Breaking Student-Concept Sparsity Barrier for Cognitive Diagnosis

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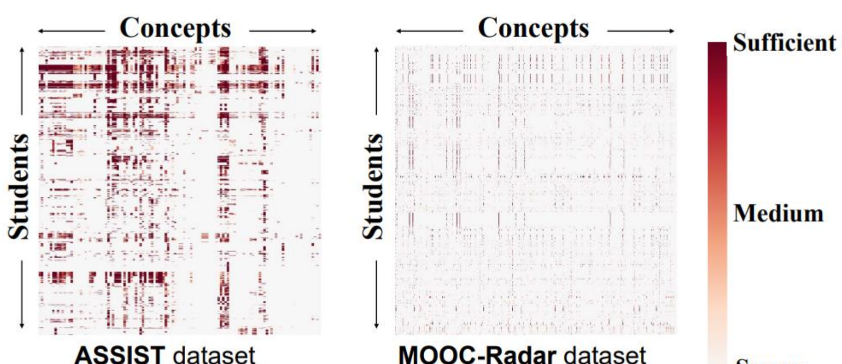
Problems & Ideas

- Problems of current Cognitive Diagnosis (CD) models
  - The Sparsity Barrier: interactions between students and certain concepts are rare or nonexistent in real-world datasets.
  - The diagnostic accuracy of CD models diminishes significantly for sparsely covered concepts.
- Ideas: current models solve this problem by collecting more data, but they suffer from high annotation costs, and wrong annotations (e.g., cyclic dependencies).

Model	η (%)	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

Analyses about sparsity between students and concepts. Students are not directly related to concepts. (a) Performance of two representative neural network-based CD models on ASSIST dataset. We manually simulate different ratios of sparsity between students and selected concepts. (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.

Main Contributions

- Contributions:
  - We find that the student-concept sparsity barrier limits CD developments, which is widely prevalent in real-world datasets;
  - we argue that student modeling should consider both practical application ability and mastery levels on concepts, and propose ESR-CD, an accurate and robust CD model;
  - Extensive experiments demonstrate the effectiveness of ESR-CD. E.g., for concept weak coverage split, ESR-CD has AUC improvements of over 1.5% on ASSIST dataset.

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**