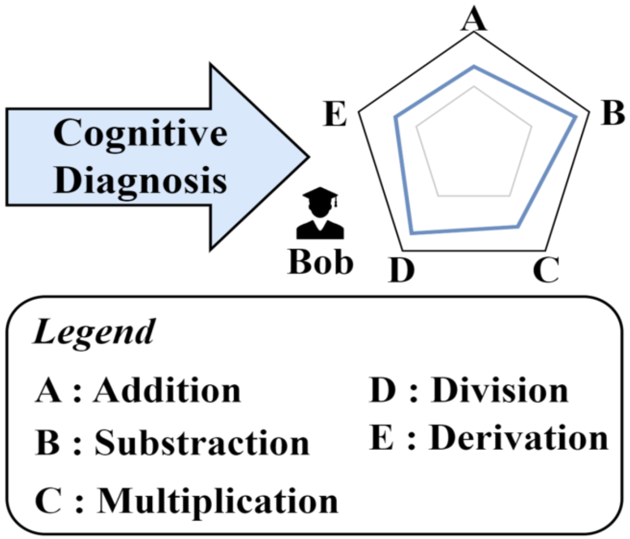
DisenGCD: A Meta Multigraph-assisted Disentangled Graph Learning Framework for Cognitive Diagnosis

Presenter：Shangshang Yang

●Background- CD task

◆ Cognitive Diagnosis Task

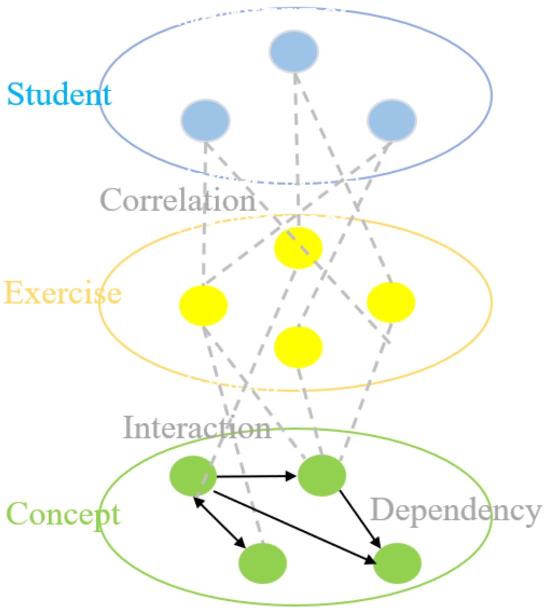
Exercise	Concept	Response
e_1	A	×
e_2	B	√
e_3	C	?
e_4	D	?
e_5	E	?



- ➢Cognitive diagnosis aims at evaluating students' proficiency levels across various knowledge concepts through exercises.
- ➢Existing approaches (based on neural network and graph neural network) take CD task as a prediction task, and judge the knowledge of students by predicting their answers.

●Motivation

The graph neural network of current graph cognitive diagnosis model



Strengths:

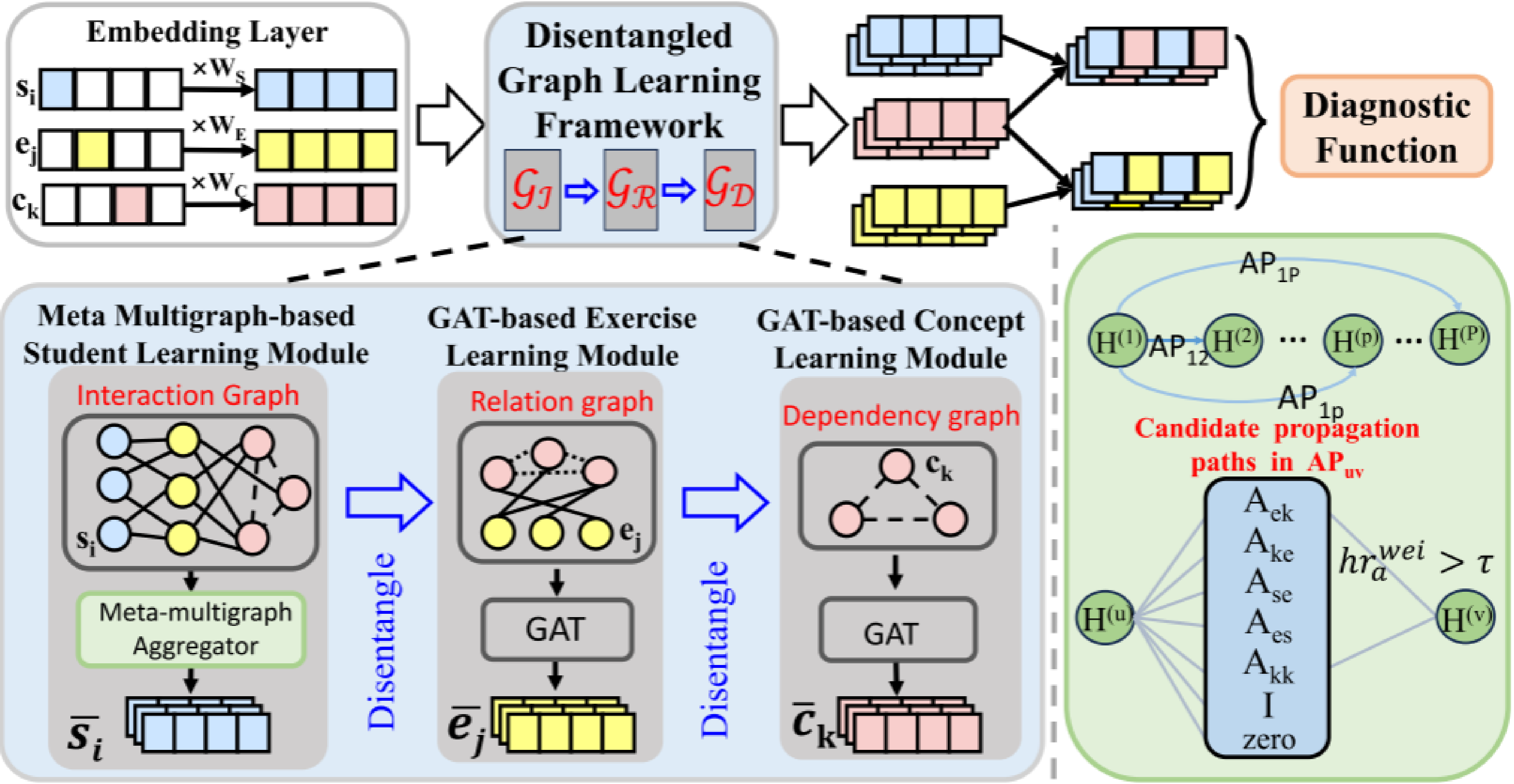
- Existing graph learning-based cognitive diagnosis (CD) methods have made relatively good results.
- The representation of students, exercises and concepts can learn higher-order semantic information of neighbor nodes through graph neural networks.

However!!!

- Exercise and concept representations be learned poorly, failing to provide high robustness against noise in students' interactions.
- lower-order exercise latent representations obtained in shallow layers are not well explored when learning the student representation.

●Overall Framework

安徽大學



The First "one":

➢ A Disentangling graph strategy.

The First "three":

➢ Three independent representation update modules.

The Second "one":

➢ A Differentiable Meta Multi-Graph Update Strategy.

How to overcome the shortcomings of the previous work? ——**1-3-1 Strategies!!!**

●Fomule

◆Representation learning

①The Meta Multigraph-based Student Learning Module

$$\mathbf{H}^{(p)} = \sum\{f(A\hat{P}_{up}, \boldsymbol{H}^{(u)})||\ 1 \leq u < p\}$$
$$A\hat{P}_{up} = \{(hr_a, hr_a^{wei})|hr_a^{wei} \geq \tau^{(u,p)}, \forall hr_a \in AP_{up}\}.$$

②The GAT-based Exercise Learning Module

$$\mathbf{e}_j^{R(l)} = \sum\nolimits_{k\in N_{e_j}} \alpha_{j(k)}^{R(l)} \mathbf{c}_k^{R(l-1)} + \mathbf{e}_j^{R(l-1)},$$
$$\mathbf{c}_k^{R(l)} = \sum\nolimits_{j\in N_{c_k}^{ec}} \alpha_{k(j)}^{R(l)} \mathbf{e}_j^{R(l-1)} + \sum\nolimits_{m\in N_{c_k}^{cc}} \alpha_{\hat{k}(m)}^{R(l)} \mathbf{c}_m^{R(l-1)} + \mathbf{c}_k^{R(l-1)}.$$

③The GAT-based Concept Learning Module

$$\mathbf{c}_k^{D(l)} = \sum\nolimits_{m\in N_{c_k}^{cc}} \alpha_{\hat{k}(m)}^{D(l)} \mathbf{c}_m^{D(l-1)} + \mathbf{c}_k^{D(l-1)}.$$

◆The Diagnosis Module

$$\mathbf{h}_{simi} = \sigma(F_{simi}(\mathbf{h}_{si} \cdot \mathbf{h}_{ej})), \mathbf{h}_{si} = F_{si}(\overline{\mathbf{S}_i} + \overline{\mathbf{C}_k}), \mathbf{h}_{ej} = F_{ej}(\overline{\mathbf{E}_j} + \overline{\mathbf{C}_k})$$
$$\hat{r_{ij}} = (\sum Q_k \cdot \mathbf{h}_{simi})/\sum Q_k$$

●Experiments-Overall Comparison

安徽大學

Table 1 Overall Performance Comparison in terms of ACC、RMSE and AUC

Datatset	Ratio	40%/10%/50%			50%/10%/40%			60%/10%/30%			70%/10%/20%		
	Method	ACC↑	RMSE↓	AUC↑	ACC↑	RMSE↓	AUC↑	ACC↑	RMSE↓	AUC↑	ACC↑	RMSE↓	AUC↑
ASSISTments	DINA	0.6388	0.4931	0.6874	0.6503	0.4862	0.4978	0.6573	0.4820	0.7071	0.6623	0.4787	0.7126
	MIRT	0.6954	0.4740	0.7254	0.7015	0.4689	0.7358	0.7096	0.4624	0.7469	0.7110	0.4617	0.7514
	NCD	0.7070	0.4443	0.7374	0.7142	0.4370	0.7423	0.7237	0.4365	0.7552	0.7285	0.4298	0.7603
	ECD	0.7154	0.4373	0.7362	0.7130	0.4373	0.7432	0.7274	0.4329	0.7543	0.7297	0.4296	0.7599
	RCD	0.7232	0.4311	0.7546	0.7253	0.4285	0.7605	0.7291	0.4262	0.7663	0.7296	0.4245	0.7687
	DisenGCD	**0.7276**	**0.4255**	**0.7635**	**0.7287**	**0.4238**	**0.7677**	**0.7335**	**0.4219**	**0.7723**	**0.7334**	**0.4209**	**0.7746**
Math	DINA	0.6691	0.4715	0.7117	0.6745	0.4674	0.7199	0.6813	0.4633	0.7222	0.6812	0.4635	0.7231
	MIRT	0.7229	0.4335	0.7427	0.7227	0.4299	0.7497	0.7279	0.4291	0.7479	0.7340	0.4256	0.7542
	NCD	0.7394	0.4157	0.7604	0.7424	0.4119	0.7660	0.7418	0.4109	0.7706	0.7447	0.4084	0.7756
	ECD	0.7335	0.4154	0.7615	0.7424	0.413	0.7657	0.7434	0.4114	0.7693	0.7484	0.4087	0.7761
	RCD	0.7446	0.41	0.7724	0.7489	0.4074	0.7751	0.7501	0.4078	0.7806	0.7534	0.4034	0.7866
	DisenGCD	**0.7479**	**0.4076**	**0.7802**	**0.7513**	**0.4052**	**0.7832**	**0.7527**	**0.4039**	**0.7867**	**0.7582**	**0.4004**	**0.7932**

●Experiments- Robust Experiment

安徽大學

Fig 1: Performance of RCD and DisenGCD with student-exercise noises

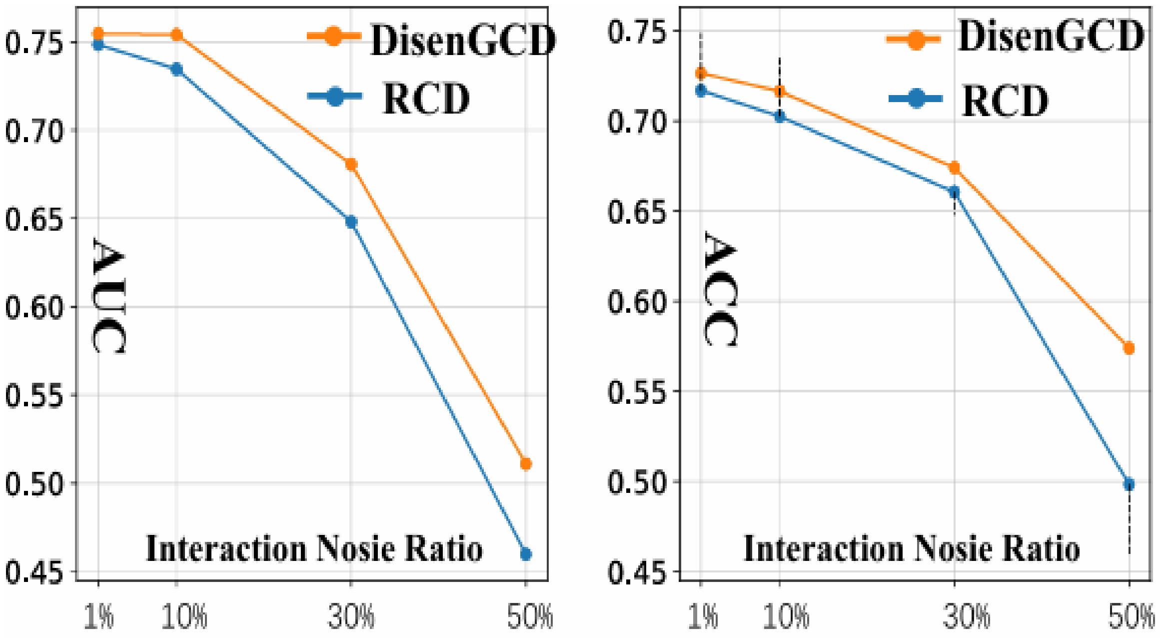
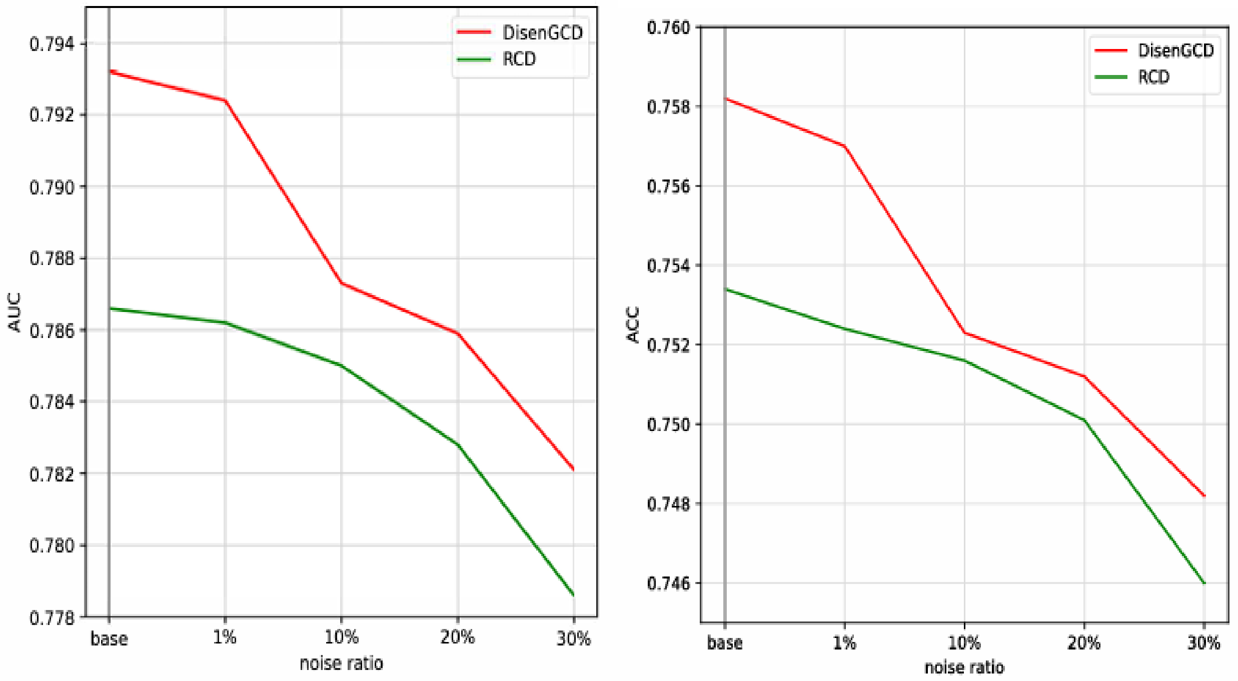


Fig 2:Performance of RCD and DisenGCD with of exercise-concept noise



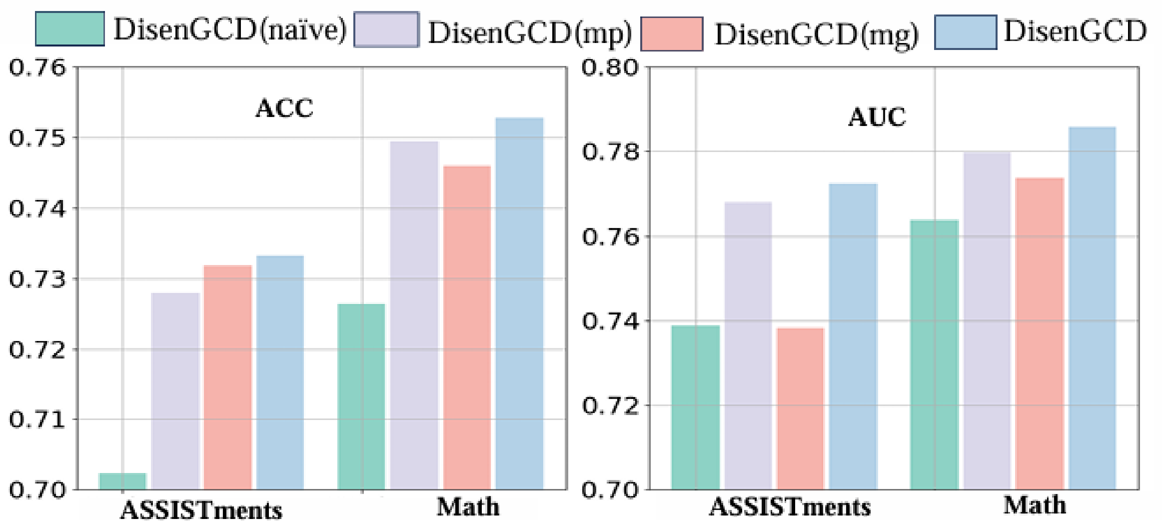
Noise was added to the student-problem interaction(Fig 1) and the problem - concept interaction(Fig 2), respectively. The results of DisenGCD are consistently better than those of RCD.

●Experiments-Ablation Experiment

Table 2:Performance of DisenGCD, RCD, and its four variants

Metric	RCD	*DisenGCD(I)*	*DisenGCD (Is+Rec)*	*DisenGCD (Ise+Rc)*	*DisenGCD (Isc+Re)*	DisenGCD
ACC↑	0.7291	0.7331	0.7321	0.7301	0.7333	**0.7335**
RMSE↓	0.4262	0.4235	0.4259	0.4235	0.4231	**0.4219**
AUC↑	0.7663	0.7678	0.7701	0.7678	0.7685	**0.7723**

Fig 3:Performance of four variants



The followings' effectiveness can be validated:

- The need for disentangling strategies.
- The Excellence of Meta Multi-graph Aggregation.

Thanks！！