzy cognition $m_t^{(k)}$ based on the fuzzy scores from the fuzzification module and the historical cognition $m_{t-1}^{(k)}$ of k, where $m_{t-1}^{(k)}$ is obtained from $(m_{t-1}^{(1)}, ..., m_{t-1}^{(K)})$ through the memory gate. FRM promotes the interpretability of FDKT because it can estimate the student cognition on knowledge components through the use of fuzzy rules, thereby explaining the result of the prediction performance. Finally, the **prediction module** obtains the future performance $\boldsymbol{y}_t$ based on $(m_t^{(1)}, ..., m_t^{(K)})$.

The pseudo-code of FDKT is detailed in Algorithm 1. The remainder of this section details the three modules.

4.2.1 Fuzzification Module. The fuzzification module fuzzifies the continuous scores into several fuzzy scores. The continuous score has a certain probability belonging to each fuzzy score, where the probability is referred to as the membership. The Gaussian fuzzy logic system is applied to describe the membership function of the fuzzy scores, as detailed in Eq. (1). It is worth noting that, after calculating the membership degrees of an individual to different fuzzy sets, we performed probability normalization on these membership degree values to ensure their sum is equal to 1. This normalization was done to transform all membership degree distributions into a standardized form, allowing for a more intuitive representation of the relative sizes and proportions of

Algorithm 1 Fuzzy deep knowledge tracing

Input: $I, J, K, T, x_t^{(k)}$
Output: $\boldsymbol{y}$
Initialize $(\boldsymbol{mc}_0^{(1)}, \boldsymbol{mc}_0^{(2)}, ..., \boldsymbol{mc}_0^{(K)})$ on K knowledge components at initial time step.
Let $t = 1$.
while $t <= T$ **do**
  Fuzzify $x_t^{(k)}$ into J fuzzy scores $\tilde{S}$ with membership values $\boldsymbol{ms}_t^{(k)}$ through the **fuzzification module**.
  Obtain $\boldsymbol{mc}_t^{(k)}$ of k from **FRM** (conducted by Algorithm 2).
  Obtain $\boldsymbol{mc}_t^{(1)}, ..., \boldsymbol{mc}_t^{(k-1)}, \boldsymbol{mc}_t^{(k+1)}, ..., \boldsymbol{mc}_t^{(K)}$ $(\boldsymbol{mc}_t^{(k')} = \boldsymbol{mc}_{t-1}^{(k')}, k' \neq k)$.
  Predict the performance $\hat{\boldsymbol{y}}_t = (\hat{y}_t^{(1)}, \hat{y}_t^{(2)}, ..., \hat{y}_t^{(K)})$.
end while
return $\hat{\boldsymbol{y}} = (\hat{\boldsymbol{y}}_1, \hat{\boldsymbol{y}}_2, ..., \hat{\boldsymbol{y}}_T)$.

probabilities.

$$ms_{t,j}^{(k)} = \exp\{-\frac{(x_t^{(k)} - \mu_j)^2}{\sigma_j^2}\}, \tag{1}$$

where $x_t^{(k)}$ denotes the continuous score at time step t related to the knowledge component k. $ms_{t,j}^{(k)}$ denotes the membership of $x_t^{(k)}$ belongs to the fuzzy score $\tilde{S}_j$. μ_j and σ_j denote the mean and std of $\tilde{S}_j$, respectively.

4.2.2 Fuzzy Reasoning Module. The network structure of FRM is designed as follows, and the process of fuzzy reasoning is detailed in Section 4.3. FRM determines the current cognition at each time step, based on both last cognition (factor A) and current performance of the exercise (factor B). The former is obtained from the fuzzy cognition at time step $(t-1)$ and the latter is the output of the fuzzification module at time step t. As shown in Fig. 5 (c), different combinations of factors A and B lead to different fuzzy cognitions. Therefore, there are $I * J$ fuzzy rules corresponding to $I * J$ combinations of factors A and B. The pseudo-code of FRM is detailed in Algorithm 2, where $r_{i,j} \in \boldsymbol{r}$ is the output of the fuzzy rule node $RN_{i,j}$, given by Eq. (2).

$$r_{i,j} = ms_{t,j}^{(k)} * mc_{t-1,i}^{(k)}. \tag{2}$$

Subsequently, the probability $mc_{t,u}^{(k)}$ that the current cognition $m_t^{(k)} \in \tilde{M}_u$ is given by Eq. (3).

$$mc_{t,u}^{(k)} = f_{\boldsymbol{w}_{2,u}}(\boldsymbol{r}) = \sum_{i=1}^{I}\sum_{j=1}^{J} w_{u,i,j} * r_{i,j}. \tag{3}$$

$\boldsymbol{w}_2 = (\boldsymbol{w}_{2,1}, \boldsymbol{w}_{2,2}, ..., \boldsymbol{w}_{2,I})$ denotes the adjustable weight, where $\boldsymbol{w}_{2,u} = (w_{u,1,1}, w_{u,1,2}, ..., w_{u,I,J}), u \in \{1, 2, ..., I\}$.

4.2.3 Prediction Module. The prediction module predicts the future performance of the students on exercises based on their current cognition of the knowledge components. Specifically, there are K outputs in the prediction process, as shown in Eq. (4), corresponding to the prediction performance on the exercise related to K knowledge components. The performance on k is calculated using a linear function as expressed in Eq. (5).

$$\hat{\boldsymbol{y}}_t = (\hat{y}_t^{(1)}, ..., \hat{y}_t^{(K)}), \tag{4}$$

where $\hat{y}_t^{(k)}, k \in \{1, 2, ..., K\}$ satisfies Eq. (5).

$$\hat{y}_t^{(k)} = f_{\boldsymbol{w}_{1,k}}(\boldsymbol{mc}_t^{(k)}) = \boldsymbol{w}_{1,k} \cdot \boldsymbol{mc}_t^{(k)}. \tag{5}$$

Algorithm 2 Fuzzy reasoning module

Input: $\boldsymbol{mc}_{t-1}^{(k)} = (mc_{t-1,1}^{(k)}, mc_{t-1,2}^{(k)}, ..., mc_{t-1,I}^{(k)})$ and $\boldsymbol{ms}_t^{(k)} = (ms_{t,1}^{(k)}, ms_{t,2}^{(k)}, ..., ms_{t,J}^{(k)})$
Parameter: $\boldsymbol{w}_2$
Output: $\boldsymbol{mc}_t^{(k)}$
Calculate $\boldsymbol{r} = (r_{1,1}, r_{1,2}, ..., r_{I,J})$ according to Eq. (2).
Let $u = 1$.
while $u <= I$ **do**
  Calculate $mc_{t,u}^{(k)}$ that $m_t^k \in \tilde{M}_u$ according to Eq. (3).
end while
return $\boldsymbol{mc}_t^{(k)} = (mc_{t,1}^{(k)}, mc_{t,2}^{(k)}, ..., mc_{t,I}^{(k)})$.

$\boldsymbol{w}_1 = (\boldsymbol{w}_{1,1}, \boldsymbol{w}_{1,2}, ..., \boldsymbol{w}_{1,K})$ denotes the adjustable parameter, where $\boldsymbol{w}_{1,k} = (w_{1,k,1}, w_{1,k,2}, ..., w_{1,k,I})$, $k \in \{1, 2, ..., K\}$. $\boldsymbol{mc}_t^{(k)} = (mc_{t,1}^{(k)}, mc_{t,2}^{(k)}, ..., mc_{t,I}^{(k)})$.

4.3 Fuzzy Reasoning

The process of fuzzy reasoning is detailed, to deduce the current fuzzy cognition from the last fuzzy cognition and the current performance. This is the core of the interpretability of FDKT.

4.3.1 Reasoning in Memory Gate. According to the network structure of FDKT at time step t in Fig. 5 (b), the current fuzzy cognition is obtained from the FRM or directly from the last fuzzy cognition through the memory gate. In other word, $\boldsymbol{mc}_t^{(k)}$ satisfies the decision rules as $\boldsymbol{R}1 = \{R1^{(1)}, R1^{(2)}, ..., R1^{(K)}\}$, where $R1^{(k)} (k \in \{1, 2, ..., K\})$ is given by Eq. (6).

$$\begin{aligned} R1^{(k)}: &\textbf{if } k = k', \textbf{ then } \boldsymbol{mc}_t^{(k)} \text{ satisfies } FRM(\boldsymbol{mc}_{t-1}^{(k)}), \\ &\textbf{else } \boldsymbol{mc}_t^{(k)} = \boldsymbol{mc}_{t-1}^{(k)}, \\ &\textbf{when } k' \text{ is the knowledge component at time step } t. \end{aligned} \tag{6}$$

The antecedent is the knowledge component k whether related to the exercise at time step t, and the consequent is the probability of the current cognition $\boldsymbol{mc}_t^{(k)}$. $FRM(\boldsymbol{mc}_{t-1}^{(k)})$ is denoted as the current cognition obtained from the FRM.

4.3.2 Reasoning in FRM. According to the network structure of the FRM in Fig. 5 (c), the current fuzzy cognition is obtained from the current performance on the exercise and the last fuzzy cognition through $I * J$ fuzzy rules, where I and J denote the numbers of the fuzzy cognition and fuzzy score sets, respectively. For each fuzzy rule node $RN_{i,j}$, its effects on $m_t^{(k)}$ belonging to $\tilde{M}_1, ..., \tilde{M}_I$ satisfy the rules expressed in Eq. (7), where the antecedents are the current performance $x_t^{(k)}$ and last cognition $m_{t-1}^{(k)}$ and the consequent is the effects of $R2_{i,j}^{(k)}$.

$$\begin{aligned} R2_{i,j}^{(k)}: &\textbf{if } m_{t-1}^{(k)} \in \tilde{M}_i \text{ with probability } mc_{t-1,i}^{(k)} \\ &\textbf{and } x_t^{(k)} \in \tilde{S}_j \text{ with probability } ms_{t,j}^{(k)}, \\ &\textbf{then } \text{the effect on } m_t^{(k)} \in \tilde{M}_1 \text{ is } w_{1,i,j} * r_{i,j}, \\ &\textbf{and } ... \textbf{ and } \text{the effect on } m_t^{(k)} \in \tilde{M}_I \text{ is } w_{I,i,j} * r_{i,j}, \end{aligned} \tag{7}$$

where $r_{i,j}$ is obtained according to Eq. (2). The fuzzy rule node $RN_{i,j}$ indicates the combination of factors A and B, where the former is $m_{t-1}^{(k)} \in \tilde{M}_i$ and the latter is $x_t^{(k)} \in \tilde{S}_j$. $m_t^{(k)}$ and $m_{t-1}^{(k)}$ denote the cognition of k at time steps t

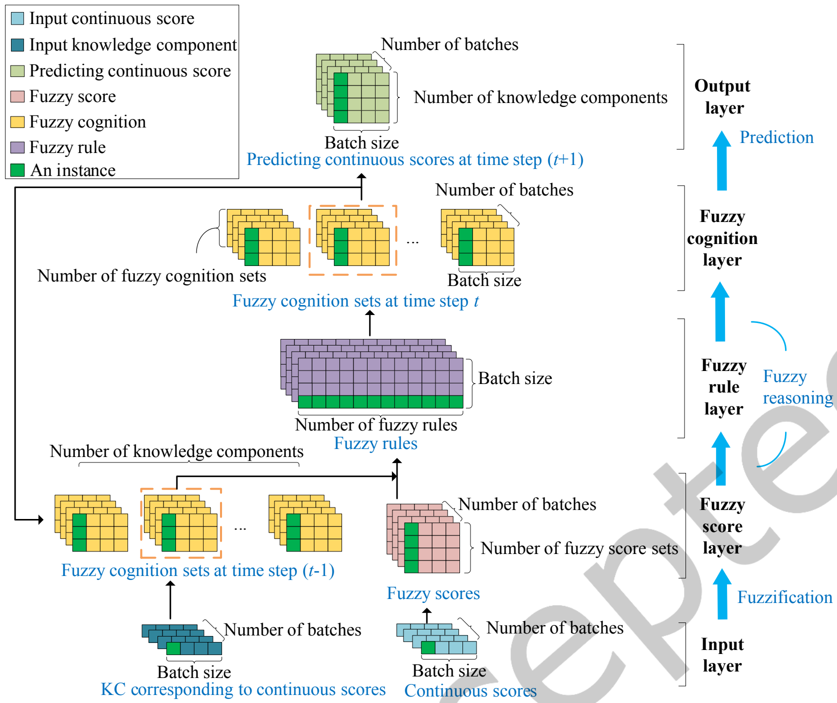

Fig. 6. The architecture of FDKT (taking the t-th time step as an example) is presented to explain the hidden semantics from the input to the output of the FDKT.

and $t-1$, respectively. $x_t^{(k)}$ denotes the continuous score of k. $\tilde{M}_i$ and $\tilde{S}_j$ represent the i-th fuzzy cognition set and the j-th fuzzy score set, respectively.

Then, the current fuzzy cognition is obtained from the fuzzy rule nodes, satisfying rule $\boldsymbol{R}3 = \{\boldsymbol{R}3^{(1)}, \boldsymbol{R}3^{(2)}, ..., \boldsymbol{R}3^{(K)}\}$. $\boldsymbol{R}3^{(k)} = \{R3_1^{(k)}, ..., R3_I^{(k)}\}(k \in \{1, 2, ..., K\})$, where $R3_u^{(k)}(u \in 1, 2, ..., I)$ satisfies Eq. (8).

$$
\begin{aligned}
R3_u^{(k)}: &\ \textbf{if} \text{ the effect of } RN_{1,1} \text{ on } m_t^{(k)} \in \tilde{M}_u \text{ is } w_{u,1,1} * r_{1,1}, \\
&\ \textbf{and} \ ... \\
&\ \textbf{and} \text{ the effect of } RN_{I,J} \text{ on } m_t^{(k)} \in \tilde{M}_u \text{ is } w_{u,I,J} * r_{I,J}, \\
&\ \textbf{then} \text{ the probability of } m_t^{(k)} \in \tilde{M}_u \text{ is} \\
&\ \sum_{i=1}^{I} \sum_{j=1}^{J} w_{u,i,j} * r_{i,j},
\end{aligned}
\tag{8}
$$

where the antecedents are the effects of the fuzzy rule nodes, and the consequent is the current cognition $m_t^{(k)} \in \tilde{M}_u$. This FRM in FDKT can be considered as a dynamic fuzzy inference system because its input contains a memory term for storing the past fuzzy cognition using the feedback unit [63].

4.4 Layered Operation of FDKT

The layered operation of the proposed model FDKT is detailed in this subsection to describe the integration of the three modules, as shown in Fig. 6. We denote $i^{(p)}(t)$ and $o^{(p)}(t)$ as the input and output in the p-th layer ($p \in \{1, 2, 3, 4, 5\}$ in the architecture) at time step t.

For the fuzzy cognition of the knowledge component at time step t, the operation for the 1, 2, 3, 4-th layers is shown in Eqs. (9) - (15). For the knowledge component that is not at time step t, the operation before the 5-th layer is shown in (16).

The input in the $(p+1)$-th layer equals the output in the p-th layer for the layer without memory terms ($p \in \{1, 3, 4\}$). In other words, $\boldsymbol{i}^{(p+1)}(t) = \boldsymbol{o}^{(p)}(t), p \in \{1, 3, 4\}$. In the 1-th layer, the output equals the input given by Eq. (9).

$$o^{(1)}(t) = i^{(1)}(t). \tag{9}$$

$$\boldsymbol{o}^{(2)}(t) = (o_1^{(2)}(t), o_2^{(2)}(t), ..., o_J^{(2)}(t)), \tag{10}$$

where $o_j^{(2)}(t)$ satisfies Eq. (11).

$$o_j^{(2)}(t) = \exp\{-\frac{(i^{(2)}(t) - \mu_j)^2}{\sigma_j^2}\}, j \in \{1, 2, ..., J\}, \tag{11}$$

where J is the number of fuzzy score sets. μ_j and σ_j denote the mean and std in the membership function of the fuzzy score set $\tilde{S}_j$, respectively.

In the 3-th layer, that is, the fuzzy rule layer with the memory terms, its input contains two aspects $\boldsymbol{is}^{(3)}(t) = (is_1^{(3)}(t), is_2^{(3)}(t), ..., is_J^{(3)}(t))$ and $\boldsymbol{ic}^{(3)}(t) = (ic_1^{(3)}(t), ic_2^{(3)}(t), ..., ic_I^{(3)}(t))$. J and I are the numbers of fuzzy score sets and fuzzy cognition sets, respectively.

$$\boldsymbol{o}^{(3)}(t) = (o_{1,1}^{(3)}(t), ..., o_{I,J}^{(2)}(t)), \tag{12}$$

where $o_{i,j}^{(3)}(t)$ satisfies Eq. (13).

$$o_{i,j}^{(3)}(t) = is_j^{(3)}(t) \prod ic_i^{(3)}(t), \tag{13}$$

where $is_j^{(3)}(t) = o^{(2)}(t)$ and $ic_i^{(3)}(t) = o^{(4)}(t-1)$.

$$\boldsymbol{o}^{(4)}(t) = (o_1^{(4)}(t), ..., o_I^{(4)}(t)), \tag{14}$$

where $o_u^{(4)}(t), u \in \{1, 2, ..., I\}$ satisfies Eq. (15).

$$o_u^{(4)}(t) = \sum_{i=1}^{I} \sum_{j=1}^{J} w_{u,i,j} * i_{i,j}^{(4)}(t), \tag{15}$$

where $w_{u,i,j} \in \{w_{1,i,j}, w_{2,i,j}, ..., w_{I,i,j}\}$ is an adjustable parameter.

For the fuzzy cognition of the knowledge components not at time step t, the operation for the 1, 2, 3, 4-th layers is given by Eq. (16).

$$\boldsymbol{o}_u^{(4)}(t) = \boldsymbol{o}_u^{(4)}(t-1). \tag{16}$$

Thus, the fuzzy cognition of all the knowledge components $\boldsymbol{o}^{(4)}(t) = \{\boldsymbol{o}_1^{(4)}(t), \boldsymbol{o}_2^{(4)}(t), ..., \boldsymbol{o}_K^{(4)}(t)\}$ is obtained, where K is the number of knowledge components. $\boldsymbol{o}_k^{(4)}(t), k \in \{1, 2, ..., K\}$ is obtained using Eq. (14) if k is the conducted knowledge component or Eq. (16) otherwise. Subsequently, the input and output of the 5-th layer are given by Eq. (17).

$$\boldsymbol{o}^{(5)}(t) = (o_1^{(5)}(t), ..., o_K^{(5)}(t)), \tag{17}$$

X where $o_k^{(5)}(t), k \in \{1, 2, ..., K\}$ satisfies Eq. (18).

$$o_k^{(5)}(t) = f(\boldsymbol{i}_k^{(5)}(t)), \tag{18}$$

where $f(\cdot)$ is a linear function. $\boldsymbol{i}_k^{(5)}(t) = \boldsymbol{o}_k^{(4)}(t)$ and $\boldsymbol{o}_k^{(4)}(t) = (o_1^{(4)}(t), ..., o_I^{(4)}(t))$.

4.5 Time Complexity

The time complexity of FDKT is analyzed as follows. The FDKT algorithm is presented in Algorithm 1, invoking Algorithm 2. The time complexity of Algorithm 2 is $O(I^2J)$, where I and J denote the numbers of fuzzy cognition sets and fuzzy score sets, respectively. Algorithm 2 is in the loop with respect to the time steps of Algorithm 1. Therefore, the time complexity of FDKT (Algorithm 1) for an epoch is $O(TI^2J)$, where T denotes the total number of time steps.

We also analyze the complexities for other KT models (shown in Table 1), which are detailed in Appendix. The time complexity of the proposed FDKT model can be observed to be lower than that of the neural network-based KT models because the values of the fuzzy cognitive and fuzzy score sets are set to integers less than 10, whereas the general representation dimension is set to tens or hundreds. Noteworthily, at lower time complexity, FDKT performs better than the general neural network-based KT models in continuous scenarios, with more convenient parameter optimization than traditional non-neural-network-based KT models.

5 INTRINSIC INTERPRETABILITY OF FDKT

As mentioned previously, there are two types of interpretability: intrinsic and post hoc. In this section, FDKT is explained using rules and hidden semantics to demonstrate its intrinsic interpretability [15], in other words, to answer the question, *how does the model work* (shown in Fig. 2 (b)). Then, an example is considered to clearly demonstrate the process followed by FDKT. The interpretability of FDKT is also illustrated from the post hoc aspect via experiments (Section 6.3).

5.1 Explanation by Rules

In this subsection, FDKT is explained with the help of the rules, where the rules may be the most powerfully explanatory model [64].

From the input to the output of FDKT, the current cognition of the students is deduced using the rules ($\boldsymbol{R}1$, $\boldsymbol{R}2$, and $\boldsymbol{R}3$) expressed in Section 4.3, and subsequently, the future performance is predicted according to the current cognition using Eq. (5). Specifically, after the fuzzification of the input continuous score, $\boldsymbol{R}1$ is to select the fuzzy cognition of the knowledge component to be updated. The selected fuzzy cognition and the fuzzy score are both fed into the FRM, and they will first meet $\boldsymbol{R}2$. The number of the rules in $\boldsymbol{R}2$ depends on the combinations of the fuzzy cognition and the fuzzy score. Each fuzzy rule node generates its effect on the current fuzzy cognition, according to its corresponding rule in $\boldsymbol{R}2$. Subsequently, each rule in $\boldsymbol{R}3$ obtains the probability of the current fuzzy cognition by summing the effects of all the fuzzy rule nodes.

In the proposed model, the network structure is constructed based on the fuzzy rules, which relying on prior knowledge. This demonstrates that FDKT has intrinsic interpretability.

5.2 Explanation by Hidden Semantics

Based on common knowledge of this field, we make sense of the semantics of the hidden layers and parameters in the model. This makes the process significantly easier to understand.

5.2.1 Semantics of Hidden Layers. The input nodes are fed into the fuzzification module to obtain the fuzzy scores. Then, the fuzzy cognition nodes are obtained from fuzzy scores through fuzzy rule nodes using the FRM. Finally, the output prediction performance is obtained from the fuzzy cognition using the prediction module.

5.2.2 Semantics of Parameters. In the **fuzzification module**, $\boldsymbol{\mu} = (\mu_1, ..., \mu_J)$, and $\boldsymbol{\sigma} = (\sigma_1, ..., \sigma_J)$ (Eq. (1)) denote the mean and std of each fuzzy score set, respectively.

In the **FRM**, $r_{i,j}$ (Eq. (2)) denotes the probability of the fuzzy rule node $RN_{i,j}$, specifically, the probability that the last cognition $m_{t-1}^{(k)} \in \tilde{M}_i$ and the current fuzzy score $x_t^{(k)} \in \tilde{S}_j$. $mc_{t,u}^{(k)}$ (Eq. (3)) represents the probability that the current cognition $m_t^{(k)} \in \tilde{M}_u$. $w_{u,i,j}$ represents the contribution of the fuzzy rule node $RN_{i,j}$ to each fuzzy cognition of $\tilde{M}_u$. When $r_{i,j}$ increases by 0.1, $mc_{t,u}^{(k)}$ increases by $0.1 * w_{u,i,j}(w_{u,i,j} \in \boldsymbol{w}_2)$ (Eq. (2)).

In the **prediction module**, $\boldsymbol{w}_1$ (Eq. (5)) represents the contribution of the fuzzy cognition to the predicting performance. If $mc_{t,u}^{(k)}$ increases by 0.1, the prediction performance on k increases by $0.1 * w_{1,k,u}(w_{1,k,u} \in \boldsymbol{w}_1)$.

5.3 Example

By reviewing Fig. 2, the interpretable model explains why the model can obtain this prediction. Based on this, a simple example is considered to discuss the interpretability of FDKT. As can be understood from Fig. 7, FDKT can not only obtain the prediction results but also explain them.

Five fuzzy cognition sets (i.e., the first to fifth bin from the best to the worst) and four fuzzy score sets (i.e., poor, medium, good, and excellent) are defined in the example. It is worth noting that, after calculating the membership degrees of an individual to different fuzzy sets, we performed probability normalization on these membership degree values to ensure their sum is equal to 1. This is for the starndardized degree distributions and the convenience of neural network computations [65–67]. Suppose that Sam performed some exercises related to three knowledge components K_a, K_b, and K_c, and the last fuzzy cognition of them is given. At time step t, Sam received a score of 0.4 when conducting an exercise related to K_a. $(0, 0.6, 0.4, 0)$ is obtained through the **fuzzification module**, representing there is a great possibility that the score of 0.4 is indicative of mediocre performance.

Then, **FRM** infers the current fuzzy cognition of K_a through different combinations of the last fuzzy cognition and the current fuzzy score of K_a. The maximum possibility of the rule is $0.4 * 0.6 = 0.24$ of Rule 6, in which the last fuzzy cognition on K_a is in 2-bin with a probability of 0.4, and the current fuzzy performance is in the medium range with a probability of 0.6. Therefore, the effect of Rule 6 on the five probabilities of the current fuzzy cognition is the largest, compared with the other 19 rules.

Finally, the prediction $(0.67, 0.25, 0.35)$ on K_a, K_b, and K_c are obtained through the **prediction module**. FDKT outputs the prediction performance for Sam, as it explains that he may obtain the highest score on K_a because has achieved a good level of mastery (2-bin) on it.

6 EXPERIMENTS

1) how does FDKT perform in continuous score scenarios (Section 6.2) and 2) how FDKT do interpretation (Section 6.3). The parameters in FDKT are analyzed in Section 6.4.

6.1 Setup

The setup is introduced, including the datasets, baselines, and evaluation index.

6.1.1 Data Sets. Four well-known datasets were used in the experiments: Algebra05, Algebra06, Bridge06 [68], and ASSISTments (https://sites.google.com/site/assistmentsdata/). To evaluate the performance of the models in continuous-score scenarios, the datasets were preprocessed as in [29], according to [69, 70]. We filtered the logs of students who practiced less than 10 exercises [26, 71]. After preprocessing, the size of the datasets is listed in Table 3.

6.1.2 Baselines. To demonstrate the prediction performance of FDKT, it was compared with the following deep learning-based KT models: DKT [1] [21], DKVMN [2] [24], DeepIRT [3] [25], SAKT [4] [34], KQN [5] [27], AKT [6] [35],

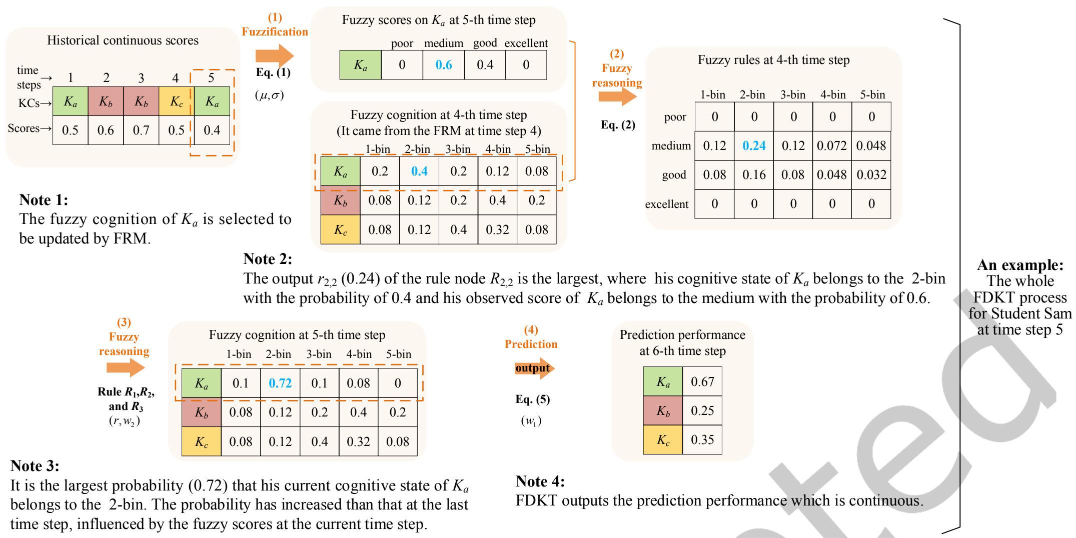

Fig. 7. An illustrative example of the whole FDKT process for an individual at a time step is provided. Five fuzzy cognition sets and four fuzzy score sets were defined. FDKT outputs the prediction performance for Sam. More importantly, it explains that he may obtain the highest score on K_a as he has a good level of mastery (2-bin) on it, where his current cognition was updated via the fuzzy reasoning.

Table 3. Description of data sets

Name	Students	Exercises	Skills	Logs
Algebra05	514	172,758	435	605,051
Algebra06	1,247	549,165	1,701	1,805,754
Bridge06	1,100	129,186	564	1,816,138
ASSISTments	4,163	17,751	149	283,105

CKT [7] [36], DMN [8] [38], ADMN [8] [38], IADMN [8] [38], DKT+ [9] [39], CL4KT [10] [42], GIKT [11] [47], and APGKT [12] [72]. The models are introduced in Section 2. We treated partially correct responses as wrong if the scores for the compared models were less than 0.5 due of their inapplicability to continuous scenarios [28].

In this paper, the Bayesian-based KT models were not included in the baselines, because they must mark the relationship between exercises and knowledge components and classify the exercises with the same knowledge

[1]https://github.com/lingochamp/tensorflow-dkt [21]
[2]https://github.com/jennyzhang0215/DKVMN [24]
[3]https://github.com/ckyeungac/DeepIRT [25]
[4]https://github.com/TianHongZXY/pytorch-SAKT [34]
[5]https://github.com/JSLBen/Knowledge-Query-Network-for-Knowledge-Tracing [27]
[6]https://github.com/arghosh/AKT [35]
[7]https://github.com/bigdata-ustc/Convolutional-Knowledge-Tracing [36]
[8]https://github.com/nathan-f-elazar/Distributed-Memory-Networks [38]
[9]https://github.com/ckyeungac/deep-knowledge-tracing-plus [39]
[10]https://github.com/UpstageAI/cl4kt [42]
[11]https://github.com/ApexEDM/GIKT [47]
[12]https://github.com/DMiC-Lab-HFUT/APGKT-PRICAI2022 [72]

Table 4. Parameter setting of FDKT

Parameter	Fuzzy score sets	Fuzzy cognition sets	Epoch
Value	6	6	100
Parameter	Optimizer	Weight decay	Learning rate
Value	Adam	0.001	0.02

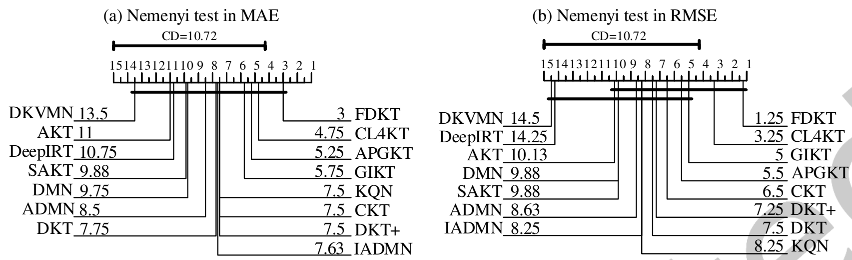

Fig. 8. Nemenyi test of the prediction performance in continuous score scenarios

components (detailed in Section 1). In this way, the temporal properties of the learning sequences would be altered after adopting this pretreatment. Thus it has less reference value when compared between them with deep-learning-based KT models. Moreover, as mentioned previously, KT can be regarded as a dynamic cognitive diagnosis task. The cognitive diagnosis models require a students' interactive matrix with the same exercises, for example, a matrix with the size of 3000*20 where there are 3000 students and 20 exercises. Note that there is no temporal relationship between these 20 exercises. However, the three data sets used in the experiments do not satisfy such an input. Students have different lengths of interaction sequences with the temporal relationship. For example, some students only have 10 interactions, while some have more than 3,000 interactions. Therefore, the cognitive diagnosis models were also not included in the baselines.

6.1.3 Evaluation. KT in continuous-score scenarios can be regarded as a regression task. Thus, two regression metrics, **RMSE** and **MAE**, were selected to quantify the prediction performance of the models [28].

The parameters used in FDKT are listed in Table 4. The batch size of the datasets was set to 128. The experiments were conducted using the **five-fold cross-validation** method to obtain stable results. All the experiments were implemented using the PyTorch public toolbox on a standard Ubuntu 16.04.7 LTS with TU102 USB Type-C UCSI Controller GPUs and 512 GB memory size.

6.2 Comparison of Prediction Performance

This subsection describes the performance of FDKT in continuous score scenarios, as compared with the baselines (**question 1**). To ensure fairness, the parameters, epochs, optimizer, weight decay, and learning rate of the models to be compared were set to be the same as those in FDKT. Smaller values of RMSE and MAE indicate better performance.

Table 5 presents the MAE and RMSE results of the prediction performance, when FDKT was compared with the deep-learning-based KT models. The prediction performance of FDKT outperforms those of both DKT and the other compared models in most cases in continuous score scenarios. This is attributed to the mechanisms such as fuzzy processing and fuzzy rules in FDKT that effectively adapt to continuous scenarios.

The Nemenyi test [73] was conducted to present a comprehensive comparison between FDKT and the baselines. The results were statistically compared over multiple datasets, as shown in Fig. 8. Lower ranks indicate better

Table 5. Comparison of prediction performance in continuous score scenarios [4]

Datasets	Metrics	FDKT (Ours)	DKT [21]	DKVMN [24]	DeepIRT [25]	SAKT [34]	KQN [27]
Algebra05	MAE	**0.1700**	0.1882	0.2111	0.2122	0.1995	0.1920
	RMSE	**0.2130**	0.2473	0.3002	0.2889	0.2516	0.2622
Algebra06	MAE	**0.1590**	0.1646	0.1989	0.1954	0.2040	0.1928
	RMSE	0.2075	0.2162	0.2703	0.2600	0.2564	0.2555
Bridge06	MAE	**0.1450**	0.1621	0.2062	0.2064	0.2065	0.1921
	RMSE	**0.1850**	0.2060	0.2672	0.2641	0.2581	0.251
ASSISTments	MAE	0.1874	0.2508	0.2002	0.1593	**0.0832**	0.1644
	RMSE	**0.2588**	0.3238	0.3102	0.3459	0.2877	0.2679
Datasets	Metrics	AKT [35]	CKT [36]	DMN [38]	ADMN [38]	IADMN [38]	DKT+ [39]
Algebra05	MAE	0.2110	0.1932	0.1997	0.1992	0.1984	0.2048
	RMSE	0.2856	0.2575	0.2670	0.2661	0.2642	0.2784
Algebra06	MAE	0.1950	0.1892	0.1944	0.1933	0.1933	0.1923
	RMSE	0.2554	0.2519	0.2577	0.2555	0.2532	0.2534
Bridge06	MAE	0.1900	0.1951	0.2062	0.2020	0.2017	0.1556
	RMSE	0.2492	0.2491	0.2603	0.2557	0.2575	0.1878
ASSISTments	MAE	0.1920	0.1669	0.1613	0.1608	0.1602	0.1624
	RMSE	0.3023	0.2679	0.2656	0.2668	0.2662	0.2721
Datasets	Metrics	CL4KT [42]	GIKT [47]	APGKT [72]			
Algebra05	MAE	0.1732	0.1849	0.1842			
	RMSE	0.2182	0.2250	0.2297			
Algebra06	MAE	0.1592	0.1593	0.1602			
	RMSE	**0.1995**	0.2077	0.2089			
Bridge06	MAE	0.1483	0.1476	0.1513			
	RMSE	0.1851	0.1905	0.1895			
ASSISTments	MAE	0.1975	0.2061	0.1906			
	RMSE	0.2842	0.2848	0.2850			

[4] The bold and underlined results refer to the first and second best values, respectively.

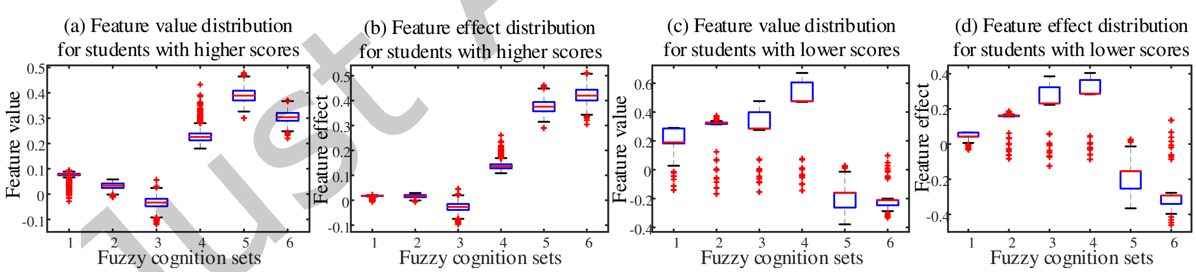

Fig. 9. Feature value and effect distributions of the students with higher (a-b) and lower (c-d) prediction scores in Algebra05. The fuzzy cognition sets from 1 to 6 denote the cognition from low to high. The better fuzzy cognition achieves high feature values and effects in (a-b), while those in (c-d) are on the contrary. This demonstrates that students with high prediction scores have high fuzzy cognition, which is in line with our initial understanding.

performance. There is no significant difference in the same crossline-connected models. FDKT was found to perform better in continuous score scenarios.

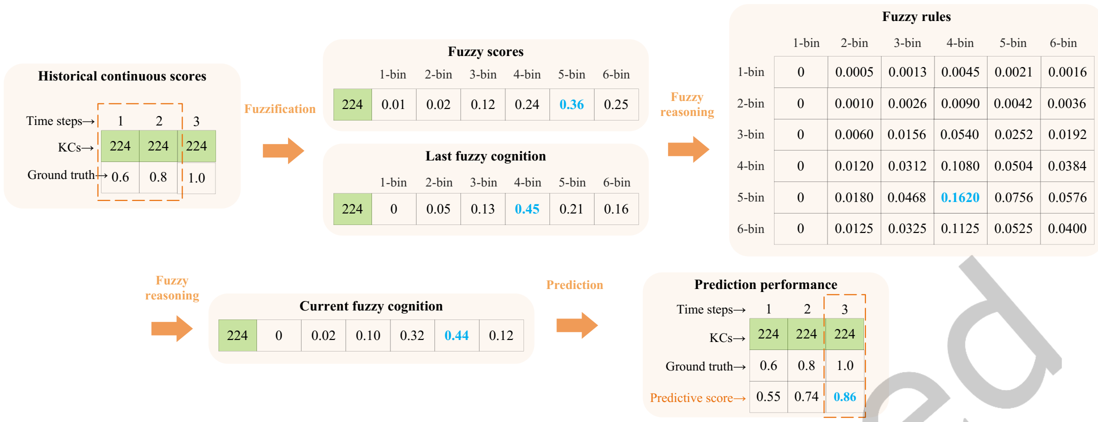

Fig. 10. Case study to demonstrate how FDKT can do intrinsic interpretation on Algebra05.

6.3 Illustratration of Interpretability

This subsection shows the case studies to demonstrate how FDKT can do interpretation, including intrinsic and post hoc interpretability.

6.3.1 Case Study of Intrinsic Interpretability. To illustrate the working process of FDKT in a visually intuitive manner, we have selected three records of a student from the Algebra05 dataset, where a student has provided consecutive responses to a particular skill (No. 224). We will demonstrate how FDKT predicts the outcome for the third record. According to Table 4, in the experiment, we set the number of fuzzy score sets and fuzzy cognition sets to 6. Firstly, after the fuzzification module of FDKT, we obtained fuzzy scores and the last fuzzy cognition with a continuous score of 0.8. We can observe that the student's last fuzzy cognition has a higher probability (0.45) of belonging to the 4-bin, while the current fuzzy score has a higher probability (0.36) of belonging to the 5-bin. Based on the inference of fuzzy rules, we obtained the current fuzzy cognition. At this point, the student's fuzzy cognition for skill 224 has a higher probability (0.44) of belonging to the 5-bin. This indicates an improvement compared to the last fuzzy cognition. As a result, FDKT predicts a score of 0.86 for the student's performance on the skill-related exercises in the next time step. This predicted score represents an improvement compared to the score of 0.8. Furthermore, when comparing FDKT's predicted scores with the ground truth, we find that the predicted score trend (continuously increasing) aligns consistently with the actual scores. The above case study demonstrates the intrinsic interpretability of FDKT, that is, FDKT provides explanations for its corresponding prediction results.

6.3.2 Results of Post Hoc Interpretability. This subsection demonstrates the post hoc interpretability of FDKT (**question 2**), that is, to answer *what else FDKT tells us* (shown in Fig. 2 (b)).

According to the domain knowledge (the basic unit of interpretability [15]) in education data mining, better performance on exercises thanks to better knowledge mastery of students. Student cognition and prediction performance are the cause and effect for the KT task, respectively. In this subsection, the interpretability of FDKT is visualized from the following two aspects: 1) From the effect (performance) to cause (fuzzy cognition), and 2) From the cause (fuzzy cognition) to effect (performance).

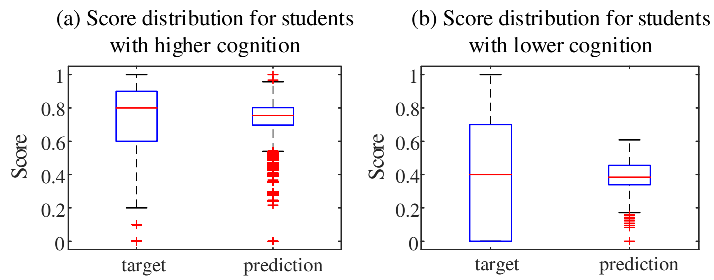

Fig. 11. Distributions of the target and prediction scores of Algebra05 for students with higher (a) and lower (b) cognition. The scores in (a) were statistically higher than those in (b). Both cases show excellent prediction performance. This demonstrates that the good prediction of FDKT is attributed to the good cognition estimate from the cause to effect.

From Performance to Cognition. The relation from the prediction scores to the fuzzy cognition is analyzed in this part. The fuzzy cognition includes its feature values and feature effects. The feature effects [64, 74] were obtained by multiplying the feature values with the weights in the optimized FDKT.

The feature value and effect distributions of the students with higher and lower prediction scores in Algebra05 are shown in Fig. 9, where the weight in the optimized FDKT is 0.23, 0.50, 0.81, 0.60, 0.96, 1.38. Higher and lower scores denote normalized prediction scores higher than 0.8 and lower than 0.2, respectively. The fuzzy cognition from the 1 to 6 level denotes cognition from low to high. Comparing the fuzzy cognition of students between the higher (Fig. 9 (a-b)) and lower prediction scores (Fig. 9 (c-d)), better fuzzy cognition achieves high feature values and effects in the former, while those in the latter are on the contrary. This demonstrates that students with high prediction scores have high fuzzy cognition, which is line with our common knowledge.

From Cognition to Performance. The relation from the fuzzy cognition to the prediction scores is analyzed as follows. The distributions of the target and prediction scores of Algebra05 for students with higher and lower cognition levels are shown in Fig. 11. The probability that students belong to the top (4-6 levels) and bottom (1-3 levels) of the three fuzzy cognition sets are denoted as p_{top} and p_{bottom}, respectively. Higher and lower cognition denote the cognition that $p_{top} > p_{bottom}$ and $p_{top} < p_{bottom}$, respectively. $|p_{top} - p_{bottom}| > \alpha(\alpha = 0.2)$ because cognition with a small probability difference cannot be arbitrarily defined.

Fig. 11 is analyzed from the following two aspects. 1) Comparing two target distributions between the higher and lower cognition, the target scores of students with higher cognition are statistically higher than those with lower cognition, according to the student cognition obtained from the proposed model. This is consistent with our domain knowledge that students with greater cognitive ability can achieve higher grades. It also shows the evaluation of student cognition is reasonable in the proposed model. 2) Comparing the target and prediction for the same level of cognition, they show a relatively consistent distribution, in which the red transverse lines represent the median values. The median values of the target and prediction data, for higher and lower-cognition students, are around 0.8 and 0.4, respectively. This demonstrates the good prediction performance of FDKT is attributed to good cognition estimation from cause to effect.

6.4 Parameter Analysis

In this subsection, an analysis of the two hyper parameters, that is, the numbers of fuzzy cognition sets I and fuzzy score sets J, is presented as follows. As shown in Table 6, the results demonstrate that the FDKT performs best when both I and J are set to six. This illustrates the applicability of the FDKT to continuous scenarios because it is equivalent to considering that the input scores are only two sets (similar to the discrete scenario) when I is set to 2. For example, for the RMSE results of FDKT on the ASSISTments dataset, the best results were

Table 6. Comparison of prediction performance in continuous score scenarios between different numbers of fuzzy sets [6]

Datasets	Metrics	Case A (2, 2)	Case B (2, 6)	Case C (6, 2)	Case D (6, 6)
Algebra05	MAE	0.1770	0.1768	0.1777	**0.1700**
	RMSE	0.2320	0.2300	0.2301	**0.2130**
Algebra06	MAE	0.1612	0.1610	0.1612	**0.1590**
	RMSE	0.2090	0.2090	0.2088	**0.2075**
Bridge06	MAE	0.1662	0.1474	0.1489	**0.1450**
	RMSE	0.2188	0.2004	0.2014	**0.1850**
ASSISTments	MAE	0.1944	**0.1864**	0.1936	0.1874
	RMSE	0.2710	0.2602	0.2596	**0.2588**

[6] (i, j) indicate that the numbers of fuzzy cognition and fuzzy score sets are i and j, respectively.

obtained in Case D (the number of both fuzzy sets is set to 6), with a 4.71% improvement over the results in Case A (the number of both fuzzy sets is set to 2).

The specific analysis is as follows. Defining a greater number of fuzzy sets (within a reasonable range) can effectively improve the accuracy of the FDKT in continuous scenarios and can be attributed to the following: 1) According to the definition of fuzzy rules in the FDKT (Section 4.2.2), the greater the number of fuzzy sets, the greater the number of fuzzy rules. 2) According to the fuzzy reasoning module in the FDKT framework (Fig. 5 (c)), the number of fuzzy rules is equal to that of hidden units in the FDKT fuzzy rule layer, which directly affects the network structure. 3) According to fuzzy theory, the higher the number of fuzzy rules, the more expert knowledge the model can incorporate [75]; moreover, according to the experience of neural networks, the higher the number of hidden units, the higher the number of network parameters and the stronger the representation capability of the model [76]. Therefore, one of the main reasons for the excellent performance of FDKT in continuous scenarios stems from the larger number of fuzzy sets.

In discrete scenarios, only two definite categories for the exercise scores exist (i.e., correct or incorrect answers, denoted by 1 and 0, respectively). That is, the score of a student on an exercise can be categorized under only two score sets (i.e., correct or incorrect set). Thus, the number of two fuzzy sets (i.e., fuzzy score sets and fuzzy cognitive sets) in FDKT is set to two to make the proposed FDKT more adaptable to discrete scenarios. Thus, the number of fuzzy rules in discrete scenarios is $2 * 2 = 4$ (according to Section 4.2.2), which is significantly smaller than that in continuous scenarios. Therefore, the FDKT has a smaller number of fuzzy rules in the discrete scenarios, which limits its accuracy according to the above analysis.

6.5 Discussion

The experiments answered the main questions in the experiments, which are summarized as follows: 1) From the prediction performance perspective, the proposed model outperforms the compared models in most cases, both on two regression metrics RMSE and MAE, in the continuous-score scenarios. 2) From the model interpretability perspective, the proposed model illustrates the post hoc interpretability both from cause to effect and effect to cause, respectively.

The reasons for the better performance of FDKT in continuous scenarios are analyzed as follows. 1) FDKT uses backpropagation to update the network parameters for improving the prediction performance by designing a reasonable loss function, similar to most neural network-based KT models. The direction of gradient descent guides the parameters to be updated in a better direction. 2) The process of updating the gradient-guided parameters is combined with domain-related expert experience through fuzzy rules for equalizing its prediction results with domain knowledge. In FDKT, educational expertise is combined in neural networks through fuzzy rules (detailed in Section 4.3). And we also demonstrated the consistency in the prediction results with expert knowledge through visualization (detailed in Section 6.3).

Compared with the existing neural-network-based KT model, the advantages of the proposed FDKT with an FNN are analyzed as follows. 1) FDKT improves the interpretability of the traditional neural-network-based KT model, both in intrinsic and post-hoc aspects. As for the intrinsic interpretability of the FDKT (detailed in Section 5), we designed a set of fuzzy rules regarding the fuzzy cognitive states and fuzzy performance scores, relying on prior knowledge. The post hoc interpretability of FDKT is illustrated through the experimental results (detailed in Section 6.3). 2) FDKT combines the advantages of both fuzzy theory and neural networks, i.e., the ability to combine language-based knowledge (e.g., expert experience) and the ease of training the model parameters (e.g., backpropagation). The FDKT combines neural networks and fuzzy theory, which solves the limitation that neural networks cannot receive linguistic knowledge, since fuzzy sets and rules are powerful tools for dealing with this type of linguistic data. 3) FDKT could address the uncertainty in the KT task, reflected in the following three aspects. a) Performance of students on exercises is uncertain. For example, if a student scores 0.55, evaluating the score as high or low is not possible. b) A student's knowledge of the knowledge component is uncertain. c) Reasoning about the current time step cognition based on the performance of a student in an exercise and the previous time step cognition is uncertain. 4) FDKT extends the application scenarios of most neural network-based KT to make them suitable for continuous scenarios. Most existing KT models cannot directly handle continuous scoring scenarios. They must be fed into the network by binarizing the continuous scores and then encoding them as 0 or 1. Instead, FDKT extends KT to continuous scoring scenarios by representing continuous inputs as fuzzy sets after a fuzzy affiliation function.

Moreover, in other fields, the approaches for designing FNNs are as follows: Combining fuzzy systems with neural networks or deep learning in uncertain application scenarios is a powerful solution. We consider that this might include the following two approaches. 1) Converting the weights or inputs of neural networks into fuzzy sets. 2) Designing expert knowledge into fuzzy rules to be added between the input and output of the neural network.

7 CONCLUSION

Most deep learning-based KT models are less interpretable because of the difficulty in explaining the achievement of accurate predictions. To address this problem, a fuzzy knowledge tracing (FDKT) model is proposed with a fuzzy reasoning module that estimates student cognition of the knowledge components. The intrinsic and post-hoc interpretability of FDKT is demonstrated through rules, hidden semantics, and visualization experiments. In addition, FDKT performs better than the deep-learning-based KT models on continuous scores, broadening the application of KT. It should be pointed out that in discrete scenarios, students' practice scores have only two definite categories (i.e. correct or wrong answers), resulting in a much smaller number of fuzzy rules and hidden units than in continuous scenarios (see Section 6.4 for details). This limits the performance of the FDKT model in discrete scenarios. In the future, the authors plan to design reasonable mechanisms to further improve applicability of FDKT to discrete scenarios.

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The authors took advantage of the source codes of all the baselines for comparison. Our code can be available at https://github.com/DMiC-Lab-HFUT/FDKT. The computation is completed on the HPC Platform of Hefei University of Technology.

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