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RESEARCH ARTICLE

# Breaking Student-Concept Sparsity Barrier for Cognitive Diagnosis

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**Abstract** Educational Cognitive Diagnosis (CD) aims to provide students' mastery levels on different concepts. One common observation is that students often conduct many exercises but engage with a small subset of concepts, leading to a sparsity barrier. Current CD models mostly adopt mastery levels on all concepts as student modeling, overlooking the sparsity barrier. If a student does not interact with all concepts, we can not ensure that each dimension of mastery levels on concepts can be well-trained. In this paper, we propose a novel *E*nhancing *S*tudent *R*epresentations in *C*ognitive *D*iagnosis (*ESR-CD*), which combines application abilities and comprehension degrees for mastery levels on concepts. To model application ability, we propose a sparsity-based mask module that solely depends on the dense student-concept entries. Simultaneously, to further enhance comprehension degrees, we propose two layers: a matrix factorization layer and a relation refinement layer. Extensive experiments on two real-world datasets demonstrate the effectiveness of ESR-CD.

**Keywords** Cognitive Diagnosis, Student Modeling, Educational Data Mining

## 1 Introduction

Educational data mining has experienced rapid developments due to easy-to-collect data in online education platforms and superior performance, e.g., cognitive diagnosis [1–4], knowledge tracing [5,6]. Cognitive Diagnosis (CD) has received much attention due to its practical significance and relatively high performance. As shown in Figure 1, CD takes students' response logs on exercises and relations between exercises and concepts (exercise-concept relations) as input, and outputs students' mastery levels on all concepts [7, 8].

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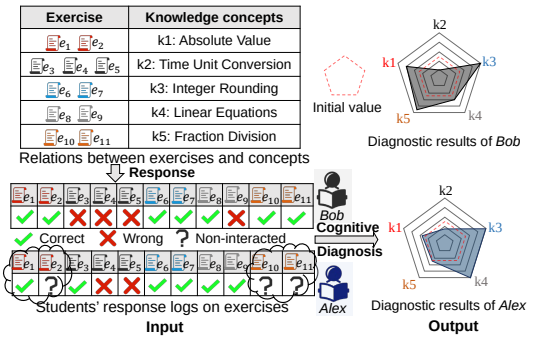



**Fig. 1** A tiny example of cognitive diagnosis.

Recently, neural network-based CD models have achieved impressive performance [7, 9, 10]. These models output students' mastery levels on all concepts. Each dimension of mastery levels is independent of each other, leading to the sparsity barrier between students and concepts (student-concept sparsity barrier). Taking Figure 1 as an example, Bob provides sufficient interactions with all five concepts while Alex does not provide sufficient interactions with concept $k1\&k5$. These CD models can provide accurate diagnostic results for Bob, but they cannot provide satisfactory results for Alex on concepts $k1\&k5$. To further analyze the existence and effects of sparsity barriers, we conduct experiments, and the experimental results are presented in Section 3.3. From the results, we observe sparsity barriers on real-world datasets (i.e., most students conduct many exercises involved with a limited number of concepts), and find that existing neural network-based CD models are heavily constrained by the sparsity barrier.

One promising direction is to use expert-annotated relationships among different concepts [11,12]. However, this requires additional costs, and there are mistakes with these annotations, e.g., the presence of cyclic concept dependencies in Junyi [11, 12]. Hence, relying on concept relationships to enhance the quality of mastery levels is not a satisfactory option. Further, previous studies have already identified incomplete annotations in exercise-concept relations [8, 13], which also leads to difficulties in improving the quality of mastery levels. We consider: *how to improve quality of mastery levels in CD with the presence of the sparsity barrier?*

To this end, we propose *E*nhancing *S*tudent *R*epresentations in *C*ognitive *D*iagnosis (*ESR-CD*), an accurate and robust CD model. Our intuition is from a conclusion from *Kay et al.* [14]: a correct answer require both knowledge and foundational abilities. We take an exercise example to show why foundational abilities are necessary: *"A road needs to be repaired with daily progress of 48 meters, and it will take 25 days. If we want to finish the task 5 days* ***earlier****, how many meters should be repaired each day?"* To correctly answer this exercise, a student should not only grasp the arithmetic concept, but also notice the essential word "earlier". Noticing the essential word can be seen as a part of reflection on this student's foundational abilities. To this end, we decompose the overall student modeling into two parts in this paper: 1) *comprehension degree* denotes how much level students master the concepts. 2) *application ability* denotes the ability to apply learned knowledge to real exercises. In the presence of the student-concept barrier, certain dimensions of comprehension degrees are not adequately trained. However, for application ability, sufficient interactions with a subset of knowledge concepts are enough. A student's application ability maintains consistency across interactions with all concepts, therefore, we can assess a student's application ability by analyzing her performance on a small subset of concepts. Specifically, to obtain application ability, we propose a sparsity-based mask module that solely depends on the dense student-concept entries. To enhance com-

prehension degrees, we propose two layers: a matrix factorization layer and an exercise-concept relation refinement layer. Extensive experiments on two real-world datasets have demonstrated the effectiveness and robustness of ESR-CD. In summary, our contributions are as follows:

- We find that the student-concept sparsity barrier limits CD developments, making it impossible to assess students' mastery levels on concepts they have not encountered. This sparsity phenomenon is widely prevalent in real-world datasets.
- To break the barrier, we argue that student modeling should consider both application ability and comprehension degrees on concepts, and propose ESR-CD, an accurate and robust CD model.
- Extensive experiments on two datasets demonstrate the effectiveness of ESR-CD. For random split, ESR-CD achieves AUC improvements of average 0.5%. For concept weak coverage split, compared to KaNCD, ESR-CD has AUC improvements of over 1.5% on the ASSIST dataset and over 6% on the MOOC-Radar dataset.

## 2 Related Work

### 2.1 Cognitive Diagnosis

CD takes students' response logs on exercises and exercise-concept relationships as input and outputs students' mastery levels on all concepts [15–19]. Classic methods include item response theory [15], meta-knowledge dictionary learning [20], and the Deterministic Inputs, Noisy And gate model [21]. Recently, researchers have focused on leveraging neural networks in CD [8, 22, 23]. Neural Cognitive Diagnosis Model (NCDM) first uses high-dimensional representations to model students' mastery level on each knowledge concept, then proposes diagnostic functions for parameter incorporation, and finally identifies students' non-mastery on their unanswered exercises [7]. The NCDM framework not only offers student performance predictions but also provides students' mastery levels on concepts. Relation map driven Cognitive Diagnosis (RCD) integrates different pre-defined graphs among students, items, and concepts to model connections [11]. For long-term development, researchers propose beginner-friendly frameworks [24], and emphasize aspects such as efficiency [25], interpretability [26, 27], and fairness [28–31].

### 2.2 Alleviating Sparsity in User Modeling

Data sparsity is a prevalent challenge in user modeling, e.g., recommender systems [32–35]. It occurs when there is limited interaction data, resulting in a scarcity of ratings or records. To address the issue, researchers have proposed effective methods including side information (e.g., social neighbors [32, 36], review text [37], and multimedia information [38]), or mining high-order user-item bipartite graph structure information [39].

**Our Distinction:** The student-concept sparsity barrier in CD and the classical definition differ in granularity. Classical user modeling tasks (e.g., recommender systems) do not pursue the interpretability of each dimension in the user representation. If a user interacts with any items, regardless of the categories, we consider this user's data is not sparse. In contrast, CD emphasizes students' mastery levels on all concepts. If student $s$ does not provide interactions with concept $k$, there is a sparsity barrier between student $s$ and concept $k$.

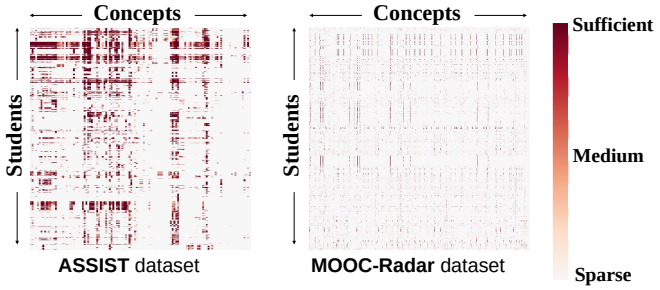
## 3 Preliminary

### 3.1 Task Overview

Suppose that there are student entities $S(|S| = M)$, exercise entities $E(|E| = N)$, and knowledge con-

| Model | $\eta$ (%) | ACC ↑ | AUC ↑ | DOA ↑ |
|---|---|---|---|---|
| NCDM | 0 | 0.7158 | 0.7687 | 0.6514 |
| | 20 | 0.7066 | 0.7480 | 0.6423 |
| | 40 | 0.7009 | 0.7389 | 0.6408 |
| | 60 | 0.6902 | 0.7220 | 0.6214 |
| | 80 | 0.6733 | 0.6976 | 0.6067 |
| | 90 | 0.6384 | 0.6451 | 0.5345 |
| | 100 | 0.6280 | 0.6075 | 0.4953 |
| KaNCD | 0 | 0.7304 | 0.7785 | 0.6752 |
| | 20 | 0.7205 | 0.7624 | 0.6545 |
| | 40 | 0.7111 | 0.7528 | 0.6489 |
| | 60 | 0.7042 | 0.7332 | 0.6285 |
| | 80 | 0.6857 | 0.7057 | 0.6167 |
| | 90 | 0.6496 | 0.6642 | 0.5675 |
| | 100 | 0.6350 | 0.6083 | 0.5185 |

(a) Performance of two representative CD models on the **ASSIST** dataset




(b) Sparsity visualization on two datasets

**Fig. 2** Analyses about sparsity between students and concepts. Students are not directly related to concepts. In CD, if a student never or rarely conducts exercises related to a concept, we think that interactions between this student and the concept are sparse. **(a)** Performance of two representative neural network-based CD models on ASSIST dataset. We manually simulate different ratios ($\eta$) of sparsity between students and selected concepts. The simulation method can be found at **Varying Sparsity Levels** in Section 5.4. **(b)** Among all student-concept entries, over 92% entries correspond to sparse interactions on the ASSIST dataset, and over 98% entries correspond to sparse interactions on the MOOC-Radar dataset.

cepts $K(|K| = T)$ in an intelligent education system. There are two types of relationships among these entities. First, students will practice some exercises, forming response logs $\{(s, e, r_{se})\}$. If student $s$ answers exercise $e$ correctly, $r_{se} = 1$. Otherwise if student $s$ answers exercise $e$ wrongly, $r_{se} = 0$. $R_{train}$ and $R_{test}$ respectively denote the training and testing response logs. Second, the relations between exercises and concepts are denoted by $\mathbf{Q} = \{q_{ek}\}_{N\times T}$, where $q_{ek}$ denotes the relation between exercise $e$ and concept $k$. If exercise $e$ is related to concept $k$, $q_{ek} = 1$; otherwise, $q_{ek} = 0$. $\mathbf{Q}_e = [q_{e1}, ..., q_{ek}, ..., q_{eT}]$ denotes the relations between exercise $e$ and all concepts. Usually, $\mathbf{Q}$ is pre-defined by experts. Finally, we formulate the CD task as follows,

*Input:* The response logs $R_{train}$ and exercise-concept relations $\mathbf{Q}$.

*Output:* A CD model to infer student modeling $\mathbf{A}$ through response log prediction.

### 3.2 The Existing NCDM Framework

Neural network-based CD models mostly adopt the NCDM framework [7, 11, 12]. The framework uses $\mathbf{A} = [\mathbf{a}_1, ..., \mathbf{a}_s, ..., \mathbf{a}_M]^\top \in \mathbb{R}^{M\times T}$ (students' mastery levels on concepts), and $\mathbf{a}_s = [a_{s1}, ..., a_{sk}, ..., a_{sT}]$. Each dimension of $\mathbf{a}_s$ has independent semantics, e.g., $a_{sk}$ denotes student $s$'s comprehension degree on concept $k$. NCDM framework also introduces exercise difficulties $\mathbf{D} = [\mathbf{d}_1, ..., \mathbf{d}_e, ..., \mathbf{d}_N]^\top \in \mathbb{R}^{N\times T}$ and discrimination $\mathbf{h}^{disc} = [h_1^{disc}, ..., h_e^{disc}, ..., h_N^{disc}]^\top \in \mathbb{R}^{N\times 1}$. Then, a diagnostic function is used to obtain the hidden representation between student $s$ and exercise $e$, formulated as:

$$\mathbf{x}_{se} = \mathbf{Q}_e \odot (\sigma(\mathbf{a}_s) - \sigma(\mathbf{d}_e)) \times h_e^{disc}, \tag{1}$$

where $\sigma$ denotes the Sigmoid activation function, and $\mathbf{x}_{se}$ denotes the hidden vector for student $s$ and exercise $e$. $\mathbf{Q}_e$ denotes the relations between concepts and exercise $e$, and $\odot$ denotes the element-wise multiplication.

### 3.3 Effects of Student-concept Sparsity Barrier

First, we present a theoretical analysis of the effects of the student-concept sparsity barrier on NCDM. For a response log $\{(s, e, r_{se})\}$, suppose that exercise $e$ is related to concept $k$, i.e., the $k$-th dimension of $\mathbf{Q}_e$ is 1 and other dimensions are 0. Element-wise multiplication $\odot$ operation will lead to the sit-

uation that only the $k$-th dimension value of $(\sigma(\mathbf{a}_s) - \sigma(\mathbf{d}_e)) \times h_e^{disc}$ is not masked. Hence, the given log $\{(s, e, r_{se})\}$ will only update $c_{sk}$. Consequently, the NCDM framework would not update corresponding comprehension degrees if students do not or rarely interact with some concepts.

Second, we conduct a laboratory experiment on real-world datasets in Fig. 2 to further investigate relationships between NCDM framework and the sparsity barrier. In Fig. 2 (a), we intentionally discard some data to simulate different sparsity ratios ($\eta\%$) between students and randomly selected concepts. According to the results, the sparsity barrier has an obvious negative impact on the performance of two representative CD models (NCDM [7] and KaNCD [13]), e.g., KaNCD has an obvious AUC decrease of over 10% when transitioning from discarding 0% to discarding 80% interactions.

Third, the wide presence of sparsity significantly limits CD developments. As visualized in Fig. 2 (b), both two real-world datasets exhibit obvious sparsity. Moreover, in computerized adaptive testing, researchers aim to minimize the exercise number given to students but keep accurate diagnosis, leading to student-concept sparsity [40].

## 4 The Proposed Model

In this section, we draw inspiration from a classic educational work [14]. This work argues that student modeling should at least consider students' learned knowledge and their foundational abilities. In other words, to correctly answer an exercise, a student should not only understand the concept, but also do well in applying her understanding to the exercise. Therefore, we propose that a student's mastery levels on all concepts should consider two parts, formulated as:

$$\forall s \in S, \forall k \in K, a_{sk} = c_{sk} + g_s. \tag{2}$$

$g_s$ denotes student $s$'s application ability. $a_{sk}$ denotes student $a$'s mastery level on concept $k$. $c_{sk}$ denotes student $a$'s comprehension degree on concept $k$. Fig.3 illustrates the overall structure of our proposed ESR-CD. In the remaining parts of this section, we will introduce ESR-CD in detail.

### 4.1 NN based Matrix Factorization Layer

Although student $s$ does not interact with concept $k$, her similar students may provide sufficient interactions. Inspired by this, we propose to utilize similar students to enhance the quality of comprehension degrees. Specifically, we transfer matrix factorization techniques into CD. We first embed entities into latent embeddings of student, exercise, and concept as: $\mathbf{U} = [\mathbf{u}_1, ..., \mathbf{u}_s, ..., \mathbf{u}_M]^\top \in \mathbb{R}^{M \times Z}$, $\mathbf{V} = [\mathbf{v}_1, ..., \mathbf{v}_e, ..., \mathbf{v}_N]^\top \in \mathbb{R}^{N \times Z}$ and $\mathbf{O} = [\mathbf{o}_1, ..., \mathbf{o}_k, ..., \mathbf{o}_T]^\top \in \mathbb{R}^{T \times Z}$. $Z$ denotes the dimension of free embeddings.

Note that, we cannot adopt any model relying on explicit discrete adjacency matrices, e.g., WRMF [41], or graph-based models [39]. The outputs of matrix factorization, i.e., comprehension degrees on concepts and exercise difficulties, are both continuous latent values without discrete ground truth labels. For these graph-based models, we cannot obtain a discrete adjacency matrix [39]. For WRMF, we cannot assign different weights to each entry without ground truth labels [41]. To this end, we adopt GMF, a neural network based method [42]:

$$c_{sk} = \mathbf{W}(\mathbf{u}_s \odot \mathbf{o}_k), d_{ek} = \mathbf{W}(\mathbf{v}_e \odot \mathbf{o}_k), \tag{3}$$

where student $s$'s comprehension degrees on all concepts $\mathbf{c}_s = [c_{s1}, ..., c_{sk}, ..., c_{sT}]$, where $c_{sk}$ denotes the comprehension degree of student $s$ on concept $k$. Students' comprehension degrees can be represented as $\mathbf{C} = [\mathbf{c}_1, ..., \mathbf{c}_s, ..., \mathbf{c}_M]^\top \in \mathbb{R}^{M \times T}$. Similarly, $\mathbf{d}_e = [d_{e1}, ..., d_{ek}, ..., d_{eT}]$, $\mathbf{D} = [\mathbf{d}_1, ..., \mathbf{d}_e, ..., \mathbf{d}_N]^\top \in \mathbb{R}^{N \times T}$. $\odot$ denotes the element-wise product, and $\mathbf{W}$ is a linear layer. Even if each row or column of $\mathbf{C}$

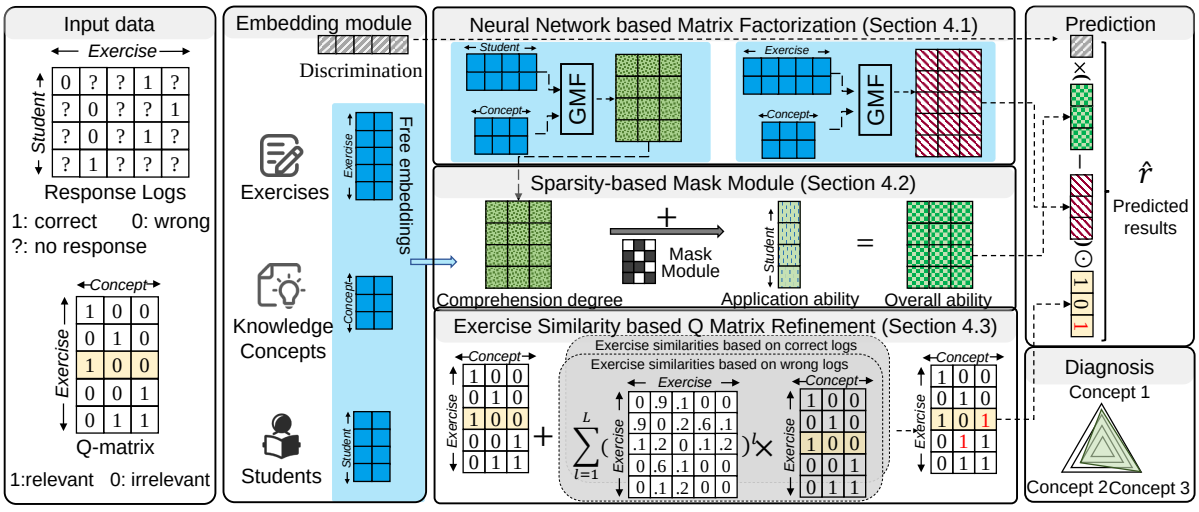



**Fig. 3** Overall structure of our proposed ESR-CD.

only involves a limited number of interactions, we can still optimize corresponding low-dimensional representations in $\mathbf{U}, \mathbf{V}$. Based on optimized low-dimensional representations, GMF enables better predicting $\mathbf{C}$ on non-interacted knowledge concepts.

## 4.2 Sparsity-based Mask Module

To model student $s$'s application ability $g_s$, previous works suggest estimating score deviation, i.e., average student scores [43], or a single learnable parameter [37]. In this paper, we propose that $g_s$ should be reflected in deviations of student performance on different concepts. Note that, $\mathbf{C}$ can also be seen as obtaining student performance on different concepts. An intuitive idea is to obtain student $s$'s application ability $g_s$ from $\mathbf{c}_s$. Furthermore, we find that dimensions in $\mathbf{C}$ corresponding to sparse student-concept interactions are less inaccurate than those corresponding to dense interactions. Therefore, we avoid effects from sparse student-concept interactions when modeling $g_s$. Following [44], we propose to estimate $g_s$ as:

$$g_s = \alpha_s\left(\frac{\sum \mathbf{b}_s \odot \mathbf{c}_s}{\sum \mathbf{b}_s}\right) + \mu_s, \tag{4}$$

where $\alpha_s$ and $\mu_s$ are both student-specific learnable parameters, and they form a student-specific mapping function. $\mathbf{b}_s = [b_{s1}, ..., b_{sk}, ..., b_{sT}]$ represents the mask module for student $s$. $b_{sk} = 1$ denotes that student $s$ has sufficient interactions with concept $k$, otherwise, $b_{sk} = 0$. $\mathbf{b}_s$ is designed for avoiding effects of sparse interactions on practical application ability $g_s$, formulated as $\frac{\sum \mathbf{b}_s \odot \mathbf{c}_s}{\sum \mathbf{b}_s}$. We provide an example to emphasize $\mathbf{b}_s$. Suppose there is a student John and five knowledge concepts. John has provided interactions with the first three concepts, and NCDM judges his mastery levels on these concepts to be 0.2, 0.8, 0.8, 0.5, and 0.5, respectively. Without $\mathbf{b}_s$, John's application ability will be estimated as (0.2 + 0.8 + 0.8 + 0.5 + 0.5) / 5 = 0.56. With $\mathbf{b}_s$, the estimated application ability should be (0.2 + 0.8 + 0.8) / 3 = 0.6. As 0.5 does not mean that John's mastery levels on the latter two knowledge concepts are exactly in an intermediate state, we choose to avoid their effects by adopting $\mathbf{b}_s$.

We argue that the small adjustment of modeling $g_s$ has important effects. To clearly show the effectiveness of $g_s$, we consider an example: student $s$ has not answered exercises related to concept $k$. We

focus on her mastery level on concept $k$ ($a_{sk}$). The estimation of $c_{sk}$ may be close to the initial value. $g_s$ can still be assessed as long as student $s$ provides sufficient interactions with any concepts as shown in Eq.(4). Therefore, we can make a preliminary estimation of $a_{sk}$ based on $g_s$.

### 4.3 Exercise Similarity based **Q** Matrix Refinement Layer

Previous studies have already identified the issue of incomplete annotations in **Q** [8, 13]. A classic work suggests that exercises with similar texts should be related to similar concepts [13]. However, it can not be adapted to datasets without exercise texts. In this paper, we borrow the idea that similar exercises should have a high probability of being assigned to the same concepts, and obtain exercise similarities based on historical response logs as follows:

$$
\begin{aligned}
I_{e_1e_2,0} &= \frac{\sum_{s\in S} \mathbb{1}_{r_{se_1}=r_{se_2}=0}}{\sqrt{|\sum_{s\in S} \mathbb{1}_{r_{se_1}=0}||\sum_{s\in S} \mathbb{1}_{r_{se_2}=0}|}}, \\
I_{e_1e_2,1} &= \frac{\sum_{s\in S} \mathbb{1}_{r_{se_1}=r_{se_2}=1}}{\sqrt{|\sum_{s\in S} \mathbb{1}_{r_{se_1}=1}||\sum_{s\in S} \mathbb{1}_{r_{se_2}=1}|}},
\end{aligned}
\tag{5}
$$

where $\mathbb{1}$ denotes the indicator function ($\mathbb{1}_{true} = 1$, $\mathbb{1}_{false} = 0$). $\sum_{s\in S} \mathbb{1}_{r_{se_1}=r_{se_2}=0}$ denotes the number of the same logs between exercise $e_1$ and $e_2$. $\sqrt{|\sum_{s\in S} \mathbb{1}_{r_{se_1}=0}||\sum_{s\in S} \mathbb{1}_{r_{se_2}=0}|}$ denotes the normalization. Quantities in $I_{e_1e_2,1}$ can be understood analogously. $I_{e_1e_2,0}$,$I_{e_1e_2,1}$ respectively denote similarities between exercise $e_1$ and $e_2$ according to incorrect/correct answers, thus forming $\mathbf{I}_0, \mathbf{I}_1 \in \mathbb{R}^{N\times N}$. Based on $\mathbf{I}_0, \mathbf{I}_1$, we propose to refine **Q** as follows:

$$
\hat{\mathbf{Q}} = (1 - \mathbf{Q}) \odot \Delta(\mathcal{D}_0^{-1}\mathbf{I}_0\mathbf{Q} + \mathcal{D}_1^{-1}\mathbf{I}_1\mathbf{Q}) + \mathbf{Q}, \tag{6}
$$

where $\mathcal{D}_0$ and $\mathcal{D}_1$ denote the degree matrices for $\mathbf{I}_0$ and $\mathbf{I}_1$, respectively. $\mathcal{D}_0^{-1}\mathbf{I}_0\mathbf{Q} + \mathcal{D}_1^{-1}\mathbf{I}_1\mathbf{Q}$ denotes the process of aggregation based on $\mathbf{I}_0, \mathbf{I}_1$. $\odot$ denotes the element-wise, and $(1 - \mathbf{Q}) \odot \Delta(\mathcal{D}_0^{-1}\mathbf{I}_0\mathbf{Q} + \mathcal{D}_1^{-1}\mathbf{I}_1\mathbf{Q})$ denotes that only zero-value elements in original **Q** will be considered. Then, we adopt a threshold operation $\Delta$. $\Delta$ sets entries in $(\mathcal{D}_0^{-1}\mathbf{I}_0\mathbf{Q} + \mathcal{D}_1^{-1}\mathbf{I}_1\mathbf{Q})$ larger than a certain value to 1, while leaving other entries as 0. $\hat{\mathbf{Q}}$ denotes updated exercise-concept relations. Note that, we also consider all one-value elements in original exercise-concept relations, and this refinement layer would ensure that more dimensions of students' comprehension degrees are adequately trained.

### 4.4 Prediction Layer

Following previous work [7, 11], we directly adopt a 1-dimensional embeddings for discrimination $\mathbf{h}^{disc} = [h_1^{disc}, ..., h_e^{disc}, ..., h_T^{disc}]$. Then, we obtain $\mathbf{x}_{se}$ as:

$$
\mathbf{x}_{se} = \hat{\mathbf{Q}}_e \odot (\sigma(\mathbf{a}_s) - \sigma(\mathbf{d}_e)) \times h_e^{disc}, \tag{7}
$$

where $\hat{\mathbf{Q}}_e$ denotes updated relations between exercise $e$ and all concepts. Then, $\hat{r}_{se} = \sigma(MLPs(\mathbf{x}_{se}))$. $\hat{r}_{se}$ is predicted response log. Similar to previous studies [7, 12, 13], we adopt a monotonicity assumption: the probability of correct response to the exercise is monotonically increasing at any dimension of the student's overall all abilities **A**. We make weight parameters in $MLPs$ be nonnegative to fit the assumption. Finally, we adopt the BCE loss:

$$
\mathcal{L} = -\sum_{s,e,r_{se}\in R_{train}} (r_{se}log(\hat{r}_{se}) + (1 - r_{se})log(1 - \hat{r}_{se})). \tag{8}
$$

To enhance clarity and facilitate understanding, we present the overall training procedures of our proposed ESR-CD in detail in Algorithm 1. We first initialize all trainable parameters, calculate exercise similarities to obtain the mask module **B** and exercise-concept relations $\hat{\mathbf{Q}}$. During training, we process batches of data by combining different embeddings based on the diagnosis function in Eq.(7, and mapping $\mathbf{x}_{se}$ to predicted response logs. After that, we minimize the loss to optimize trainable parameters. This process will be conducted repeatedly until the model converges.

**Algorithm 1** Training procedures of ESR-CD.

**Require:** Training response logs $R_{train}$, exercise-concept relations $\mathbf{Q}$.

**Ensure:**

Initialize all trainable parameters,
Calculate exercise similarities $\mathbf{I}_0$ and $\mathbf{I}_1$ (Eq.(5)), and obtain the mask module $\mathbf{B}$ (Eq.(4)),
Update $\hat{\mathbf{Q}}$ based on $\mathbf{I}_0$ and $\mathbf{I}_1$,
**repeat**
  Get a batch of training data $((s, e, r_{se}))$,
  **for** each $(s, e, r_{se})$ in the batch **do**
    Obtain $\mathbf{U}_s$, $\mathbf{V}_e$, $h_e^{disc}$,
    Obtain comprehension degrees $\mathbf{c}_s$ and difficulty $\mathbf{d}_e$ (Eq.(3)),
    Obtain application ability $g_s$ (Eq.(4)),
    Obtain mastery levels $\mathbf{a}_s$ (Eq.(2)),
    Incorporate $\hat{\mathbf{Q}}$, $\mathbf{a}_s$, $\mathbf{d}_e$, and $h_e^{disc}$ (Eq.(7)),
    Obtain prediction $\hat{r}_{se} = \sigma(MLPs(\mathbf{x}_{se}))$, and calculate loss (Eq.(8)),
  **end for**
  Minimize loss to optimize parameters.
**until** Model convergence.

## 5 Experiments

In this section, we will answer the following Research Questions (RQ):

RQ1: Does ESR-CD have consistently superior performance? (Section 5.2)

RQ2: Are all components essential? (Section 5.3)

RQ3: How do choices of hyper-parameters or model structures affect ESR-CD? (Section 5.4)

RQ4: Are mastery levels from ESR-CD consistent with all response logs? (Section 5.5)

RQ5: What are the detailed diagnosis results of ESR-CD? (Section 5.6)

**Table 1** The detailed statistics of two datasets.

| Dataset | ASSIST | MOOC-Radar |
|---|---|---|
| #Students | 2,493 | 14,224 |
| #Exercises | 17,746 | 2,513 |
| #Knowledge concepts | 123 | 580 |
| #Response logs | 267,415 | 898,933 |
| #Response logs per student | 107.266 | 63.198 |
| #Knowledge concepts per exercise | 1.192 | 1 |
| #Sparsity in student-concept interactions | 92.212% | 98.985% |

### 5.1 Experimental Settings

*Datasets.* We select two publicly available datasets, i.e., ASSIST and MOOC-Radar. ASSIST is an open dataset containing abundant student-exercise logs and expert-labeled exercise-concept relationships $\mathbf{Q}$. MOOC-Radar is a recently collected dataset from students' learning records in MOOCs [45], which contains abundant response logs. In addition to response logs and exercise-concept relationships, MOOC-Radar also provides much rich side information, e.g., exercise-related cognitive level labels, exercise texts, interactions between students and videos, and so on. In this paper, we focus on how to mine rich information only from response logs to alleviate data sparsity. The statistics of these two datasets are in Table 1.

For comprehensive validation, we employ two data split settings. One is *Random Split*. We randomly divide the student-exercise response logs into training, validation, and testing sets with a ratio of 7:1:2. The other is *Concept Weak-coverage Split* [13]. For each student, we first identify all the concepts they have encountered. Then, we randomly select 20% of the concepts for each student and assign the student-exercise pairs related to these selected concepts to the testing set. After that, we divide the remaining response logs into the training and validation sets with a ratio of 7:1. In this way, 180,463/25,781/61,171 logs are assigned to the training/validation/testing set on the ASSIST

dataset, respectively. 596,269/85,182/217,482 logs are assigned to the training/validation/testing set on the MOOC-Radar dataset.

*Metrics.* Following previous works [7, 11, 12], we employ Accuracy (ACC) and Area Under the Curve (AUC) to evaluate response log prediction performance. Additionally, to assess the consistency between predicted logs in the testing set and students' mastery levels on concepts, we adopt a common Degree Of Agreement (DOA) metric [1, 7, 13]. We calculate the DOA values over the whole dataset, denoted as DOA@w.

*Baselines.* We choose two kinds of models. One kind is classic models without providing detailed students' comprehension degrees on concepts, therefore, we cannot measure DOA for them.

- IRT [15]. It uses one dimensional variables to model student abilities and exercise difficulties.
- MIRT [46]. It allows for high dimensions to enhance prediction performance.

The other kind is representative neural network based CD models. Apart from prediction, these models can provide students' mastery levels each knowledge concept.

- DINA [21]. It utilizes binary variables to represent student and exercise entities and adopts guess and slip parameters.
- NCDM [7]. It adopts high dimensional representations for comprehension degrees and difficulties with a classic diagnostic function.
- CDMFCK [47]. Compared to NCDM, it considers different effects of knowledge concepts.
- RCD [11]. It further utilizes concept relationships and student-exercise-concept relationships.
- KSCD [48]. It uses probabilistic matrix factorization and devises a novel interaction function.
- KaNCD [13]. Compared to NCDM, it utilizes collaborative information between students and concepts via matrix factorization.

*Hyper-parameters.* For fair comparisons, we set the dimension of latent representations in KSCD, KaNCD, and ESR-CD to 64 on the ASSIST dataset, and 256 on the MOOC-Radar dataset. For the MLP mapping $\mathbf{x}_{se}$ to prediction, we adopt the same structure (hidden dimensions are 256, 128, respectively) for all neural network based CD models. We search the learning rate in the range of {0.0001, 0.0005, 0.001, 0.005, 0.01, 0.02}, and set the batch size to 8,192 for all models. If student $s$ does not interact with concept $k$, we set $b_{sk} = 0$ on both two datasets; otherwise, $b_{sk} = 1$. As for the threshold $\Delta$ in the refinement layer, we set the threshold to 0.5.

## 5.2 Overall Performance (RQ 1)

We report overall performance in Table 2-3. We have several observations from these tables.

- First, ESR-CD has the best performance on two datasets and two experimental settings. E.g., ESR-CD has nearly 0.5% AUC improvements under two settings on the ASSIST dataset. Compared to the representative neural network based CD model KaNCD, ESR-CD has an AUC improvement of over 6% under the concept weak-coverage split on MOOC-Radar dataset.
- Second, ESR-CD shows stronger robustness than other neural network-based CD models. E.g., compared to KaNCD, ESR-CD has a slight AUC improvement of less than 0.5% under the random splits and an AUC improvement of over 7% under the challenging concept weak-coverage split on MOOC-Radar.
- Last but not least, NCDM retains some predictive performance under the concept weak-coverage setting. Most comprehension degrees in NCDM would be close to initial values under this setting, however, NCDM achieves AUC scores of

**Table 2** Overall performance on the ASSIST dataset. We use bold font to emphasize the best results.

| Model | Random Split | | | Concept Weak-coverage Split | | |
|---|---|---|---|---|---|---|
| | AUC ↑ | ACC ↑ | DOA ↑ | AUC ↑ | ACC ↑ | DOA ↑ |
| **IRT** | 0.7298 ± 0.0010 | 0.7096 ± 0.0004 | - | 0.6976 ± 0.0016 | 0.7137 ± 0.0002 | - |
| **MIRT** | 0.7454 ± 0.0003 | 0.7132 ± 0.0006 | - | 0.6936 ± 0.0014 | 0.7108 ± 0.0012 | - |
| **DINA** | 0.7178 ± 0.0017 | 0.6703 ± 0.0109 | 0.5998 ± 0.0034 | 0.6169 ± 0.0031 | 0.4774 ± 0.0211 | 0.5305 ± 0.0173 |
| **NCDM** | 0.7209 ± 0.0002 | 0.6745 ± 0.0021 | 0.5985 ± 0.0124 | 0.6499 ± 0.0007 | 0.6709 ± 0.0006 | 0.5109 ± 0.0041 |
| **CDMFKC** | 0.7431 ± 0.0011 | 0.7038 ± 0.0016 | 0.6040 ± 0.0051 | 0.6742 ± 0.0005 | 0.6798 ± 0.0090 | 0.4995 ± 0.0079 |
| **RCD** | 0.7472 ± 0.0010 | 0.7111 ± 0.0003 | 0.5809 ± 0.0110 | 0.6924 ± 0.0034 | 0.7026 ± 0.0019 | 0.5623 ± 0.0049 |
| **KSCD** | 0.7586 ± 0.0002 | 0.7207 ± 0.0005 | 0.5092 ± 0.0031 | 0.7009 ± 0.0009 | 0.7114 ± 0.0039 | 0.4987 ± 0.0150 |
| **KaNCD** | 0.7599 ± 0.0003 | 0.7271 ± 0.0011 | 0.6486 ± 0.0110 | 0.6952 ± 0.0045 | 0.7098 ± 0.0034 | 0.5808 ± 0.0089 |
| **ESR-CD** | **0.7640 ± 0.0004** | **0.7297 ± 0.0003** | **0.6550± 0.0095** | **0.7051 ± 0.0006** | **0.7153 ± 0.0024** | **0.6104 ± 0.0145** |

**Table 3** Overall performance on the MOOC-Radar dataset. We use bold font to emphasize the best results.

| Model | Random Split | | | Concept Weak-coverage Split | | |
|---|---|---|---|---|---|---|
| | AUC ↑ | ACC ↑ | DOA ↑ | AUC ↑ | ACC ↑ | DOA ↑ |
| **IRT** | 0.8534 ± 0.0010 | 0.8522 ± 0.0008 | - | 0.7625 ± 0.0019 | 0.8328 ± 0.0013 | - |
| **MIRT** | 0.8727 ± 0.0022 | 0.8629 ± 0.0016 | - | 0.7671 ± 0.0036 | 0.8371 ± 0.0017 | - |
| **DINA** | 0.8070 ± 0.0009 | 0.7729 ± 0.0005 | 0.6000 ± 0.0079 | 0.5745 ± 0.0022 | 0.4978 ± 0.0014 | 0.5106 ± 0.0114 |
| **NCDM** | 0.8656 ± 0.0022 | 0.8526 ± 0.0010 | 0.6024 ± 0.0089 | 0.6701 ± 0.0004 | 0.7876 ± 0.0003 | 0.5027 ± 0.0062 |
| **CDMFKC** | 0.8678 ± 0.0028 | 0.8559 ± 0.0015 | 0.6050 ± 0.0080 | 0.6831 ± 0.0037 | 0.7756 ± 0.0014 | 0.4962 ± 0.0136 |
| **RCD** | 0.8699 ± 0.0045 | 0.8634 ± 0.0031 | 0.6344 ± 0.0101 | 0.6903 ± 0.0064 | 0.7814 ± 0.0082 | 0.5332 ± 0.0230 |
| **KSCD** | 0.8754 ± 0.0048 | 0.8598 ± 0.0020 | 0.5283 ± 0.0094 | 0.6952 ± 0.0023 | 0.7935 ± 0.0029 | 0.4949 ± 0.0125 |
| **KaNCD** | 0.8809 ± 0.0008 | 0.8646 ± 0.0005 | 0.6918 ± 0.0115 | 0.7182 ± 0.0022 | 0.8264 ± 0.0013 | 0.6051 ± 0.0032 |
| **ESR-CD** | **0.8836 ± 0.0006** | **0.8671 ± 0.0002** | **0.7249 ± 0.0047** | **0.7718 ± 0.0004** | **0.8430 ± 0.0011** | **0.6601 ± 0.0066** |

0.6499 and 0.6701 on two datasets. The reason is that NCDM still assesses high-quality exercise parameters in Eq.(7) for prediction.

### 5.3 Ablation Study (RQ 2)

We compare these settings: base models (NCDM), NCDM with incorporation (Eq.(2)), NCDM with incorporation and Q refinements (Eq.(6)), and NCDM with incorporation and matrix factorization (Eq.(3)).

There are some observations from Table 4 and Table 5. First, incorporation achieves AUC scores of 0.7004 and 0.7670 on two datasets. The improvements are over 7% compared to the basic model NCDM, demonstrating the effectiveness of $g_s$. Second, incorporation brings a much smaller improvement on the random split setting (nearly 1% improvement on the MOOC-Radar dataset). Third, the refinement leads to obvious improvements. E.g., incorporation with refinement (AUC 0.7619) performs much better than only incorporation (AUC 0.7541) under the random split setting on the ASSIST dataset. Fourth, factorization also has obvious positive effects. E.g., there is a significant performance improvement in the random split setting when comparing $g_s$ with/without MF (As shown in the second and fourth rows in Table 4, AUC 0.7541 → 0.7619). Finally, by combining all modules, ESR-CD achieves the best performance.

### 5.4 Model Analyses (RQ 3)

**Comparisons among Different Matrix Factorization Techniques.** In this part, we compare some feasible methods, i.e., PMF [43], GMF and NCF [42]. As shown in Fig.4, we first find that GMF and NCF demonstrate stable comparable performance on both two datasets. For example, on the MOOC-Radar dataset, GMF achieves AUC scores of 0.8836, and NCF achieves AUC scores of 0.8847 on the ran-

**Table 4** Ablation study on the ASSIST dataset. The last row represents our proposed ESR-CD.

| Incorporation | Refinement | Factorization | Random Split | | | Concept Weak-coverage Split | | |
|---|---|---|---|---|---|---|---|---|
| Eq.(2) | Eq.(6) | Eq.(3) | AUC ↑ | ACC ↑ | DOA ↑ | AUC ↑ | ACC ↑ | DOA ↑ |
| ✗ | ✗ | ✗ | 0.7209 | 0.6745 | 0.5985 | 0.6499 | 0.6709 | 0.5109 |
| ✓ | ✗ | ✗ | 0.7541 | 0.7209 | 0.6462 | 0.7004 | 0.6814 | 0.6014 |
| ✓ | ✓ | ✗ | 0.7598 | 0.7271 | 0.6403 | 0.7014 | 0.7032 | 0.5715 |
| ✓ | ✗ | ✓ | 0.7619 | 0.7283 | 0.6456 | 0.7030 | 0.7120 | 0.5868 |
| ✓ | ✓ | ✓ | **0.7640** | **0.7297** | **0.6550** | **0.7051** | **0.7153** | **0.6104** |

**Table 5** Ablation study on the MOOC-Radar dataset. The last row represents our proposed ESR-CD.

| Incorporation | Refinement | Factorization | Random Split | | | Concept Weak-coverage Split | | |
|---|---|---|---|---|---|---|---|---|
| Eq.(2) | Eq.(6) | Eq.(3) | AUC ↑ | ACC ↑ | DOA ↑ | AUC ↑ | ACC ↑ | DOA ↑ |
| ✗ | ✗ | ✗ | 0.8656 | 0.8526 | 0.6024 | 0.6701 | 0.7676 | 0.5027 |
| ✓ | ✗ | ✗ | 0.8781 | 0.8590 | 0.7131 | 0.7670 | 0.8334 | 0.6510 |
| ✓ | ✓ | ✗ | 0.8827 | 0.8646 | 0.7230 | 0.7710 | 0.8414 | 0.6524 |
| ✓ | ✗ | ✓ | 0.8824 | 0.8653 | 0.7201 | 0.7703 | 0.8364 | 0.6509 |
| ✓ | ✓ | ✓ | **0.8836** | **0.8671** | **0.7249** | **0.7718** | **0.8430** | **0.6601** |

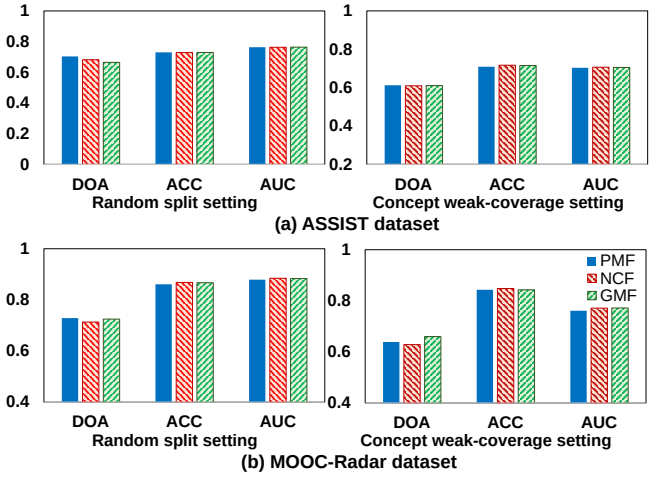



**Fig. 4** Comparisons about different matrix factorization techniques on ASSIST and MOOC-Radar datasets.

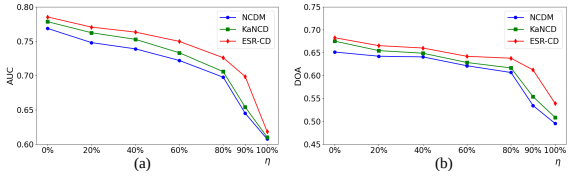



**Fig. 5** (a) AUC and (b) DOA performance with varying sparsity ratios $\eta$ (%) on the **ASSIST** dataset.

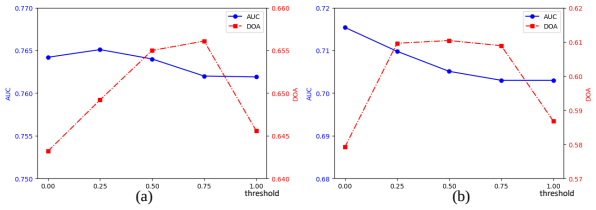



**Fig. 6** Varying threshold $\Delta$ on the ASSIST dataset under (a) random split and (b) concept weak coverage split settings.

dom split setting. Second, we find that these two models slightly outperform PMF on both two datasets especially for accuracy performance (e.g., AUC) under the concept weak-coverage split. E.g., on MOOC-Radar, PMF achieves AUC scores of 0.7610, while GMF and NCF achieve AUC scores of 0.7718 and 0.7711, respectively. In conclusion, GMF and NCF have similar performance and both outperform PMF. Considering the relatively simpler structure of GMF, we choose GMF.

## 5.5 Consistency on the Whole Dataset (RQ 4)

**Varying Sparsity Levels.** To evaluate performance under different data sparsity levels, we conduct a comparative analysis between ESR-CD, NCDM [7] and KaNCD [13]). To simulate sparsity levels $\eta$, we first select 20 concepts for each student. For each student and selected concepts: 1. The interactions between each student and selected concepts are split into a candidate set and a test set at a ra-

**Table 6** Comparisons among $\sigma(c_{sk} \cdot g_s)$, $\sigma(\sigma(c_{sk}) \cdot g_s)$ and $\sigma(c_{sk} + g_s)$ on the ASSIST dataset.

| Formulation | Random Split | | | Concept Weak-coverage Split | | |
|---|---|---|---|---|---|---|
| | AUC ↑ | ACC ↑ | DOA ↑ | AUC ↑ | ACC ↑ | DOA ↑ |
| $\sigma(c_{sk} \cdot g_s)$ | 0.7610 ± 0.0006 | 0.7283 ± 0.0004 | 0.6537 ± 0.0092 | 0.7025 ± 0.0008 | 0.7122 ± 0.0011 | 0.6004 ± 0.0120 |
| $\sigma(\sigma(c_{sk}) \cdot g_s)$ | 0.7556 ± 0.0008 | 0.7239 ± 0.0005 | 0.6506 ± 0.0101 | 0.7045 ± 0.0011 | 0.7147 ± 0.0031 | 0.5959 ± 0.0166 |
| $\sigma(c_{sk} + g_s)$ | **0.7640 ± 0.0004** | **0.7297 ± 0.0003** | **0.6550± 0.0095** | **0.7051 ± 0.0006** | **0.7153 ± 0.0024** | **0.6104 ± 0.0145** |

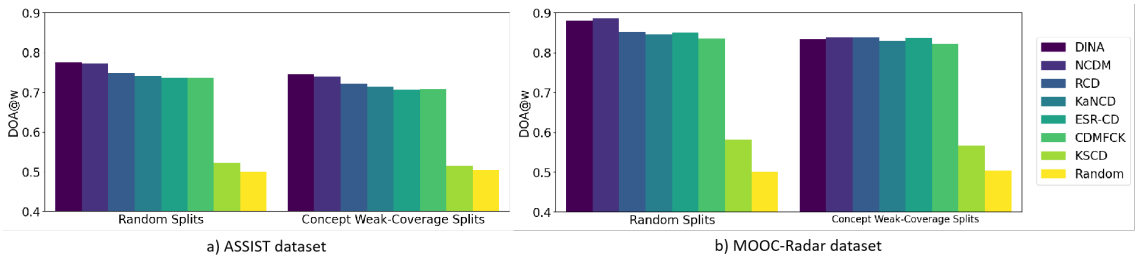



**Fig. 7** DOA@w on both ASSIST and MOOC-Radar datasets.

tio of 8:2. The candidate set is used to augment the training set; 2. To control interaction data sparsity, we randomly remove a ratio ($\eta$) of interactions from the candidate set. The process is consistent with Fig.2 (a). The larger value of $\eta$ denotes the higher sparsity levels.

We have several observations from Fig.5. First, ESR-CD outperforms KaNCD and NCDM under different sparsity levels, demonstrating the effectiveness and robustness of ESR-CD. Second, as the data becomes abundant ($\eta$=0%), KaNCD approaches ESR-CD. When $\eta$=0%, KaNCD achieves an AUC score of 0.7785, and ESR-CD achieves 0.7854. Third, as the data becomes very sparse ($\eta$=100%), all three models have an obvious performance decrease. However, ESR-CD performs much better than both NCDM and KaNCD. These results prove the stable effectiveness of ESR-CD.

**Varying Threshold in the Refinement Layer.** To further explore the effects of the **Q** matrix refinement, we conduct additional experiments by adjusting parameters related to the refinement layer to verify its impacts. Specifically, we adjust the threshold operation $\Delta$ on the ASSIST dataset, setting it to 0, 0.1, 0.25, 0.5, 0.75, and 1. The results are recorded in Figure 6. As the threshold decreases, ESR-CD allows more entries to be marked as 1, which improves student performance prediction (AUC) to some extent. However, this severely impacts the consistency metric (DOA), indicating that the diagnosis performance is compromised. To strike a balance between AUC and DOA, we set the threshold to 0.5 in our experiments.

**Comparing Different Combination Ways.** In this part, we discuss how to combine $g_s$ and $c_{sk}$. Apart from $\sigma(c_{sk} + g_s)$ in ESR-CD, we also consider $\sigma(c_{sk} \cdot g_s)$ and $\sigma(\sigma(c_{sk}) \cdot g_s)$, where $\sigma$ denotes the Sigmoid activation function. If we adopt $a_{sk} = \sigma(c_{sk} \cdot g_s)$, the derivative with respect to $g_s$ becomes: $\frac{\partial a_{sk}}{\partial g_s} = c_{sk} \cdot \sigma(c_{sk} \cdot g_s) \cdot (1 - \sigma(c_{sk} \cdot g_s))$. Obviously, $\sigma(c_{sk} \cdot g_s)$ and $(1 - \sigma(c_{sk} \cdot g_s))$ are both positive. The maintenance of positive correlation depends on whether $c_{sk}$ is positive. One option is to apply another Sigmoid activation to $c_{sk}$. If sigmoid activation is applied to both $c_{sk}$ and $a_{sk}$, the derivative becomes: $\frac{\partial a_{sk}}{\partial g_s} = \sigma(c_{sk}) \cdot \sigma(\sigma(c_{sk}) \cdot g_s) \cdot (1 - \sigma(\sigma(c_{sk}) \cdot g_s))$. The use of consecutive sigmoid layers can result in gradient vanishing.

We also conduct additional experiments to compare $\sigma(c_{sk} \cdot g_s)$, $\sigma(\sigma(c_{sk}) \cdot g_s)$ and $\sigma(c_{sk} + g_s)$. The

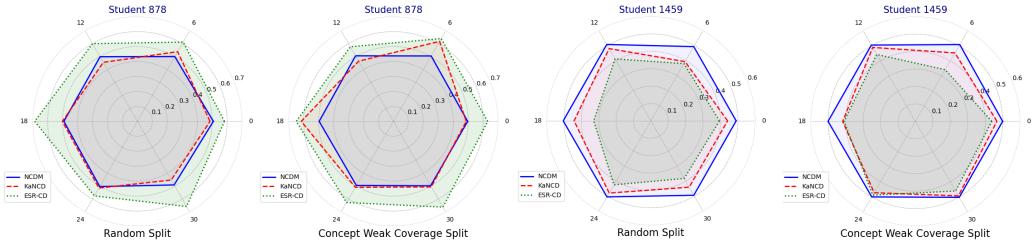



**Fig. 8** Examples of cognitive diagnosis results on the ASSIST dataset.

relevant experimental results are recorded in Table 6. First, we find that $\sigma(c_{sk} + g_s)$ outperforms $\sigma(c_{sk} \cdot g_s)$ and $\sigma(\sigma(c_{sk}) \cdot g_s)$ under both experimental settings. Second, when comparing $\sigma(c_{sk} \cdot g_s)$ and $\sigma(\sigma(c_{sk}) \cdot g_s)$, we find that $\sigma(c_{sk} \cdot g_s)$ achieves better performance under the classic random split setting, indicating that the conventional diagnosis task setup heavily relies on optimizing $c_{sk}$. This is also an answer to why we do not completely remove $c_{sk}$ and only use $g_s$. Third, under the concept weak-coverage setting, $\sigma(\sigma(c_{sk}) \cdot g_s)$ yields better results than $\sigma(c_{sk} \cdot g_s)$, which proves that the positive correlation between $g_s$ and $a_{sk}$ is more crucial if we need to predict a student's mastery levels on non-interacted concepts.

In Table 2-3, we calculate DOA on the testing set. Some works suggest that calculating *DOA* on the *w*hole dataset (DOA@w) [1, 7, 13]. To better display the performance of our proposed ESR-CD, we also report DOA@w. As shown in Figure 7, DINA and NCDM achieve the highest DOA@w on both two datasets. Our proposed ESR-CD maintains similar performance to other neural network-based CD models (KaNCD, RCD, and CDMFCK) (slightly worse than DINA and NCDM), which proves the effectiveness of our proposed ESR-CD. Note that, both KSCD and KaNCD argue that the outputs of matrix factorization represent students' mastery levels on concepts. However, KaNCD directly uses the mastery levels in the diagnostic function, whereas KSCD introduces an additional feature fusion layer, which leads to a decrease in consistency.

### 5.6 Case Study (RQ 5)

To display detailed cognitive diagnosis results, we randomly select two students (878 and 1459) from the ASSIST dataset and record their mastery levels on concepts 0, 6, 12, 18, 24, and 30. As a comparison, we include two classic neural network-based cognitive diagnosis models (NCDM and KaNCD). The results are plotted in radar charts in Figure 8.

As illustrated in Figure 8, our proposed ESR-CD tends to push the mastery levels away from 0.5. It is important to emphasize that the range for mastery levels on concepts is 0-1. From the perspective of the information theoretic, 0.5 represents maximum uncertainty, as it indicates the equal likelihood of mastery or non-mastery. For student 1459, it pushes the values furthest towards 1. For student 878, it pushes furthest towards 0. All these results can prove that our proposed ESR-CD can push mastery levels $a_{sk}$ more away from 0.5 than NCDM and KaNCD, which conveys more useful information for diagnosis.

## 6 Conclusion and Future Work

In this paper, we pointed out that the student-concept sparsity barrier would limit CD development. To

this end, we proposed ESR-CD, which simultaneously considers application abilities and comprehension degrees for modeling students' mastery levels on concepts. One one hand, for application abilities, we proposed a sparsity-based mask module that solely to avoid unwanted effects from sparse entries between students and concepts. On the other hand, we also proposed a neural network based matrix factorization layer and a exercise-concept relation refinement layer to enhance the optimization of comprehension degrees. Extensive experiments on two real-world datasets demonstrated the stable effectiveness of our proposed ESR-CD. In the future, we aim to explore other directions in CD, e.g., exploring concept dependencies by prompting large language models or preventing the amplification of unwanted biases in CD.

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**Competing interests** The authors declare that they have no competing interests or financial conflicts to disclose.

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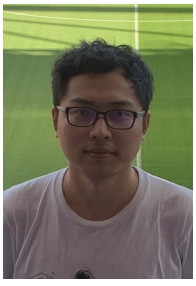

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