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Modeling Context-aware Features for Cognitive Diagnosis in Student Learning

Yuqiang Zhou[1], Qi Liu[1,*], Jinze Wu[1], Fei Wang[1], Zhenya Huang[1], Wei Tong[1], Hui Xiong[2], Enhong Chen[1] , Jianhui Ma[1]

[1]Anhui Province Key Laboratory of Big Data Analysis and Application, University of Science and Technology of China,
[2]The State University of New Jersey

Introduction

Motivation: Cognitive Diagnosis (CD) is one of the most fundamental tasks in intelligent education, aiming at diagnosing the cognitive states (e.g., proficiency level on specific knowledge concepts) of each student. However, to the best of our knowledge, the problem of how educational contexts affect student's knowledge proficiency is still underexplored.

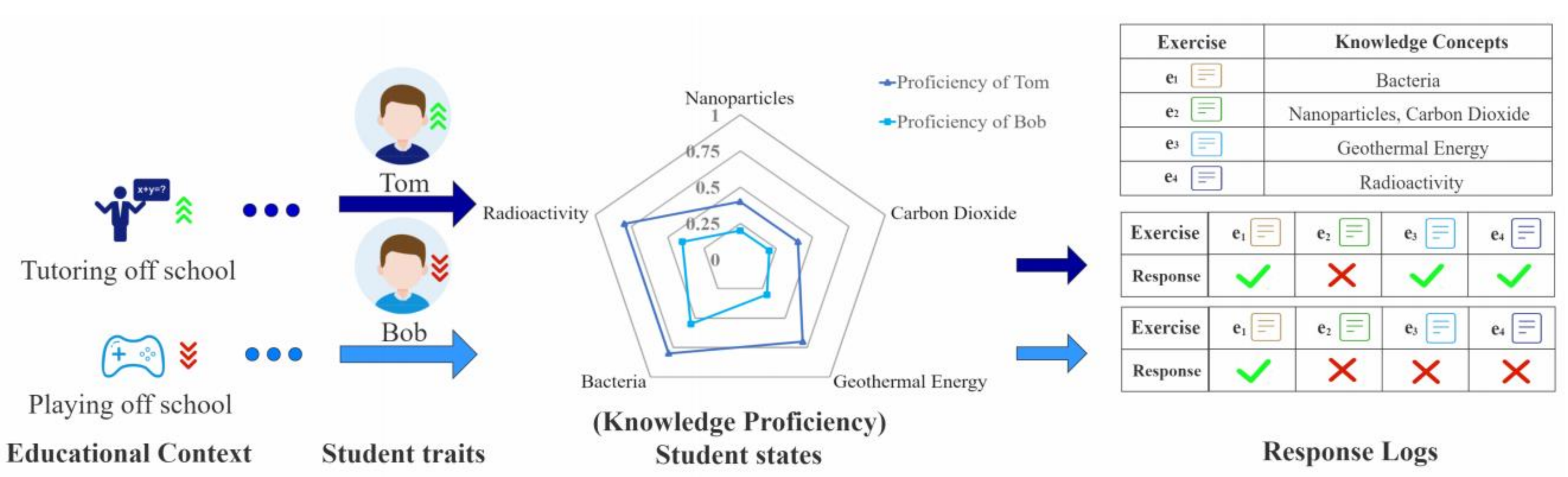


Figure 1: An illustration of students' learning process.

Key Problem: How to model the educational context-aware features and further apply them to diagnosing the cognitive states?

Challenges:

- The educational contexts may involve contents from different aspects and are not directly concerned with specific knowledge concepts.
- Different students may get different influence even from the same context.
- Educational contexts may interact with each other while influencing students.

Problem Statement

Given:

- N Students $\mathcal{S} = \{s_1, s_2, \dots, s_N\}$, T educational context questions $\mathcal{Q} = \{q_1, q_2, \dots, q_T\}$, M exercises $\mathcal{E} = \{e_1, e_2, \dots, e_M\}$.
- Students' logs $R = (\boldsymbol{R_q}, \boldsymbol{R_e})$:
  - Educational context question response records $R_q = \{(s, q, r_q), \dots\}$, where $s \in \mathcal{S}, q \in \mathcal{Q}$
  - Exercise response records $R_e = \{(s, e, r_e), \dots\}$, where $s \in \mathcal{S}, e \in \mathcal{E}$.

Goal:

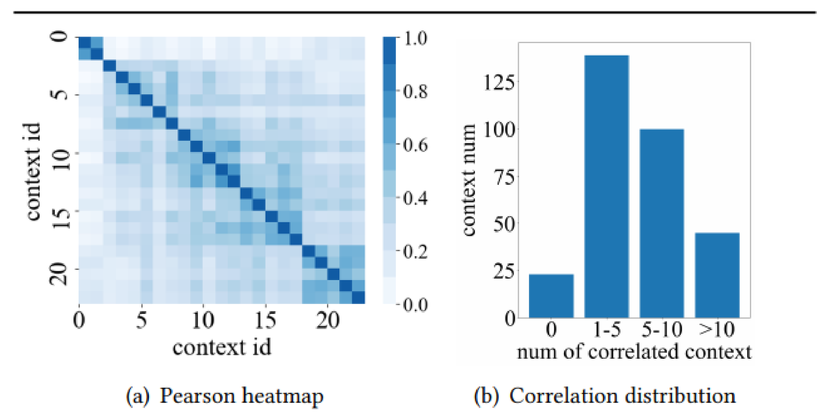
- To Infer students' proficiency on knowledge concepts through student performance (i.e., exercise answering) prediction with predict model F and context model H:

$$r_e = \mathrm{F}(\theta_s, s, e),\ \theta_s = \mathrm{H}(s, q, r_q) \rightarrow \theta_s$$

Datasets

Table 3: The statistics of datasets from PISA.

Datasets	Students	Educational contexts	Context records	Exercise	Exercise records
Asia	76,609	300	14,586,482	260	2,172,516
Europe	69,016	300	18,127,964	260	1,952,577
America	62,091	300	14,205,515	260	1,746,899



(a) Pearson heatmap (b) Correlation distribution

Figure 3: The correlations between context features.

Table 1: Educational context examples.

Aspect	Context examples
Home	Highest education degree of parents
	Parents involvement in children's study
	Home Economic, Social and Cultural Status (ESCS)
School	Method of school teaching and learning
	Teacher' attitude to teaching and students
	Information and Communication Technology (ICT)
	Duration in early childhood education
Person	Whether students have a grade repetition experience
	Science activities experience out of school

ECD Framework

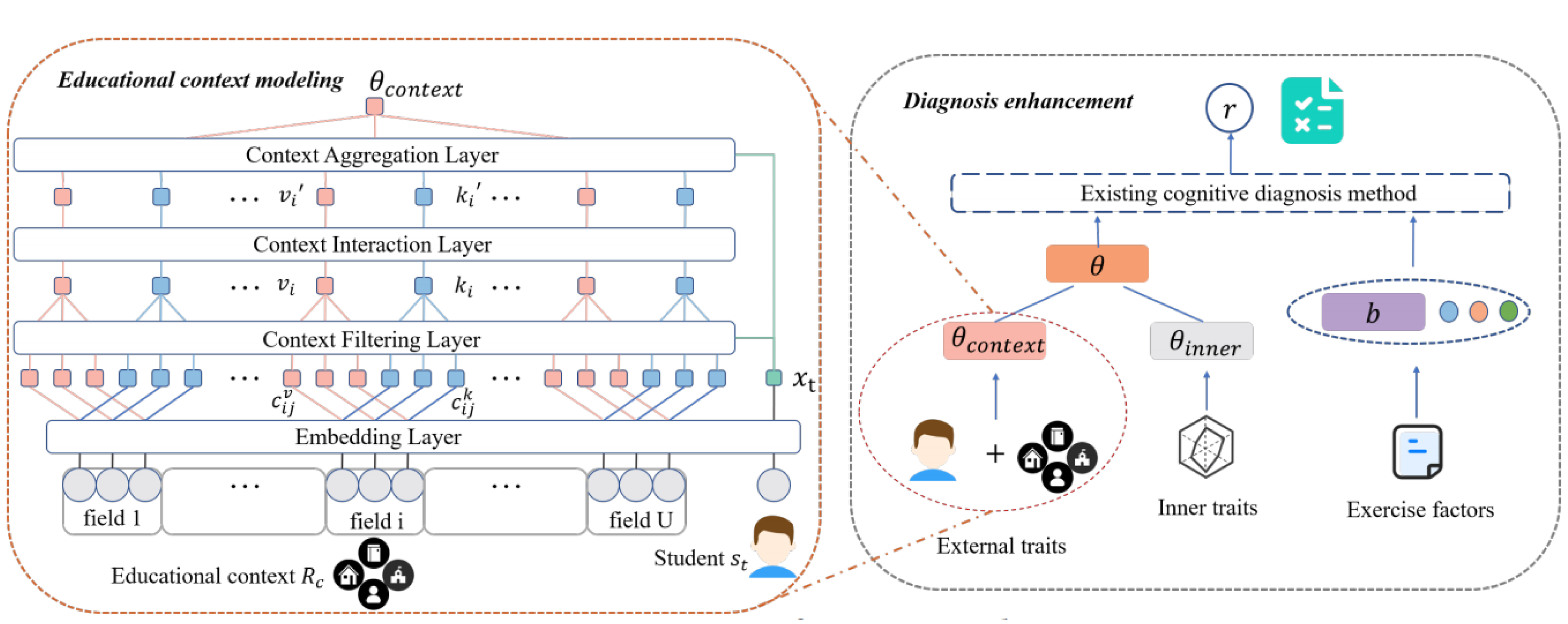


Figure 2: The ECD framework.

Two stage

- **Educational context modeling:**
  - **Embedding layer:** Assign trainable embeddings to each educational context entry u_j and each s_t.
  - **Context filtering layer:** Group contexts into U fields by content. Obtain personalized context influence by field with attention module.
  - **Context interaction layer:** model the inherent relevance between different educational context fields with a self-attention module.
  - **Context aggregation layer:** Utilize another attention module to assemble the influence from different context fields and finally get the student external trait.
- **Diagnosis enhancement:**
  - $\theta = \boldsymbol{d_t} * \theta_{context} + (\boldsymbol{1} - \boldsymbol{d_t}) * \theta_{inner}$
  - $r_e = \mathrm{CDMethod}(\theta, \varphi_e)$

Experiments

Student Performance Prediction

- In general, **context modeling methods** outperform the original cognitive diagnosis methods.
- **ECD**-models achieve best performance on all evaluation metrics in datasets.

Table 2: Results on student performance prediction.

Model	Asia AUC	Asia RMSE	Asia ACC	Europe AUC	Europe RMSE	Europe ACC	America AUC	America RMSE	America ACC
Random	0.499	0.578	0.499	0.500	0.577	0.501	0.502	0.577	0.501
NeuralCD	0.714	0.490	0.658	0.718	0.476	0.659	0.712	0.495	0.665
DeepFM-NeuralCD	0.728	0.488	0.660	0.745	0.455	0.688	0.743	0.472	0.661
NFM-NeuralCD	0.722	0.483	0.660	0.718	0.494	0.667	0.717	0.486	0.652
ECD-NeuralCD	**0.745**	**0.468**	**0.677**	**0.770**	**0.443**	**0.700**	**0.764**	**0.445**	**0.699**
IRT	0.734	0.460	0.675	0.741	0.456	0.687	0.736	0.455	0.678
DeepFM-IRT	0.736	0.459	0.673	0.753	0.450	0.689	0.768	0.443	0.701
NFM-IRT	0.724	0.464	0.670	0.752	0.452	0.679	0.771	0.441	0.703
ECD-IRT	**0.757**	**0.449**	**0.689**	**0.760**	**0.447**	**0.699**	**0.773**	**0.439**	**0.703**
MIRT	0.669	0.484	0.622	0.696	0.493	0.650	0.691	0.475	0.655
DeepFM-MIRT	0.744	0.460	0.676	0.741	0.454	0.684	0.738	0.459	0.678
NFM-MIRT	0.736	0.463	0.665	0.757	0.452	0.692	0.755	0.449	0.688
ECD-MIRT	**0.786**	**0.435**	**0.704**	**0.790**	**0.432**	**0.710**	**0.795**	**0.427**	**0.715**

Ablation

- **Each layer** contributes to the final performances, which indicates the effectiveness of these attentive modules modeling personized influence and inherent relevance.
- **Aggregation layer** personalization in context field level) plays the most important role in our educational context modeling.

Table 4: Results of ablation experiment.

Model	Asia AUC	Asia RMSE	Asia ACC	Europe AUC	Europe RMSE	Europe ACC	America AUC	America RMSE	America ACC
ECD-NeuralCD	**0.745**	**0.468**	**0.677**	**0.770**	**0.443**	**0.700**	**0.764**	**0.445**	**0.699**
- Filtering	0.743	0.469	0.669	0.764	0.445	0.699	0.762	0.445	0.699
- Interaction	0.736	0.471	0.665	0.752	0.451	0.687	0.746	0.463	0.684
- Aggregation	0.738	0.465	0.668	0.747	0.456	0.678	0.747	0.450	0.690
ECD-IRT	**0.757**	**0.449**	**0.689**	**0.760**	**0.447**	**0.699**	**0.773**	**0.439**	**0.703**
- Filtering	0.745	0.456	0.680	0.752	0.451	0.695	0.757	0.447	0.694
- Interaction	0.745	0.455	0.677	0.756	0.449	0.694	0.768	0.442	0.699
- Aggregation	0.739	0.456	0.680	0.755	0.450	0.688	0.754	0.448	0.687
ECD-MIRT	**0.786**	**0.435**	**0.704**	**0.790**	**0.432**	**0.710**	**0.795**	**0.427**	**0.715**
- Filtering	0.781	0.440	0.695	0.787	0.433	0.706	0.788	0.434	0.709
- Interaction	0.779	0.443	0.695	0.787	0.433	0.708	0.788	0.433	0.704
- Aggregation	0.773	0.443	0.698	0.777	0.438	0.700	0.763	0.442	0.692

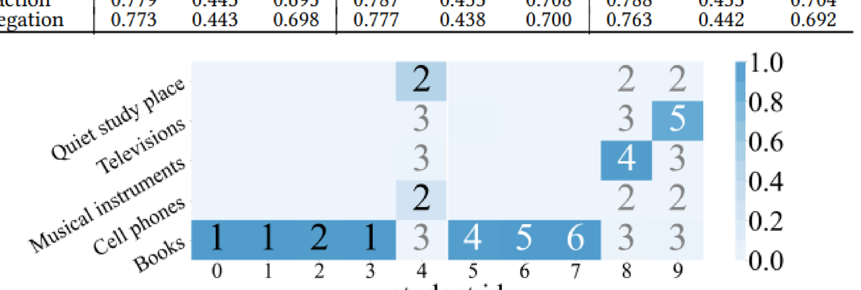


Figure 8: Attention weight and coded response of context features for different students.

Parameter Analysis

- **Visualization of x_t:** Personalization characteristic of educational contexts may reflect to students' general ability.
- **Visualization of attention:** Students focus on context inputs that fits to their score level.
- **Distribution of d_t :** Both the context influence and the historic exercise records are not ignorable for a general diagnosis.

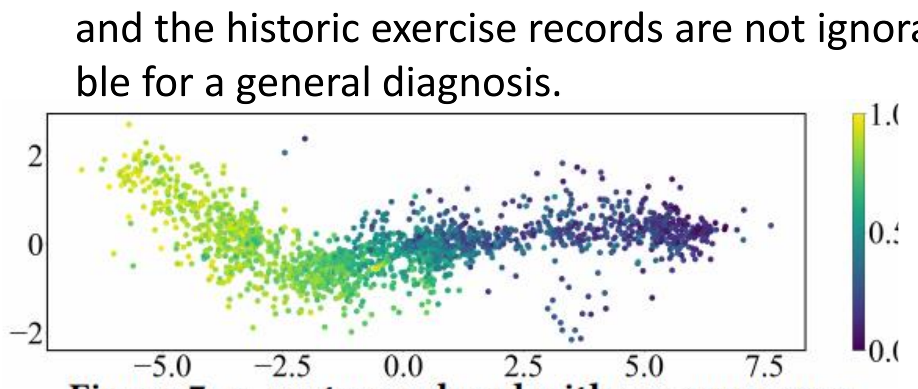
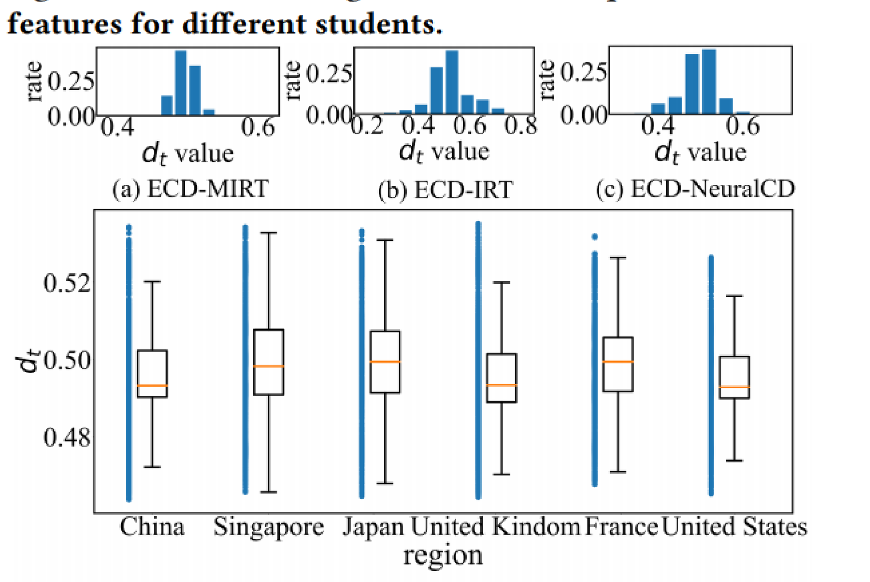


Figure 7: x_t vectors colored with average score.



(a) ECD-MIRT (b) ECD-IRT (c) ECD-NeuralCD

(d) d_t in MIRT from regions

Figure 9: The distribution of d_t values.

Cognitive States Visualization

- The order of regions are consistent with the report of PISA.
- ECD can further discriminate these specific difference in knowledge concepts between regions.

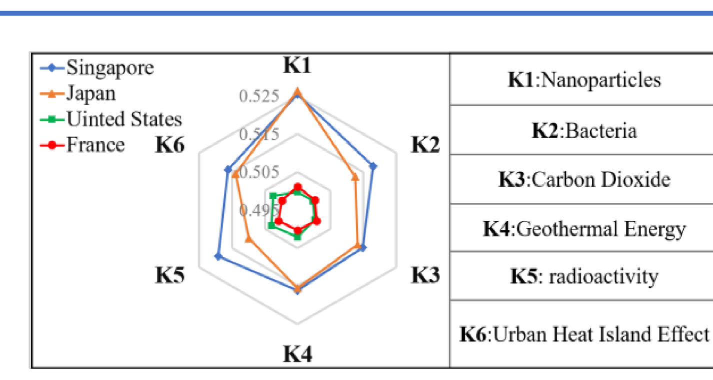


Figure 11: Visualization of average knowledge proficiency.

Discussion

- All regions give much attention in educational context that can be related to education resource (e.g., "Home ESCS", "School ICT", "ICT Usage").
- Context "Parent education" are focused in China and Korea, which can be concerned with the similar local tradition in education.
- Contexts "School learning" and "Teaching attitude" shows difference between regions from Aisa and the others.

Table 5: Important educational contexts in different regions.

Regions	Context
Uinted States	"Home ESCS", "School learning", "Teacher Attitude", "Self-efficacy"
Uinted Kindom	"Home ESCS", "School learning", "Teacher Attitude", "School ICT", "ICT Usage", "Self-efficacy"
France	"Home ESCS", "School learning", "Teacher Attitude", "School ICT", "ICT Usage"
Germany	"Home ESCS", "School learning", "Teacher Attitude", "School ICT", "ICT Usage"
Italy	"Home ESCS", "School learning", "Teacher Attitude", "School ICT", "ICT Usage"
Singapore	"Home ESCS", "School ICT", "ICT Usage", "Interest on science", "Self-efficacy"
Japan	"Home ESCS", "School ICT", "ICT Usage", "Self-efficacy"
Korea	"Parent education", "Home ESCS", "School ICT", "ICT Usage"
China	"Parent education", "Home ESCS", "School ICT", "ICT Usage"

Conclusion

- We presented **a novel framework ECD** for students' cognitive diagnosis, which is also a quantitive perspective for educational context understanding.
- We **conducted extensive experiments on real-world datasets** to demonstrate the effectiveness as well as interpretability of ECD framework.
- We analyzed and discussed **the difference of important context features** for students from **different regions** with our ECD framework.

Speaker: Yuqiang Zhou
Email: zyq1998@mail.ustc.edu.cn
Github: github.com/bigdata-ustc/ECD