A Cognitive Diagnosis Framework for Student Ability Assessment Based on Meta-Continual Learning

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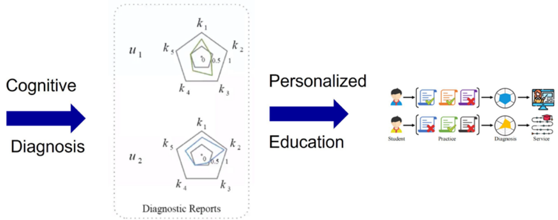
Introduction

- **Cognitive diagnosis:** aims to gain a comprehensive understanding of students abilities and clearly model their cognitive processes.

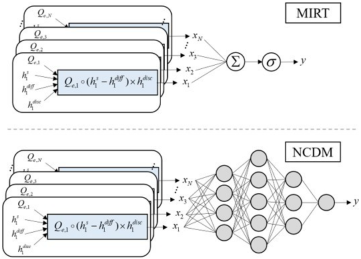
Tasks	Skills	Responses u_1	Responses u_2
e_1	k_1	✓	✓
e_2	k_2	✗	✓
e_3	k_3	✓	✗
e_4	k_2, k_5	✗	✓
e_5	k_3, k_4	✓	✗
Overall Score		60	60



* **Hypothesis 1:** Students' cognitive state is fixed in a certain period of time.

* **Hypothesis 2:** Students' behavior (cognition) is determined by their potential cognitive state.

Introduction



Traditional cognitive diagnosis methods, represented by **IRT**, measure the relationship between questions and student abilities by modeling item characteristics (such as **difficulty, discrimination, guessing parameters**, etc.) and student ability levels. However, compared to NN-based methods, these approaches still have certain limitations.

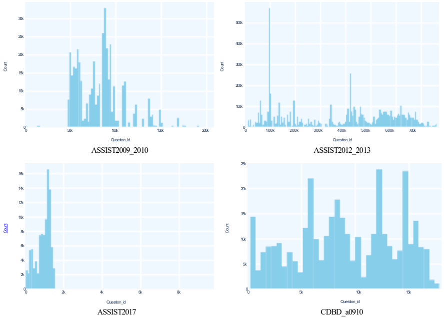
Introduction

- Traditional measurement models **can only handle numerical (structured) data**.
- Traditional measurement models like **IRT** and **MIRT** achieve macro-level cognitive state modeling **but fail to detail students' specific mastery levels**.
- The **sparsity** and **imbalance** caused by the long-tailed problem challenge the assumptions of IRT, limiting its effectiveness in handling diverse and complex questions scenarios.
- The data distribution no longer conforms to the assumption of being **independent and identically distributed (I.I.D.)**, and IRT is unable to capture such dynamic processes.

Model	Level	Trait variable	Trait Dimension	Cognitive Function
CTT	Macro	Fixed Ratio	Single Dimension	×
MF	Macro	-	Multi-Dimension	×
IRT	Macro	Ordinal Scale	Single Dimension	Expert Definition
MIRT	Macro	Ordinal Scale	Multi-Dimension	Expert Definition
DINA/DINO	Microscopic	Ordinal Scale	Multi-Dimension	Expert Definition
NN-based CD	**Microscopic**	**Ordinal Scale**	**Multi-Dimension**	**Machine Learning**

The neural network-based cognitive diagnosis model leverages **neural networks** to automatically learn interaction functions. It can be seen as a **generalization** of traditional Cognitive Diagnosis Models (CDMs) in psychometrics. Compared to conventional diagnostic models, deep learning models include additional parameters, offering certain advantages.

After data statistics, we found that most cognitive diagnosis data sets have the problem of **long-tailed distribution**.



The long-tailed distribution problem leads to a large number of **sparse interaction records**, which limits the performance of the model.

Overcome the limitations of **CTT**, but only **considers a single ability** and requires large sample sizes **without accounting for multidimensional skills**.

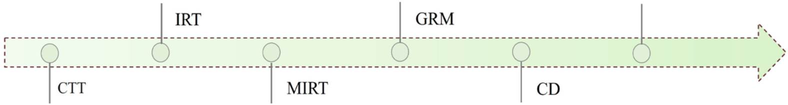
The 0/1 scoring model can no longer meet our needs. For example, **a question may have multiple scores**, or be scored in parts, so a **multi-level** scoring model came into being.

- Black box characteristics
- Uncertainty of cognitive diagnosis results
- Long-tailed data (imbalanced data)
- Dynamics of cognitive changes
- ……

Item Response Theory

Grade Response Model

NN-based Cognitive Diagnosis Model



Classical Test Theory

Multi-Item Response Theory

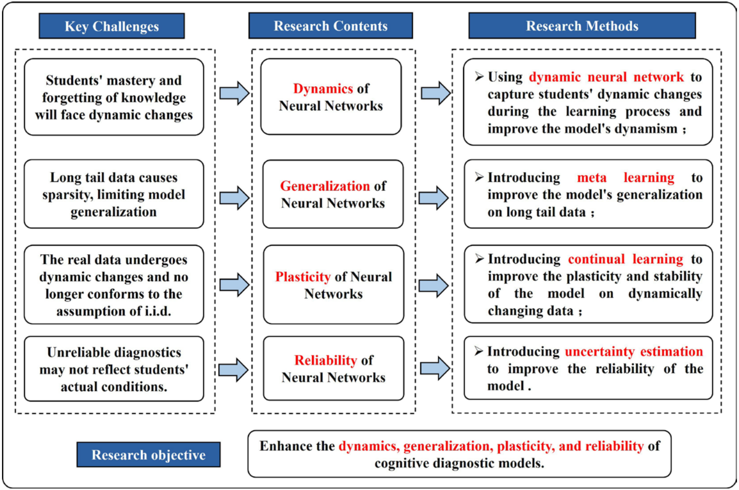
Cognitive Diagnostic Model

Lack objectivity, and the results may be influenced by the sample characteristics.

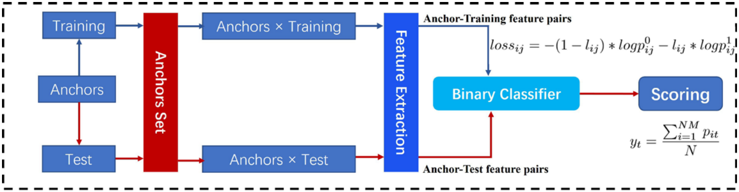
Reflect students' abilities in **multi-dimensions.**

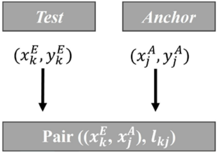
The above models only **handle structured data**, while cognitive diagnosis models add cognitive status (e.g., knowledge point attributes) to assess students' mastery during learning.

Methods


Key Challenges
Research Contents
Research Methods
Students' mastery and forgetting of knowledge will face dynamic changes
Dynamics of Neural Networks
➢ Using dynamic neural network to capture students' dynamic changes during the learning process and improve the model's dynamism ;
Long tail data causes sparsity, limiting model generalization
Generalization of Neural Networks
➢ Introducing meta learning to improve the model's generalization on long tail data ;
The real data undergoes dynamic changes and no longer conforms to the assumption of i.i.d.
Plasticity of Neural Networks
➢ Introducing continual learning to improve the plasticity and stability of the model on dynamically changing data ;
Unreliable diagnostics may not reflect students' actual conditions.
Reliability of Neural Networks
➢ Introducing uncertainty estimation to improve the reliability of the model .
Research objective
Enhance the dynamics, generalization, plasticity, and reliability of cognitive diagnostic models.

Methods

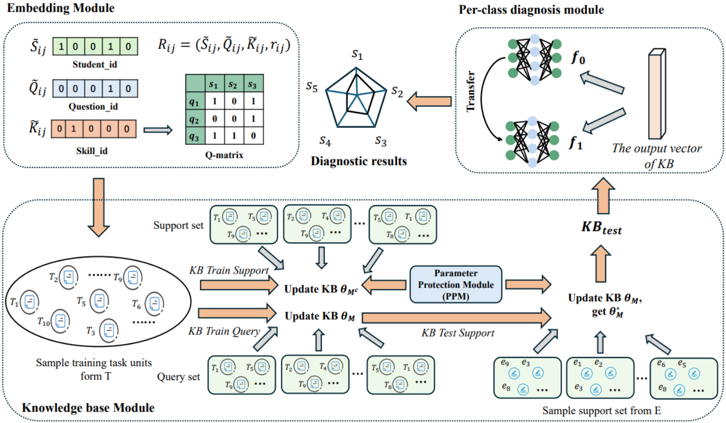




$$l_{ij} = \begin{cases} 1, y^T_i > y^A_j \\ 0, y^T_i \le y^A_j \end{cases}$$

We design a few-shot (meta-learning) contrastive learning framework with anchor samples.

Methods



We proposed a cognitive diagnosis framework for student ability assessment based on meta-continual learning.

Methods

- We add a **meta learning** based knowledge base module to ensure that the model can alleviate the problem of long-tailed distribution through few data, achieving the reliability and robustness of MetaCD on sparse data.

- We use **parameter protection mechanism** (PPM) to ensure the stability and plasticity of the model, enabling MetaCD to adapt to the dynamic changes of data and achieve its continual learning ability.

- We use a knowledge extraction method based on **Kullback-Leibler divergence** to avoid fuzzy boundaries of diagnostic results, thereby improving the classification accuracy of the model.

Methods

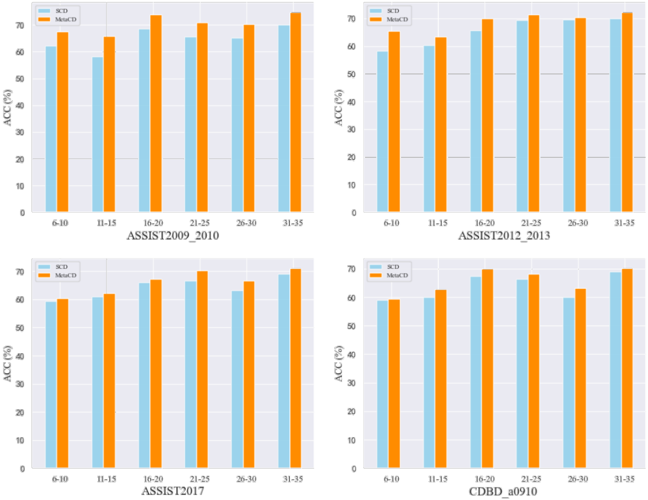
Table 4: Performance comparison of different models on student cognitive diagnostic.

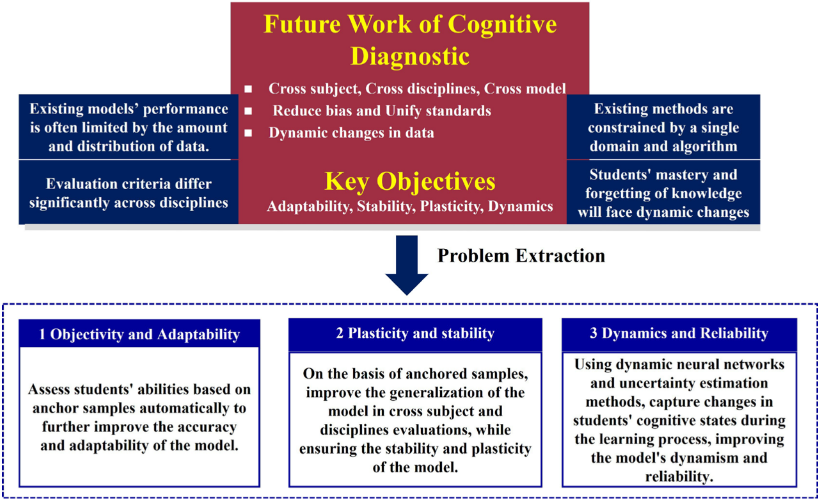
Work	ASSIST2009_2010			ASSIST2017		
	ACC	RMSE	AUC	ACC	RMSE	AUC
MetaCD	**0.753**	0.425	**0.771**	**0.715**	**0.439**	**0.726**
IRT	0.654	0.472	0.681	0.658	0.464	0.668
MIRT	0.707	0.461	0.716	0.668	0.461	0.678
DINA	0.644	0.495	0.680	0.613	0.519	0.654
BCD	0.729	0.426	0.763	0.701	0.447	0.713
NCD	0.726	0.441	0.752	0.685	0.453	0.699
RCD	0.724	0.427	0.761	0.694	0.450	0.709
SCD	0.731	**0.423**	0.729	0.703	0.442	0.710

Table 5: Performance comparison of models based on the ASSIST 2009_2010 under different data amounts.

Amounts	5,000			100,000			150,000			190,000		
Work	ACC	RMSE	AUC	ACC	RMSE	AUC	ACC	RMSE	AUC	ACC	RMSE	AUC
MetaCD	**0.569**	**0.517**	**0.557**	**0.659**	**0.483**	**0.687**	**0.738**	**0.459**	**0.724**	**0.753**	0.425	**0.771**
IRT	0.463	0.693	0.419	0.532	0.690	0.526	0.585	0.591	0.613	0.654	0.472	0.681
MIRT	0.469	0.690	0.428	0.549	0.675	0.568	0.605	0.570	0.628	0.707	0.461	0.716
DINA	0.476	0.667	0.462	0.596	0.607	0.585	0.651	0.519	0.633	0.644	0.495	0.680
BCD	0.556	0.572	0.539	0.621	0.549	0.618	0.722	0.473	0.706	0.729	0.426	0.763
NCD	0.503	0.581	0.529	0.628	0.536	0.629	0.719	0.493	0.703	0.726	0.441	0.752
RCD	0.557	0.569	0.535	0.615	0.542	0.626	0.705	0.479	0.698	0.724	0.427	0.761
SCD	0.560	0.522	0.542	0.637	0.505	0.679	0.725	0.466	0.709	0.731	**0.423**	0.729

Methods


SCD
MetaCD
ACC (%)
6-10
11-15
16-20
21-25
26-30
31-35
ASSIST2009_2010
ASSIST2012_2013
ASSIST2017
CDBD_a0910


Future Work of Cognitive Diagnostic
Cross subject, Cross disciplines, Cross model
Reduce bias and Unify standards
Dynamic changes in data
Key Objectives
Adaptability, Stability, Plasticity, Dynamics
Existing models' performance is often limited by the amount and distribution of data.
Evaluation criteria differ significantly across disciplines
Existing methods are constrained by a single domain and algorithm
Students' mastery and forgetting of knowledge will face dynamic changes
Problem Extraction
1 Objectivity and Adaptability
Assess students' abilities based on anchor samples automatically to further improve the accuracy and adaptability of the model.
2 Plasticity and stability
On the basis of anchored samples, improve the generalization of the model in cross subject and disciplines evaluations, while ensuring the stability and plasticity of the model.
3 Dynamics and Reliability
Using dynamic neural networks and uncertainty estimation methods, capture changes in students' cognitive states during the learning process, improving the model's dynamism and reliability.

Thank You !