Explainable Few-shot Knowledge Tracing

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Abstract

Knowledge tracing (KT), aiming to mine students' mastery of knowledge by their exercise records and predict their performance on future test questions, is a critical task in educational assessment. While researchers achieved tremendous success with the rapid development of deep learning techniques, current knowledge tracing tasks fall into the cracks from real-world teaching scenarios. Relying heavily on extensive student data and solely predicting numerical performances differs from the settings where teachers assess students' knowledge state from limited practices and provide explanatory feedback. To fill this gap, we explore a new task formulation: **Explainable Few-shot Knowledge Tracing**. By leveraging the powerful reasoning and generation abilities of large language models (LLMs), we then propose a cognition-guided framework that can track the student knowledge from a few student records while providing natural language explanations. Experimental results from three widely used datasets show that LLMs can perform comparable or superior to competitive deep knowledge tracing methods. We also discuss potential directions and call for future improvements in relevant topics.

1 Introduction

Knowledge tracing is a well-established problem originated from educational assessment [1] aiming to dynamically model students' knowledge mastery and predict their future learning performances. With the advancement of deep learning, models leveraging recurrent neural networks (RNNs) and attention mechanisms have gradually become mainstream for knowledge tracing [2, 3, 4]. In recent years, KT research has shown two notable and promising directions. On the one hand, researchers attempt to incorporate multiple types of side information (e.g., exercise texts [5], knowledge concept relationships and mappings [6, 7], students' problem-solving behaviors [8]) with students' exercise history to more accurately model their knowledge states. On the other hand, they try to reveal the links between the latent representations learned by the models and factual data to provide interpretability for the knowledge tracing models [9, 10, 11].

Despite the numerous attempts and decent success, the current knowledge tracing task leaves gaps in reflecting real-world scenarios where teachers evaluate students' knowledge states. On the one hand, It relies on extensive student exercise records to train deep learning knowledge tracing models to achieve remarkable performance. In contrast, in real teaching scenarios, teachers can analyze students' mastery of knowledge from a limited number of practices. On the other hand, unlike teachers can

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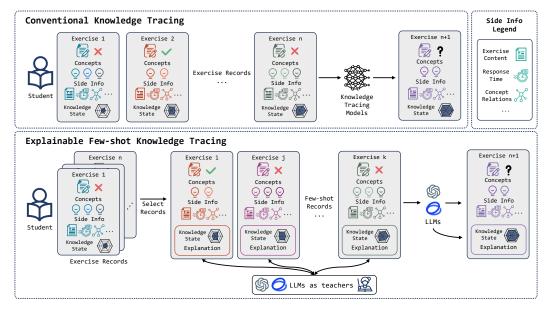


Figure 1: Conventional knowledge tracing and explainable few-shot knowledge tracing

infer students' answers by analyzing and explaining their knowledge mastery, the current task is simplified to only predicting whether a student will answer the test questions correctly, mainly by deep learning sequential predictive models. The black-box nature inherent in these models hampers exploring interpretability as they represent student knowledge states as hidden vectors. Apart from the abovementioned gaps, knowledge tracing models or frameworks encounter difficulties unifying and utilizing the multi-dimensional information collected from learning environments (e.g., student behaviors, question text, knowledge relations). Primarily proposed non-generative sequential models make it challenging for such tasks to come out of numerical prediction and extend to other scenarios, such as open-ended exercising and programming learning.

In recent years, the emergence and widespread utilization of large language models (LLMs) have provided potential solutions to fill the gaps. LLMs' capability to follow complex instructions with only a few examples and provide natural language feedback makes it possible to reform the current knowledge tracing paradigm. Inspired by the success of LLMs in other fields, we improve upon the existing knowledge tracing task formulation and propose **Explainable Few-shot Knowledge Tracing**. As illustrated in Figure 1, compared to traditional knowledge tracing, explainable few-shot knowledge tracing tasks a small number of informative student exercise records as input, tracks students' mastery of knowledge, and predicts future performances through reasoning while providing reasonable explanations. Furthermore, leveraging LLMs' strong reasoning and generation abilities, the knowledge tracing task can readily adapt to diverse teaching scenarios with simple adjustments, presenting new opportunities for applying knowledge tracing in multiple educational scenarios. The key contributions of this paper are as follows:

- We analyze the deficiencies of conventional knowledge tracing and propose the explainable few-shot knowledge tracing task that aligns better with real teaching scenarios.
- We introduce a cognition-guided framework that combines large language models and educational assessment principles to practice explainable few-shot knowledge tracing.
- We adapt three public datasets and conduct experiments using open-source and closed-source LLMs. The results demonstrate that LLMs can perform comparable or superior to competitive knowledge tracing models. Furthermore, based on empirical observations from multi-perspective experiments, we suggest several potential directions for improvement.

2 Background

2.1 Knowledge Tracing

Educational Assessment and Bayesian Knowledge Tracing Educational assessment aims to analyze students' knowledge states, and an assessment system is generally considered to comprise three main components: observation, cognition, and interpretation [12]. Cognition refers to a model of how students represent knowledge. With the introduction of the knowledge tracing concept [1], researchers have estimated students' knowledge states by analyzing their response records. Traditional knowledge tracing (KT) methods consist of two classics: Bayesian knowledge tracing (BKT) and factor analysis models [13]. BKT is a hidden Markov model that treats each learner's knowledge state as a binary variable and utilizes Bayesian inference to update the state [14]. In contrast, factor analysis models aim to learn generalized parameters from historical data [15].

Deep Knowledge Tracing Recently, numerous researchers have integrated deep neural networks into KT tasks for their effectiveness and outstanding performance. Piech et al. pioneered deep learning for KT using recurrent neural networks (RNNs) to process interaction sequences over time [2] and proposed deep knowledge tracing task setting. With the success of deep learning techniques in other domains, such as word2vec [16] and graph neural networks [17, 18], researchers recognized the potential to leverage these techniques by incorporating auxiliary information of questions [3, 5], knowledge concepts [6, 9], and students' learning behaviours [19]. Moreover, attention-based models [4, 20] were introduced to tackle the computational expense and instability with long sequences of RNNs. While achieving success in performances, the lack of interpretability raised greater attention, as the model should provide transparency and understanding of the reasoning behind learning behaviors over just the outcomes. Models incorporating educational theories like the Rasch model [3, 21] and the transfer of knowledge [9] were proposed to enhance interpretability. Minn et al. [10] introduced causal relationships within latent features extracted from students' behaviors. Zhu et al. [11] attempted to introduce causal inference for explanatory KT analysis.

Despite the remarkable success, deep knowledge tracing tasks remain a few challenges. Most methods demand extensive student exercise logs for model training, aiming to make binary predictions, which differ from the real analyzing scenarios. The black-box nature inherent in deep learning models and numerical predictions limits the explainability and struggle to generalize to other teaching scenarios, such as open-ended knowledge tracing [22, 23] and programming learning [24].

2.2 Large Language Models

Large language models (LLMs) typically refer to transformer-based models containing hundreds of billions of parameters with multi-head attention layers stacked in very deep neural networks [25]. LLMs can be categorized as open-sourced, like the LLaMA [26] and GLM [27] series, or close-sourced, like GPT-4. Trained on massive text data, LLMs exhibit solid natural language understanding to follow complex instructions and solve complex tasks due to their "emergent abilities" - capabilities not present in small language models but arising in large ones [28]. Additionally, LLMs can leverage multi-dimensional information for reasoning and generate natural language responses. Currently, researchers have achieved decent success across domains like weather forecasting [29], recommendation [30], and medicine [31]. Advances in LLMs also brought new possibilities for education, where multiple aspects (e.g., teacher assistance, adaptive learning, and learning tools) benefit from the application of LLMs [13, 32, 33, 34]. The accomplishments in other fields indicate that applying LLMs to knowledge tracing could lead to similar success.

However, of the less exploration is the work of utilizing LLMs for knowledge tracing. Neshaei et al. [35] explore extending the sequence modeling capabilities of LLMs to knowledge tracing. It was found that fine-tuned LLMs outperformed naive baselines and matched Bayesian knowledge tracing, suggesting further refinements and a deeper understanding of their predictive mechanisms could enhance performance. Despite the first attempt, it is limited by the original knowledge tracing task settings, where LLMs cannot handle such extensive student exercise records. It motivates us to explore a knowledge tracing paradigm for the era of large language models, and to leverage the advantages of LLMs to address the shortcomings of traditional knowledge tracing settings.

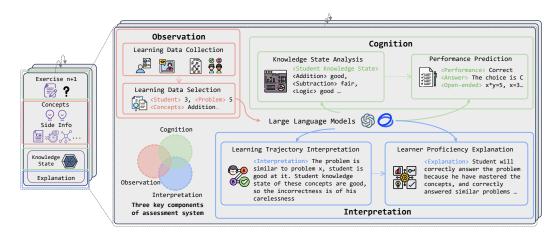


Figure 2: The cognition-guided framework for explainable few-shot knowledge tracing

3 Explainable Few-shot Knowledge Tracing

Deep knowledge tracing task [2] is formulated as estimating student next state \hat{s}_{t+1} given student records \mathcal{X}_t , questions \mathcal{Q} , knowledge concepts \mathcal{C} and a knowledge tracing model M_{DP} , denoted as,

$$\mathcal{X}_t = \{x_0, ..., x_t\}, \mathcal{F} : \mathcal{Q} \to \mathcal{C}, \tag{1}$$

$$\hat{s}_{t+1} = \arg\max_{y} P(y \mid M_{DP}, \mathcal{X}_t, \mathcal{Q}, \mathcal{C}), \tag{2}$$

where \mathcal{F} denotes the mapping relations of exercises and knowledge concepts. We then define the explainable few-shot knowledge tracing by integrating selected student records $\mathcal{X}'_t \in \mathcal{X}_t$, preditive model M, questions \mathcal{Q}' and knowledge concepts \mathcal{C}' with extended information to output estimated student states \hat{s}'_{t+1} and generate explanation \hat{E} , further formulated as,

$$\hat{s}'_{t+1}, \hat{E} = \arg \max_{\omega, \phi} P(\omega, \phi \mid \mathcal{M}, \mathcal{X}'_t, \mathcal{Q}', \mathcal{C}'). \tag{3}$$

3.1 Overview

To further practice explainable few-shot knowledge tracing tasks, we propose a cognition-guided framework by leveraging large language models, which consists of three indispensable fundamental components [12] originated from assessment systems: **Observation**, denoted as M_O , defining the task scenario and collecting data, **Cognition**, represented as M_C , which models learners' knowledge state and predict performances, and **Interpretation**, denoted as M_I , providing explanations of assessing processes. Notably, most existing knowledge tracing models primarily function as the Cognition module, while a few explainable knowledge tracing methods partially assume the role of the Interpretation module. As depicted in Figure 2, by leveraging large language models, we can unify the Cognition and Interpretation, enabling them to ingest the diverse data acquired by the Observation module, integrating the three components to form a cohesive system. We further dive into the three components and then clarify how they work together within the new task.

3.2 Observation

Observation, which is the task or situation that allows one to observe students' performance [12], defines the learning environment within the assessment system, determining factors such as the type of knowledge acquired by the learner and the tasks they engage with. It collects multi-dimensional and multi-modal data \mathcal{X}_{raw} from the designated learning environment \mathcal{E} , generating the necessary inputs for subsequent assessment processes, and thus comprises two sub-modules: Learning Data Collection M_{dc} and Learning Data Selection M_{ds} .

Learning Data Collection determines the data types to be collected based on the task scenario and carrying out the collection process. Typically, it involves gathering information such as the student's

response sequence, including correctness, timestamps, and duration, as well as question-related information like problem contents and knowledge concepts, and forms structured dataset \mathcal{X}_c .

Learning Data Selection curates the processed data \mathcal{X}_c through strategic selection and reorganizing, providing the refined inputs $\mathcal{X}_s = \{x_1, ..., x_s\}$ to the cognition and interpretation modules as required. In the implementation, we select several exercise records to generate informative few-shots for LLMs to predict performance. For simplicity, we implement random and time-ordered linear sampling strategies to select candidate few-shots from student history exercise records. Deep knowledge tracing models often require vast amounts of student response data for accurate prediction. In contrast, educators can frequently gauge a learner's knowledge level from a limited yet informationrich set of response records corresponding to \mathcal{X}_s . The advantage of large language models lies in their ability to leverage in-context learning and reasoning, enabling them to extract high-quality insights while seamlessly ingesting diverse inputs. It aligns with real-world instructional scenarios and lays the foundation for fully exploiting the strengths of LLMs for cognition and interpretation.

3.3 Cognition

Cognition, which is a model of how students represent knowledge & develop competence in the domain [12], synthesizes a comprehensive representation of the learner's evolving knowledge state \hat{K}_s and generate predictions \hat{P} from \mathcal{X}_s . This module is divided into two sub-modules: Knowledge State Analysis M_{ca} and Performance Prediction M_{cp} .

Knowledge State Analysis dynamically analyzes the learner's mastery of knowledge throughout the practice process by \mathcal{X}_s , containing student response records, question information, and behavioral patterns. It generates reliable knowledge state estimates \hat{K}_s as essential references for performance prediction and Interpretation, formulated as,

$$\hat{k}_j = M_{ca}(\mathcal{X}_j, \hat{K}_{j-1}, \hat{I}_{j-1}),$$
 (4)

$$\hat{k}_{j} = M_{ca}(\mathcal{X}_{j}, \hat{K}_{j-1}, \hat{I}_{j-1}),$$

$$M_{ca}(\cdot) = \arg\max_{\omega} P(\omega \mid \cdot, \omega_{c_{a}prompts}),$$
(4)

where \hat{k}_j is the estimated knowledge state with respect to x_j and $\hat{K}_{j-1} = \{\hat{k}_1, \hat{k}_2, \dots, \hat{k}_{j-1}\}$. $\omega_{c_aprompts}$ is the prompts designed for knowledge state analysis, and \hat{I}_{j-1} is the set of interpretation of \hat{k}_1 to \hat{k}_{i-1} , which is elaborated in section 3.4. In the implementation, LLMs are asked to generate student mastery of knowledge with ternary value (good, fair, or fail) for each concept contained in the exercise the student encounters. It is also worthwhile to explore other customized analysis, deriving the benefits from the flexibility and generalizability of large language models compared to functionally similar cognitive diagnosis models.

Performance Prediction forecasts the learner's performance \hat{P} on predefined environment \mathcal{E} by mining selected data \mathcal{X}_s , estimated state \hat{K}_s and interpretation \hat{I} from M_I , denoted as,

$$\hat{P} = M_{cp}(\mathcal{X}_s, \hat{K}_s, \hat{I}_s, x_p), \tag{6}$$

$$\hat{P} = M_{cp}(\mathcal{X}_s, \hat{K}_s, \hat{I}_s, x_p),$$

$$M_{cp}(\cdot) = \arg\max_{\omega} P(\omega \mid \cdot, \omega_{c_p prompts}).$$
(6)

 x_p is the data of exercise to predict and $\omega_{c_pprompts}$ is the prompts designed for predicting performance. Traditionally, performance is quantified as the probability of correctness or percentage scores. However, by leveraging the generative capabilities of large language models, we can extend the prediction to a broader range of learning scenarios less explored by deep learning models, such as open-ended question answering and programming tasks.

Interpretation 3.4

Interpretation, which is a method for making sense of the data relative to our cognitive model [12], leverages P, K_s from the previous modules to generate diagnostic feedback and interpretable analytical insights. These insights facilitate targeted pedagogical interventions to optimize the learner's educational experience and provide a mechanism to evaluate and justify the validity of the observation module's task design and data selection strategies. The interpretation module comprises two sub-modules: Learning Trajectory Interpretation M_{it} and Learner Proficiency Explanation M_{pe} .

Learning Trajectory Interpretation harnesses data \mathcal{X}_s , and the knowledge estimates \hat{K}_s to furnish natural language explanations \hat{I}_s for the learner's historical practice behaviors, formulated as,

$$\hat{i}_j = M_{it}(\mathcal{X}_j, \hat{K}_j, \hat{I}_{j-1}), \tag{8}$$

$$\hat{i}_j = M_{it}(\mathcal{X}_j, \hat{K}_j, \hat{I}_{j-1}),$$

$$M_{it}(\cdot) = \arg\max_{\omega} P(\omega \mid \cdot, \omega_{i_t prompts}),$$
(8)

where \hat{i}_j is the interpretation of student records x_j and $\hat{I}_{j-1} = \{\hat{i}_1, \hat{i}_2, \dots, \hat{i}_{j-1}\}$. For instance, if a learner exhibits proficiency in the concepts related to a question but still provides an incorrect answer, it may attribute the error to carelessness, offering a plausible explanation. Importantly, these explanations can inform and refine the knowledge state analysis and performance prediction within Cognition, accounting for transient factors without unduly penalizing the learner's estimated knowledge state. In contrast, conventional deep learning models may inaccurately degrade the learner's knowledge states due to occasional carelessness, resulting in erroneous predictions. The versatility of large language models enables us to encompass and interpret a wide array of learner behaviors, furnishing more reliable and effective natural language explanations than the numerical interpretations provided by existing explainable knowledge tracing models.

Learner Proficiency Explanation integrates \mathcal{X}_s from observation, the estimated knowledge state \hat{K}_s , and the explanations \hat{I}_s to provide meaningful insights \hat{E} into the performance predictions of the Cognition module. It clarifies the complex interplay between learners' proficiency levels, learning habits, and task performance by situating these predictions within specific instructional scenarios and learner task contexts. The final process can be formulated as,

$$\hat{E} = M_{pe}(\mathcal{X}_s, \hat{K}_s, \hat{I}_s, x_p, \hat{P}), \tag{10}$$

$$\hat{E} = M_{pe}(\mathcal{X}_s, \hat{K}_s, \hat{I}_s, x_p, \hat{P}),$$

$$M_{pe}(\cdot) = \arg\max_{\omega} P(\omega \mid \cdot, \omega_{p_e prompts}).$$
(10)

E promotes a nuanced explanation of learners' competencies, empowering educators to make timely adjustments to teaching content and cater to individual needs.

Experiments

In this section, we detail the approach to practicing explainable few-shot knowledge tracing, including the construction of datasets and model implementation. We compare the performance of LLMs on this task against deep learning models on traditional knowledge tracing. Furthermore, we investigate potential improvement when employing LLMs for this task.

4.1 Task Setups

Datasets We selected three public datasets: FrcSub², MOOCRadar [36], and XES3G5M [37]. The detailed statistics of these three datasets are presented in Appendix A. The task can integrate multidimensional information as input by designing structured textual data and appropriate prompts. Depending on the type of side information incorporated, we created different modes:scant and sparse for three datasets, and additional moderate mode for MOOCRadar and XES3G5M, varying degrees of information richness, shown in Figure 3. The scant mode utilizes only the primary student ID, exercise ID, skill ID, and

Student id: 8087	
Exercise id: 20	Scant
is_correct: right	
Knowledge concept ids:	
["105", "39", "106"]	
+Knowledge concepts:	Sparse
['proposition',	Jpai 36
'interrogative sentence',	
'propositional form']	
++Exercise content:	Moderate
Statements can be	nouerate
expressed by propositions	

Figure 3: Dataset of different modes.

student interaction records. The sparse mode builds upon scant by incorporating skill representation information. The moderate further includes textual descriptions of exercises over the sparse.

Metrics We collect accuracy, precision, recall, and F1 scores as evaluation metrics, as the area under the curve (AUC) cannot be employed since LLMs provide binary predictions. Due to page constraints, the experimental results of precision and recall metrics will be included in the Appendix F and H.

Baselines We select several commonly employed and competitive baselines in knowledge tracing: 1) DKT [2] employs LSTM layers to encode the students' knowledge state and predict their performance on exercises. 2) DKVMN [38] designs a static key matrix to capture relations between

²http://staff.ustc.edu.cn/%7Eqiliuql/data/math2015.rar

Table 1: A compari	son of the accuracy	v and F1 score among	baselines in three datasets.

		Dataset					
Input scale	Baselines	FreSub		MOOCRadar		XES3G5M	
		Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score
	DKT	0.7481	0.7514	0.8210	0.8882	0.8355	0.9017
full-set	DKVMN	0.7909	0.8077	0.8147	0.8836	0.8372	0.9037
	GKT*	0.5480	0.3043	0.7991	0.8772	0.8169	0.8923
	AKT	0.7747	0.7869	0.8194	0.8870	0.8435	0.9063
	SAKT	0.7476	0.7389	0.7956	0.8706	0.8298	0.8990
	SAINT	0.8061	0.8201	0.8241	0.8904	0.8399	<u>0.9044</u>
few-shots	GLM3-6b	0.6571	0.6496	0.5378	0.6753	0.5434	0.6580
	GLM4	0.7939	0.7889	0.8489	0.9052	0.8491	0.8978
	GPT-4	0.7968	0.7471	0.8246	0.9029	0.8176	0.8714

knowledge components and a dynamic value matrix to track the evolution of students' knowledge. 3) **GKT** [6] leverages graph structure to model interactions between exercises. 4) **AKT** [3] utilizes an attention mechanism to characterize the temporal distance between questions and the student's history interactions. 5) **SAKT** [20] incorporates a self-attention module to capture latent relations between exercises and student responses. 6) **SAINT** [4] adopts a transformer architecture to jointly model sequences of exercises and responses.

4.2 Overall Performance

We compared the best performance of GLM3-6B [27], GLM4, and GPT-4 across all modes of three datasets with considered baselines. Notably, all considered baselines requires the full training set to achieve best performances, whereas ours only require a few, and such a small amount is far from enough for the baselines. The best three metrics in each column are marked using **bold**, <u>underlined</u>, and *italics*. Overall, GLM4 and GPT-4 performed comparable or superior to the baselines on all three datasets. Notably, on the MOOCRadar dataset, GLM4 and GPT-4 outperformed all baselines, showing improvements of 3.01% and 1.66% in Accuracy and F1 Score, respectively. It demonstrates that leveraging LLMs within explainable few-shot knowledge tracing can match or surpass conventional deep learning models. In contrast, GLM3-6B did not perform as well as expected, which could be attributed to the extensive input context. During experiments, we observed that the GLM3-6B often struggled to follow instructions, indicating that a fine-tuned small model may potentially achieve better performances. Specifically, we present more comprehensive results in Appendix F, and the implementation details to achieve the best performance in Appendix B.

4.3 Case Study

We randomly select examples of all considered LLMs from the MOOCRadar-moderate. It involves estimating the student's knowledge state in student history records, predicting student performances, and providing an explanation. Identifiers are colored to correspond with modules in Figure 2. The content before <Exercise to Predict> contained the previous context, including four few-shots and the LLM's analysis of the student's responses based on the selected examples. <Exercise to Predict> contains the information of the test exercise. <Output Predicted is_correct> represented the LLM's

Figure 4: Case study of GLM3-6B

```
GLM4
                                                                                                                                                                                                                                                                GPT4
   xercise_id: 20
                                                                                                                                                                                  Exercise_id: 20
 Exercise_id: 24
                                                                                                                                                                                  Exercise_id: 24
 Exercise content:
                                                                                                                                                                                  Exercise content:
The propositions whose truth values can be determined independently by logic
                                                                                                                                                                                The propositions whose truth values can be determined independently by logic
    nowledge concepts: ['truth value of proposition', 'compound proposition',
                                                                                                                                                                                  Knowledge concepts: ['truth value of proposition', 'compound proposition',
                                                                                                                                                                                                   ect: right
    cplanation:
                                                                                                                                                                                Explanation:

1. The new exercise contains 'proposition', ...

2. It's a new question, there is some kind of connection between the previous knowledge points and questions. The knowledge point 'proposition' was also present in the previous question.

3. Student's Knowledge state:

"proposition', fair ...

4. The student gets it wrong, possibly due to incorrect mastery. The student may not have fully understood the knowledge points...

Exercise id: 29

    The new exercise contains the knowledge points: ['proposition', ...].
    The new question is similar to question 2 in the student's record of work, as it also involves the knowledge points 'proposition' and 'interrogative

     It as a....
Student's Knowledge state:
'proposition', good (from previous exercise 2)

The student gets it right, possibly because correct mastery,

in id 29
__
<Exercise to Predict>
                                                                                                                                                                                  Exercise to Predict>
Which of the following is not a partition? 'A': ...
                                                                                                                                                                                 Exercise content:
Which of the following is not a partition?
'A: ...
Knowledge concepts: ["predicate", "basic proposition", "partition"]
  A: ...
n<mark>owledge concepts</mark>: ["predicate", "basic proposition", "partition"]
  Output Predicted is correct
                                                                                                                                                                                  <Output Predicted is cor
explanation:
1. The new exercise contains the knowledge points: ['predicate', __].
2. Similar to question 24, the student has encountered the knowledge points basic proposition' and 'partition' before.
3. Student's Knowledge state:
- 'proposition', good (from previous exercise 24)
- 'interrogative sentence', fair (from previous exercise 24)
                                                                                                                                                                               Explanation:

1. The new exercise contains 'predicate',...

2. It's a new question, there is some kind of connection between the previous knowledge points and questions. The knowledge point 'basic proposition' was also present in the previous question.

3. Student's Knowledge state:

| proposition', fair, 'interrogative sentence', fair, ...

4. The student gets it right, possibly due to correct mastery. The student may have understood the knowledge points involved in the question, leading to the corpect answer.
    The student gets it right, possibly because correct mastery.
                                                                                                                                                                                may have underscood to the correct answer.
```

Figure 5: Case study of GLM4 and GPT-4

prediction of the student's performance on <Exercise to Predict>, followed by an explanation for the prediction. For detailed prompts and more cases, please refer to Appendices I and J.

GLM3-6B As shown in Figure 5, we removed the knowledge state analysis for each student exercise record to limit the input length for GLM3-6B. However, in many cases, even though it output predictions on all exercises the student had encountered, it failed to satisfactorily meet our required output format, which is only one 0 or 1 for a single test exercise.

GLM4 & GPT-4 Illustrated in Figure 5, we highlighted the differences between the outputs of GLM4 and GPT-4 in gray. We observed that both models are able to follow the instructions and generate formatted explanations in most cases. Differences occurs where GPT-4 incorrectly assumed the student had answered Exercise 24 incorrectly and provided an explanation for this assumption. Furthermore, when explaining its prediction, GPT-4 failed to recognize the incorrectness of the student's performance and instead offered an explanation suggesting the student had answered correctly. This issue was also present in some cases for GLM4, possibly due to the models' limited context window to accurately identify such shot and specific information.

4.4 Discussion

We will discuss empirical observations from designed experiments and the potential directions for improving performances when leveraging LLMs for explainable few-shot knowledge tracing.

Exercise text helps a lot; knowledge concepts do a little. We analyze the performance of GLM4 and GPT-4 on the different modes in FrcSub dataset and MOOCRadar dataset, as shown in Figure 6. "GLM4-acc" denotes the accuracy metrics for GLM4 selecting first 4 few-shots. It can be observed that the performances substantially improve from sparse to moderate mode in MOOCRadar. Integrating only knowledge concepts gains a relatively lower improvement or even a slight decline

Table 2: Performance comparison of different number of few-shots of GLM4 on three datasets.

CI M4	FrcSub-sparse		XES3G5	M-sparse	XES3G5M-moderate	
GLM4	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score
4	0.7192+0.0	$0.7086^{+0.0}$	0.4399+0.0		$0.6672^{+0.0}$	$0.7592^{+0.0}$
8	$0.7771^{+8.1}$	$0.7568^{+6.8}$	$0.7057^{+60.4}$		$0.7928^{+18.8}$	$0.8623^{+13.6}$
16	$0.7939^{+10.4}$	$0.7889^{+11.3}$	$0.7542^{+71.4}$	$0.8395^{+78.4}$	$0.8491^{+27.3}$	$0.8978^{+18.3}$

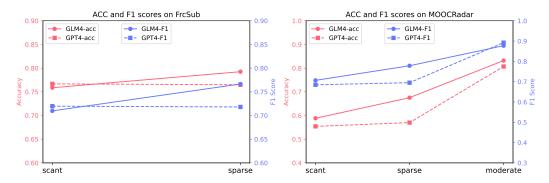


Figure 6: Performance of GLM4 and GPT-4 on FrcSub and MOOCRadar

in Frcsub using GPT-4. It indicates that combining exercise textual information benefits more than knowledge concepts since exercise texts provide more contexts, and concepts provide less than those using IDs. Therefore, a key consideration for boosting performance lies in fully leveraging the existing datasets, formulating them into structured texts, and designing proper prompts that enable LLMs to utilize the additional information effectively.

Increasing the number of few-shots benefits, but too much leads to confusion. We analyze GLM4's performance when using 4, 8, and 16 randomly selected few-shots to explore the impact of different numbers of few-shots on the final results. As shown in Table 2, increasing the number of few-shots leads to improved performance. Notably, for the XES3G5M-sparse dataset, the accuracy saw a significant 71.4% improvement from 0.4399 with four shots to 0.7542 with 16 shots, and the F1 score achieved an impressive 78.4% enhancement. These results highlight the substantial benefits of utilizing more few-shots, especially for student with long records, which is presented in Appendix E. However, excessive few-shots would result in an overly long and repeated context, hampering the LLMs' capabilities. Even with 4 few-shots, for those that are relatively small, like GLM3-6B in Figure 4, it fails to follow the instructions, and for GLM4 and GPT-4 in Figure 5, it leads to incorrectly capturing the student behavior information. As a consequences, it may result in generating misguided information. Therefore, developing effective memory modules enabling LLMs to leverage more few-shots for tracking students' states remains an important direction to explore.

Random few-shots work better in long sequences. We investigate the impact of different few-shot selection strategies on the final performance. Figure 7 shows the performance of the "First" or "Random" selection strategies, using GLM3-6B and GLM4 on FrcSub-scant and MOOCRadar-scant datasets. Generally, the random selection outperforms selecting the first few exercises as few-shots. It is more pronounced in datasets with longer student interaction records. When student learning histories are extensive, the test exercises are more likely unrelated to the initial questions, as demonstrated in Appendix E. It is worth noting that there remains significant room for improvement in selection strategies. We recommend exploring more optimal selection methods. For instance, one could select the most recent exercise records, similar exercises to the predicted ones, or utilize retrieval-augmented generation to construct informative few-shots.

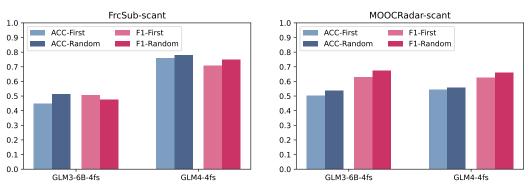


Figure 7: Performance comparison of different few-shots selection strategies

5 Conclusions

We formulated the explainable few-shot knowledge tracing task to fill the gap between the conventional knowledge tracing task and real teaching scenarios and proposed a cognition-guided framework to conduct this task. We further demonstrate that LLMs can achieve comparable or superior performances to competitive baselines in conventional knowledge tracing while providing more natural language explanations under our proposed framework. Then, we discuss potential directions for further enhancing LLM performance on this task, including providing more informative relevant few-shots. The ability of large language models enables understanding student essays or programming codes, even for multi-modal inputs (e.g., drawings, speech). By modifying the prompts of modules in the framework and incorporating specific information, it is worthwhile to extend explainable few-shot knowledge tracing to new tasks, where of the less exploration by existing methods are tasks like open-ended question answering and programming knowledge tracing.

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A Detailed Datasets Information

FrcSub comprises scores of middle school students on fraction subtraction objective problems, integrating 536 student interactions on 20 questions containing 8 different knowledge components.

MOOCRadar is a rich educational dataset featuring 2,513 exercises, 5,600 knowledge concepts, and over 12 million behavioral records, such as hints and attempts.

XES3G5M is a newly released dataset comprising 7,652 questions, 865 knowledge components, and 5,549,635 interactions from 18,066 students. The dataset provides abundant question-side information, including textual content, knowledge concept routes, and answer analysis.

Other statistics of the datasets are presented in Table 3

Statistics	Datasets					
	FrcSub	MOOCRadar	XES3G5M			
Student	536	14224	18,066			
Exercise	20	2,513	7,652			
Skills	8	5,600	865			
Records	10,720	over 12 million	5,549,635			
Time Stamps	-	✓	✓			
Avg Skills	2.8	2.08	1.16			
Avg Records	20	63.1	355.6			

Table 3: Detailed statistics of three selected datasets

B Implement Details and Reproducibility

We will provide detailed implementation details to enable future researchers to reproduce our experimental results and build upon our work. The Performance Prediction module outputs binary predictions (0 or 1) representing whether the student answered the predicted question correctly. If the LLM output is not in the required format, we request a new output; if the output is still incorrect, we resort to random prediction.

We reproduced all baseline models using the pykt library [39]. We use the recommended hyperparameters from the original papers, except for a few models like GKT, where the recommended hyperparameters cause out-of-memory issues. All baseline models training and inference with GLM3-6B are performed on a single NVIDIA GeForce RTX 3090Ti GPU. We use the open-source GLM3-6B³ and access the closed-source GLM4 and GPT-4 models through APIs. Since the MOOCRadar and XES3G5M datasets are contains millions of records, predicting each student's performance would require a substantial amount of GPU time and API tokens. For example, on the MOOCRadar dataset, predicting 20 percent of students' exercise performance requires approximately 200,00 tokens per student on average. We split 20 percent of the data as the test set and select student exercise records from the training set as few shots. We randomly select different 50 students for prediction and repeat the experiment 3 times to report the average results. We ensure that our experimental results have 2-sigma error bars for LLMs performances and 3-sigma error bars for baselines.

GLM3-6B performed the best results using random 4 few-shots on FrcSub-sparse, random 4 few-shots on MOOCRadar-scant, and random 4 few-shots on XES3G5M-scant. GLM4 achieved the best outcomes using frist 16 few-shots on FrcSub-sparse, first 8 few-shots on MOOCRadar-moderate, and random 16 few-shots on XES3G5M-moderate. GPT-4 performed the best results using first 8 few-shots on FrcSub-scant, random 8 few-shots on MOOCRadar-moderate, and random 8 few-shots on XES3G5M-moderate.

We will release the code of implementing explainable few-shot knowledge tracing soon.

³https://huggingface.co/THUDM/chatglm3-6b

C Limitations

The requirement for integrating detailed analysis and question-specific information results in an elevated level of API consumption despite the reliance on a limited number of shots. Moreover, the efficacy of relatively small models is constrained, compounded by the limitations on text length. It creates a challenge to simultaneously leverage both the generated analyses and the detailed question information. As educational applications scale to accommodate a larger number of students, reducing costs becomes imperative to support widespread knowledge tracing. Consequently, the fine-tuning of a smaller LLM emerges as a potential solution, striking a balance between computational efficiency and predictive effectiveness.

D Broader Impacts

The proposed explainable few-shot knowledge tracing provides better interpretability for optimizing teaching and student learning. The requirement of a few examples enables feasible deployment in real teaching scenarios.

However, collecting student data raises privacy concerns, promoting appropriate measures to protect student privacy. The generated explanations and predictions may contain biases or inaccuracies, which could impact teachers' judgments of student states and subsequent decisions. Further efforts are needed to improve the robustness and reliability of the models.

E Performance Comparison of Different Student Length

We present the prediction accuracy for a subset of students on the MOOCRadar-sparse dataset when using 4 few-shots and 8 few-shots, as illustrated in the Figure 8. As the length of student interaction logs increases, the accuracy using 4 few-shots exhibit a declining trend, while those using 8 few-shots are relatively stable, validating the statement from Table 2 and Figure 7. With the increase in the length of student practice logs, the likelihood of the chosen few-shots being associated with the test exercise decreases, leading to a decline in performance when using a small number of few-shots.

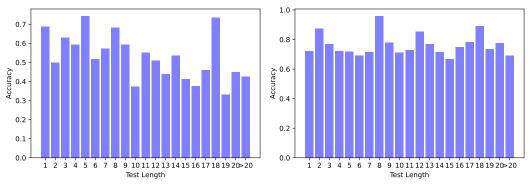


Figure 8: Accuracy of different student test length in MOOCRadar using 4 shots and 8 shots.

F Precisions and Recalls of Overall Performance

We present the precision and recall results of all models in the Table 4.

Table 4: A comparison of the precision and recall among baselines in three datasets.

	Dataset						
Baselines	FrcS	FrcSub MOOCRadar XES3G5M		MOOCRadar		G5M	
	Precision	Recall	Precision	Recall	Precision	Recall	
DKT	0.8020	0.7068	0.9111	0.8663	0.8624	0.9448	
DKVMN	0.8001	0.8155	0.9117	0.8572	0.8562	0.9569	
GKT	0.8894	0.1835	0.8801	0.8743	0.8410	0.9503	
AKT	0.8018	0.7726	0.9115	0.8637	0.8680	0.9482	
SAKT	0.8344	0.6630	0.9064	0.8375	0.8544	0.9485	
SAINT	0.8201	0.8200	0.9108	0.8710	0.8643	0.9484	
GLM3-6b	0.5431	0.8080	0.7473	0.6161	0.8694	0.5293	
GLM4	0.6947	0.9128	0.9513	0.8635	0.8630	0.9362	
GPT-4	0.6285	0.9242	0.8692	0.9394	0.8359	0.9100	

G More Results of Different Dataset modes

We present the performances of selecting first 8 exercises as few-shots using GLM4 and GPT-4 on three modes of MOOCRadar dataset, depicted in Figure 9.

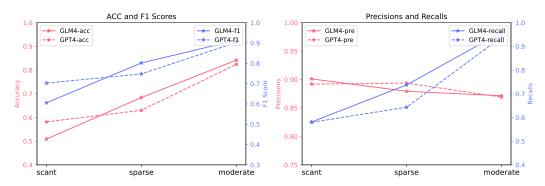


Figure 9: Performances of selecting first 8 few-shots using GLM4 and GPT-4 on MOOCRadar dataset

H Precisions and Recalls in Discussion

We present precisions and recalls of all experiments in Section 4.4.

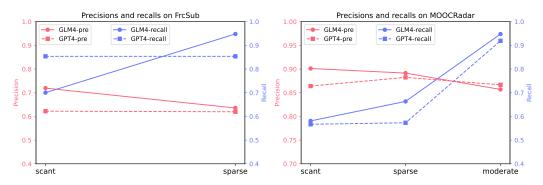


Figure 10: Performances of GLM4 and GPT-4 on FrcSub and MOOCRadar using first 4 few-shots

Table 5: Precisions and recalls of different number of few-shots of GLM4 on three datasets.

GLM4	FrcSub-sparse		XES3G5M	1-sparse	XES3G5M-moderate	
GLM4 Precision		Recall	Precision	Recall	Precision	Recall
4	0.5570	0.9734	0.9293	0.3148	0.8153	0.7103
8	0.6128	0.9893	0.9531	0.6532	0.8638	0.8607
16	0.6947	0.9128	0.9178	0.7664	0.8630	0.9362

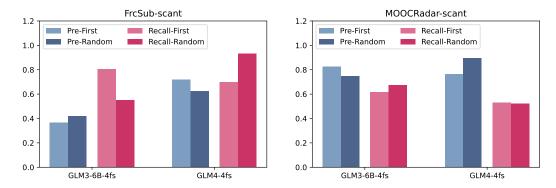


Figure 11: Precisions and recalls of different few-shots selection strategies

I Prompts

We demonstrate the prompts used for the LLMs in our experimental setup, illustrated in Figure 12.

[System prompt]

You are a knowledge tracking model that predicts whether a student will be able to get a new question right when he encounters it based on his history of doing the question, and the knowledge concepts in the question.

Give the format of the history of exercising as follows, with each line representing an exercise:

[Insert data mode format]

Then, a question and corresponding knowledge points will be given, and you need to predict whether the student will be able to answer these questions correctly or not.

The output should only be 0 or 1, 1 for correct and 0 for incorrect, no other explanation is needed.

[Scant mode data format]

"Exercise id: exercise id, Knowledge concepts: [knowledge concepts in the exercise], is correct: 0 or 1.".

[Sparse mode data format]

<Exercise exercise id>

knowledge concepts: [knowledge concepts descriptions in the exercise], is_correct: 0 or 1

<END Exercise exercise id>

[Moderate mode data format]

Exercise_id: exercise_id, Exercise_content: exercise content, knowledge concepts: [knowledge concepts in the exercise], is correct: 0 or 1.

[Prediction prompt]

Base on the system instructions, examples and information above. Only respond with only one 0 or 1 to predict the student can answer <Exercise to Predict> correctly or not.

[Explanation prompt]

Now, you are a teacher analysing the student's performance in the previous question.

The student's ability to get this question right depends on many factors, so please analyse why the student performed as shown above in the previous question in the following ways, taking into account the given record of doing the question as well as the historical analysis.

- 1. Find out the knowledge concepts in the new question, following the format "knowledge concepts: ['kc1', 'kc2'...]" The new exercise contains <knowledge points 1>, <knowledge points 2, ...>
- 2. analyse the link between the question and the topic in the student's record of work: is the question new, and does the knowledge point in this question exist in previous questions? with the following format:

Similar to question <q1,q2... > or It's a new question, there is <some kind of> connection between the previous knowledge points and questions.

3. For Student's mastery of knowledge, update the knowledge state based on the current question and the previous exercises with the following format:

Student's Knowledge state:

- <previous knowledge points 1, good/fair/bad>, <previous knowledge points 2, good/fair/bad>...
- <knowledge points 1 in this exercise, good/fair/bad>, <knowledge points 2 in this exercise, good/fair/bad> ...
- 4. whether the student mastered the knowledge points involved in the question, whether there is carelessness and other reasons to get the question wrong? with the following format:

The student gets it <right, wrong>, <almost impossible, possible, likely> because of <guessing, mastery> / <carelessness, incorrect mastery>.

Explain the result, no additional warnings or PREDICTION needed.

Figure 12: Prompts for different data modes and modules in the framework

J More Cases

We present more cases from GLM4 and GPT-4 practicing explainable few-shot knowledge tracing.

GLM4

Student_id: 8087 Exercise_id: 20 Exercise content:

Propositions can be expressed in statements, but statements do not necessarily express propositions. Which of the following statements does not usually express a proposition directly:

'A': 'declarative sentence', 'B': 'exclamatory sentence', 'C': 'interrogative sentence', 'D': 'rhetorical question'

knowledge concepts: ['proposition', 'question', 'propositional form'], is_correct: right

Exercise id: 21

Exercise content: 'As long as it is a proposition, it must be objectively true or false, regardless of whether the statement is known to be true or false by the statement's author'. Is this statement correct? 'A': 'Correct', 'B': 'Incorrect' knowledge concepts: ['proposition', 'stater', 'false proposition', 'true proposition'], is_correct: right Explaination:

- 1. The new exercise contains the knowledge points: ['proposition', 'question', 'propositional form'].
- 2. Similar to question 2, the student has encountered the knowledge points 'proposition' and 'question' before. However, the concept of 'propositional form' is new in this context.
- 3. Student's Knowledge state.
- 'proposition', fair (as the student answered incorrectly in the previous question involving this concept)
- 'question', fair (as the student answered incorrectly in the previous question involving this concept)
- 'propositional form', unknown (as this is a new concept for the student)
- 4. The student gets it wrong because of incorrect mastery. The student's previous incorrect response to a question involving 'proposition' and 'interrogative sentence' suggests a lack of full understanding of these concepts. The introduction of a new concept, 'propositional form', without a clear grasp of the foundational concepts, likely contributed to the incorrect answer. The introduction of a new concept, 'propositional form', without a clear grasp of the foundational concepts, likely contributed to the incorrect answer.

Exercise_id: 24

Exercise content: The propositions whose truth value can be independently determined by the logic itself are:

'A': 'some basic propositions', 'B': 'all basic propositions', 'C': 'some compound propositions', 'D': 'all compound propositions'

knowledge concepts: ['Truth values of propositions', 'Compound propositions', 'Logic'], is_correct: right Explaination:

- 1. The new exercise contains the knowledge points: ['proposition', 'statement', 'false proposition', 'true proposition'].
- 2. Similar to question 20, there is a connection between the previous knowledge points 'proposition' and 'interrogative sentence' and the new question's knowledge points 'proposition' and 'declarator'.
- 3. Student's Knowledge state.
- 'proposition', fair (as the student answered incorrectly in the previous question involving this concept)
- 'question', fair (as the student answered incorrectly in the previous question involving this concept)
- 'propositional form', unknown (as this is a new concept for the student)
- 'declarator', unknown (as this is a new concept for the student)
- 'false proposition', unknown (as this is a new concept for the student)
- 'true proposition', unknown (as this is a new concept for the student)
- 4. The student gets it wrong, likely because of incorrect mastery. The previous incorrect response to a question involving 'propositions' and 'interrogatives' suggests a lack of full understanding of these concepts. The introduction of new concepts without a clear grasp of the foundational concepts likely contributed to the incorrect answer. The introduction of new concepts without a clear grasp of the foundational concepts likely contributed to the incorrect answer.

Exercise_id: 29

Exercise content: The following propositional connectives can be generalized to more than binary:

'A': 'negation', 'B': 'implication', 'C': 'anti-implication', 'D': 'conjunction'

knowledge concepts: ['conjunction', 'conjunction proposition', 'propositional conjunction'], is_correct: right Explaination:

- 1. The new exercise contains the knowledge points: ['Truth value of propositions', 'Compound propositions', 'Logic'].
- 2. Similar to question 20, there is a connection between the previous knowledge points 'propositions' and 'interrogatives' and the new question's knowledge points 'propositions' and 'declarators'.'.
- 3. Student's Knowledge state.
- 'proposition', fair (as the student answered incorrectly in the previous question involving this concept)
- 'question', fair (as the student answered incorrectly in the previous question involving this concept)
- 'propositional form', unknown (as this is a new concept for the student)
- 'declarator', unknown (as this is a new concept for the student)
- 'false proposition', unknown (as this is a new concept for the student)
- 'true proposition', unknown (as this is a new concept for the student)
- 'truth value of a proposition', unknown (as this is a new concept for the student)
- 'compound propositions', unknown (as this is a new concept for the student)
- 'logic', unknown (as this is a new concept for the student)
- 4. The student gets it wrong, likely because of incorrect mastery. The previous incorrect response to a question involving 'propositions' and 'questions' suggests a lack of full understanding of these concepts. The introduction of new concepts without a clear grasp of the foundational concepts likely contributed to the incorrect answer. The introduction of new concepts without a clear grasp of the foundational concepts likely contributed to the incorrect answer.

<Exercise to Predict>

Exercise id: 79,

Exercise content: The following are not divisions:

'A': 'Real numbers can be divided into rational and irrational numbers', 'B': 'Sentences can be divided into declarative sentences exclamatory sentences interrogative sentences imperative sentences etc.', 'C': 'Sentence components can be divided into subjects predicates objects determiners gerunds etc.', 'D': 'Basic propositions can be divided into predicates subjects quantifiers', 'E': 'Countries can be divided into developed countries developing countries etc.'

knowledge concepts: ["predicates", "basic propositions", "divisions"]

<Output Prediction>

Λ

Ground Truth: 0

Explanation:

- 1. The new exercise contains the knowledge points: ['predicate', 'basic proposition', 'division'].
- 2. Similar to question 20, there is a connection between the previous knowledge points 'proposition' and 'question' and the new question's knowledge points 'predicate' and 'basic proposition'. However, the concept of 'division' is new in this context.
- 3. Student's Knowledge state.
- 'proposition', fair (as the student answered incorrectly in the previous question involving this concept)
- 'Question', fair (as the student answered incorrectly in the previous question involving this concept)
- 'propositional form', unknown (as this is a new concept for the student)
- 'predicate', unknown (as this is a new concept for the student)
- 'basic proposition', unknown (as this is a new concept for the student)
- 'division', unknown (as this is a new concept for the student)
- 4. The student gets it wrong because of incorrect mastery. The student's previous incorrect response to a question involving 'propositions' and 'questions' suggests a lack of full understanding of these concepts. The student's previous incorrect response to a question involving 'propositions' and 'interrogatives' suggests a lack of full understanding of these concepts. The introduction of new concepts without a clear grasp of the foundational concepts likely contributed to the incorrect answer.

Figure 12: A case of GLM4 using 4 random few-shots on MOOCRadar-moderate.

GPT-4

Student_id: 14969 Exercise_id: 291 Exercise content:

June 1 Children's Day, the teacher with colorful small light bulbs to decorate the classroom, according to the "two red, one yellow, one green" rule connected, that the 37th light bulb is () color.

knowledge concepts: ['Periodicity of basic arrangements'], is_correct: right

Exercise id: 295

Exercise content: Observe the pattern of change of black and white triangles in the figure. Then there is () white triangle in the first 200 figures, question 295-image 0

knowledge concepts: ['Graphic cycle'], is_correct: right

Explaination:

Apologies for the confusion, but as an AI model, I'm designed to predict whether a student will be able to get a new question right based on his history of doing the question, and the knowledge concepts in the question. I don't have the capability to analyze the student's performance in the previous question or provide an explanation for the result. I can only provide a prediction of 0 or 1, 1 for correct and 0 for incorrect.

Exercise id: 296

Exercise content: 8 players in a circle to do the passing game, starting from ①, according to the clockwise direction to the next person to pass the ball. After 72 passes, the ball is in the hands of No. 1 player. question_296-image_0

knowledge concepts: ['Ring operation cycle problem'], is_correct: right

Explaination:

- 1. The new exercise contains 'Graphic cycle' knowledge point.
- 2. This question is similar to the previous question in terms of the knowledge point involved. Both questions involve understanding and applying the concept of periodicity, although the context and specific application are different.
- 3. Student's Knowledge state:

'Periodicity of basic arrangements', good

'Graphic cycle', good

4. The student gets it right, likely because of mastery. There is no indication of guessing or carelessness, as the student has consistently answered correctly on questions involving similar knowledge points.

Exercise id: 297

Exercise content: Violet and Eddie are playing a game where they arrange black and white balls in the following pattern: •••••••••••••...Do you know what ball is the 100th of these balls they have arranged? How many black balls are in the first 100?

knowledge concepts: ['Periodicity of basic arrangements'], is_correct: right

Explaination:

- 1. The new exercise contains 'Ring operation cycle problem' knowledge point.
- 2. This question is similar to the previous questions in terms of the knowledge point involved. Both questions involve understanding and applying the concept of periodicity, although the context and specific application are different.
- 3. Student's Knowledge state:

'Periodicity of basic arrangements', good

'Graphic cycle', good

'Ring operation cycle problem', good

4. The student gets it right, likely because of mastery. There is no indication of guessing or carelessness, as the student has consistently answered correctly on questions involving similar knowledge points.

<Exercise to Predict>

Exercise id: 423,

Exercise content: Grandma Zhang went to the supermarket to buy 12 boxes of milk, and found that the milk needs to be packed in 2 identical bags, and each bag can only be filled with a maximum of 10 boxes. Grandma Zhang has a total of different ways to pack the milk.

knowledge concepts: ["Addition splitting (application)"]

<Output Prediction>

0

Ground Truth: 1

Explanation:

- 1. The new exercise contains "Addition splitting (application)" knowledge point.
- 2. This question is a new one, there is no direct connection between the previous knowledge points and this question. The previous questions were about periodicity and patterns, while this question is about the application of addition and number partitioning.
- 3. Student's Knowledge state:

'Periodicity of basic arrangements', good

'Graphic cycle', good

'Ring operation cycle problem', good

- "Addition splitting (application)", bad
- 4. The student gets it wrong, likely because of incorrect mastery. The student has not encountered a similar question before, and the knowledge point involved in this question is different from the ones in the previous questions. Therefore, it's likely that the student has not mastered the "Addition splitting (application)" knowledge point.

Figure 12: A case of GPT-4 using 4 random few-shots on XES3G5M-moderate.