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DGCPL: Dual Graph Distillation for Concept Prerequisite Relation Learning

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01 Introduction

Background

Stochastic process → Markov chain

Probability

- **Knowledge Update**

  Rapid pace in the information age demands efficient learning.

- **Concept Prerequisite Relation Learning (CPRL)**

  Essential for logical knowledge structure and effective learning.

- **Application Scenario**

  Such as:
  - *Learning Path Planning*
  - *Knowledge Tracing*
  - *Cognitive Diagnosis*
  - *Learning Resource Recommendation*

01 Introduction

Motivation

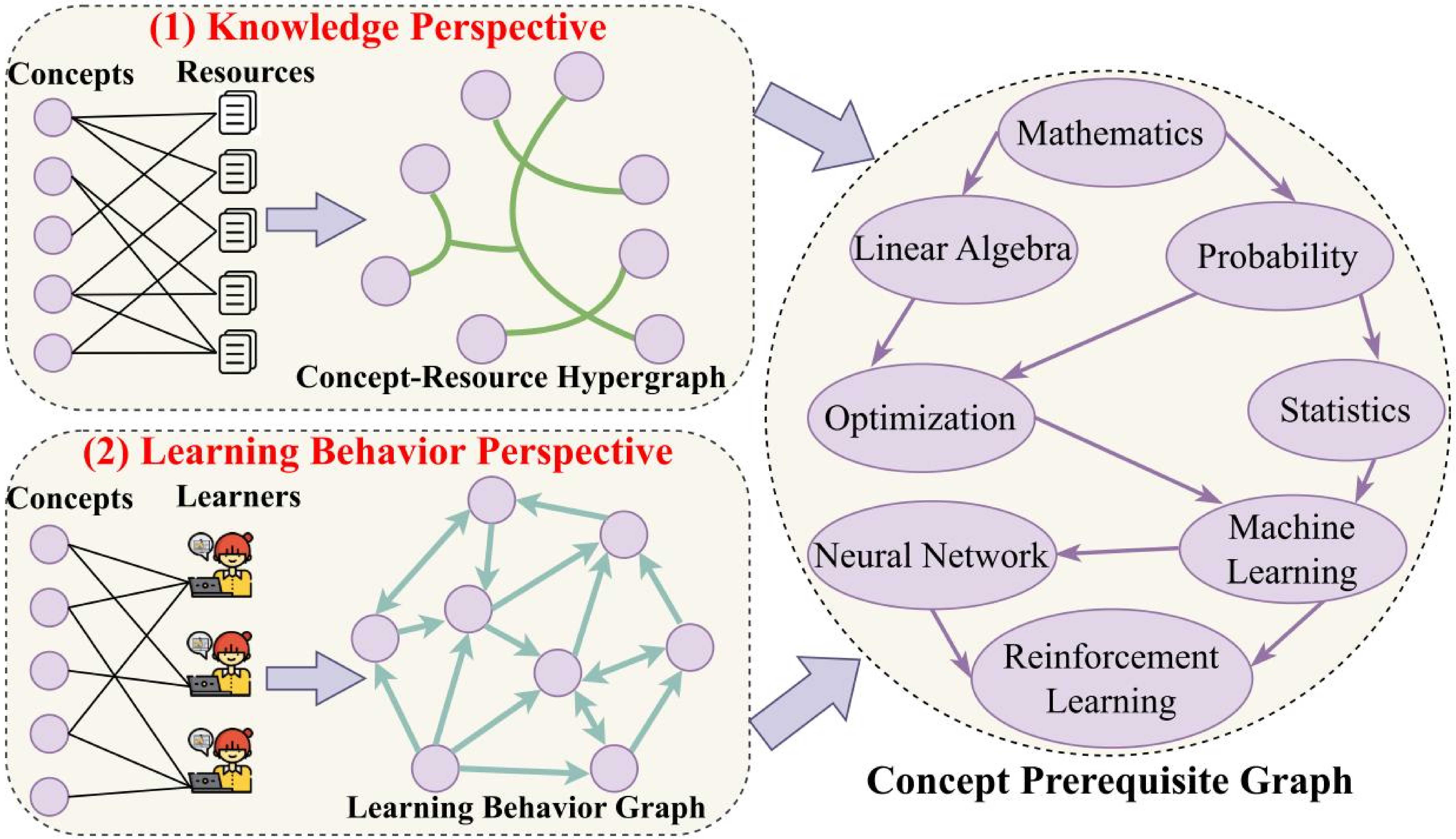


Figure 1: Learning concept prerequisite relations from the perspective of knowledge and the perspective of learning behavior.

★ Existing Limitation:

Current research rarely pays attention to the role of learners' learning behavior.
Limited to pairwise relations, such as concept-concept or concept-resource.

01 Introduction

Research Problem

This paper aims to explore and address a key problem in the field of education:

how to predict prerequisite relations from both the knowledge and learning behavior perspectives is an urgent research question.

Challenges:

① *How to capture higher-order knowledge structures?*

② *How to leverage learning behavior features for prerequisite prediction?*

③ *How to integrate knowledge and behavior effectively?*

02 Model Architecture

Dual Graph Distillation Method for Concept Prerequisite Relation Learning (DGCPL)

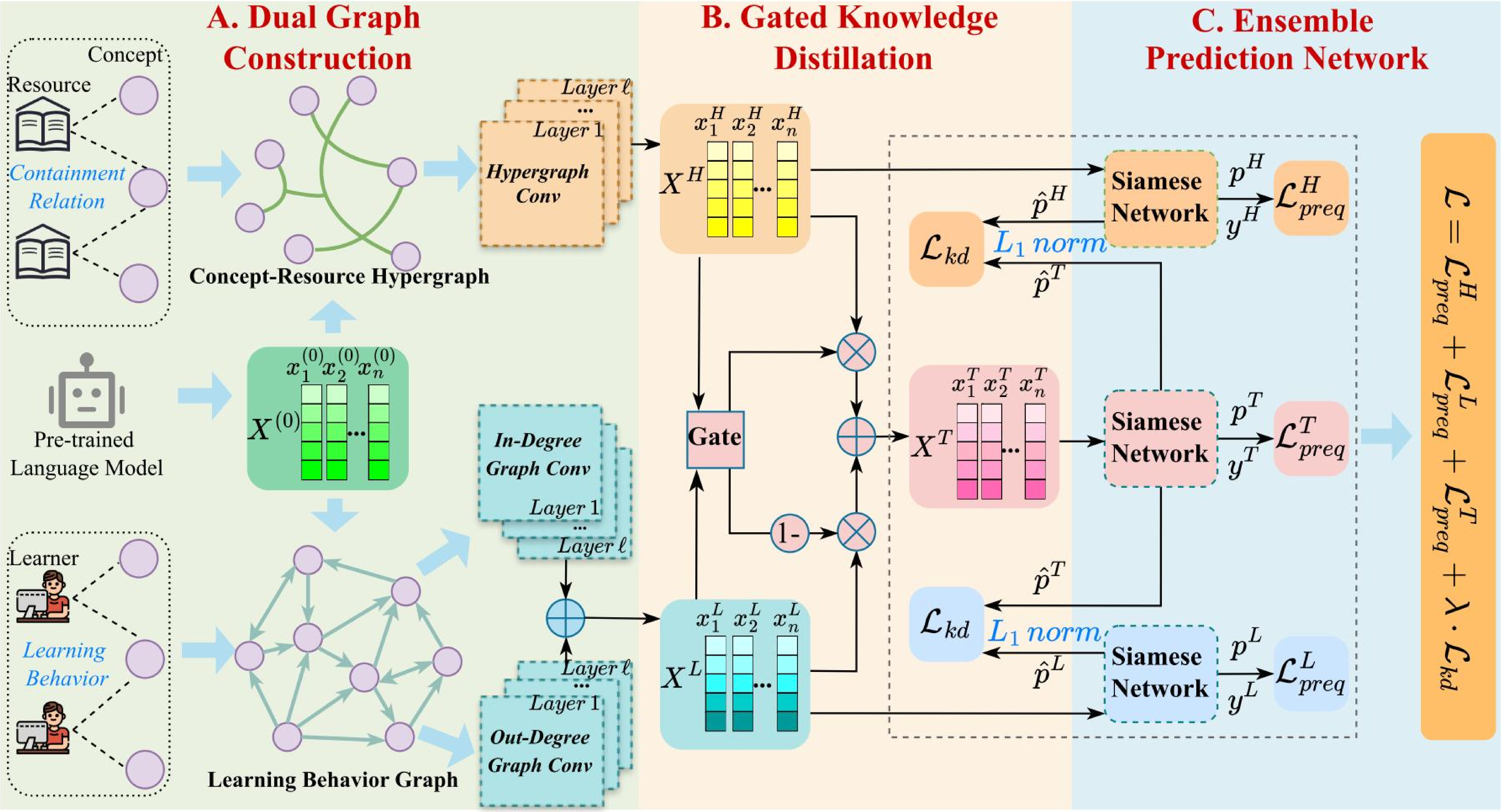


Figure 2: The overall structure of the proposed DGCPL.

02 Model Architecture

A. Dual Graph Construction

Concept-Resource Hypergraph

We adopt a hypergraph to *capture the high-order knowledge relations between knowledge concepts and learning resources*, thereby learning concept embeddings within the hypergraph.

$$\mathbf{x}_i^{(l+1)} = \phi(\mathbf{D}^{-1/2}\mathbf{H}\mathbf{W}\mathbf{B}^{-1}\mathbf{H}^T\mathbf{D}^{-1/2}\mathbf{x}_i^{(l)}\Theta^{(l+1)} + \mathrm{Linear}(\mathbf{x}_i^{(l)}))$$

We obtain the concept embeddings from the concept-resource hypergraph: $\mathbf{x}_i^H \in \mathbb{R}^d$

A. Dual Graph Construction

Learning Behavior Graph

We *utilize a directed graph convolutional network to learn concept embeddings* from the learning behavior graph.

➢ For the in-degree directed graph:

$$\mathbf{x}_i^{(l+1),-} = \phi\Big(\sum_{v_j \in N(i)^-} \frac{A_{j,i}^{(in)}}{\sqrt{deg_i^{(in)} \cdot deg_j^{(out)}}} \Theta_N^{(l+1),-} \mathbf{x}_j^{(l)}\Big)$$

➢ For the out-degree directed graph:

$$\mathbf{x}_i^{(l+1),+} = \phi\Big(\sum_{v_j \in N(i)^+} \frac{A_{i,j}^{(out)}}{\sqrt{deg_i^{(out)} \cdot deg_j^{(in)}}} \Theta_N^{(l+1),+} \mathbf{x}_j^{(l)}\Big)$$

✓ For the entire learning behavior graph:

$$\mathbf{x}_i^{(l+1)} = \phi(\mathrm{Linear}(\mathbf{x}_i^{(l+1),+}) + \mathrm{Linear}(\mathbf{x}_i^{(l+1),-})).$$

We obtain the concept embeddings from the learning behavior graph: $\mathbf{x}_i^L \in \mathbb{R}^d$

02 Model Architecture

B. Gated Knowledge Distillation

We treat the concept-resource hypergraph and the learning behavior graph as *two independent student models*.

Subsequently, we regard these two graph modules as *equivalent student models* and employ a *gating mechanism* to achieve their effective integration.

$$\mathbf{x}_i^T = g \odot \mathbf{x}_i^H + (1 - g) \odot \mathbf{x}_i^L,$$

$$g = \sigma(\mathbf{W}_f[\mathbf{x}_i^H, \mathbf{x}_i^L] + \mathbf{b}_f).$$

Finally, we obtain the final embedding of the teacher model: $\mathbf{x}_i^T \in \mathbb{R}^d$

C. Ensemble Prediction Network

➢ Calculate the *prediction loss*:

$$\mathbf{logit}_{ij} = \mathbf{W}_p \cdot [\tilde{\mathbf{x}}_i \| \tilde{\mathbf{x}}_j \| (\tilde{\mathbf{x}}_i - \tilde{\mathbf{x}}_j) \| (\tilde{\mathbf{x}}_i \odot \tilde{\mathbf{x}}_j)] + \mathbf{b}_p, \qquad p(c_i, c_j) = \sigma(\mathbf{logit}_{ij})$$

$$\mathcal{L}_{preq} = \frac{1}{|\mathcal{D}|} \sum_{(c_i, c_j) \in \mathcal{D}} \mathrm{BCE}(p(c_i, c_j), y_{c_i c_j})$$

➢ Calculate the *distillation loss*:

$$\hat{p}(c_i, c_j) = \sigma(\mathbf{logit}_{ij} / \tau)$$

$$\mathcal{L}_{kd} = \frac{1}{|\mathcal{D}|} \sum_{(c_i, c_j) \in \mathcal{D}} \left\| \hat{p}^T(c_i, c_j) - \hat{p}^H(c_i, c_j) \right\|_1 + \\ + \left\| \hat{p}^T(c_i, c_j) - \hat{p}^L(c_i, c_j) \right\|_1,$$

The distillation loss encourages each student model to *align its predictions* with those of the teacher model.

✓ **Global Loss Function:**

$$\mathcal{L} = \mathcal{L}_{preq}^H + \mathcal{L}_{preq}^L + \mathcal{L}_{preq}^T + \lambda \cdot \mathcal{L}_{kd}$$

03 Experimental Results

RQ1. Overall Performance

Method	UCD			LectureBank			MOOC		
	ACC	F1	AUC	ACC	F1	AUC	ACC	F1	AUC
NB	0.5495	0.5845	0.5369	0.5207	0.5323	0.5262	0.5124	0.5288	0.5357
SVM	0.5743	0.6161	0.5601	0.5455	0.5669	0.5361	0.5821	0.6000	0.5923
RF	0.6683	0.6455	0.7419	0.6777	0.6723	0.8245	0.7363	0.7135	0.8084
RefD	0.7620	0.7110	0.7520	0.3900	0.5570	0.4760	0.5870	0.4140	0.4900
PREREQ	0.5433	0.5866	0.6702	0.4975	0.5130	0.5557	0.5429	0.5746	0.6248
GAE	0.6642	0.6631	0.6955	0.6877	0.6864	0.7651	0.6721	0.6700	0.6995
VGAE	0.6933	0.6927	0.7552	0.6907	0.6898	0.7534	0.6664	0.6656	0.7144
R-VGAE(T)	0.6849	0.6618	0.7646	0.6660	0.6345	0.7942	0.5926	0.5435	0.6602
R-VGAE(P)	0.7369	0.7220	0.8325	0.5678	0.4714	0.8107	0.5344	0.4108	0.8730
ConLearn	0.7822	0.7684	0.8529	0.8017	0.7931	0.8541	0.7562	0.7200	0.8472
MHAVGAE	0.7875	0.7952	0.8645	0.7263	0.7401	0.8213	0.7475	0.7642	0.8759
HGAPNet	0.8200	0.8043	0.8998	0.8167	0.8136	**0.8803**	0.8550	0.8497	0.9014
LCPRE	0.8366	0.8216	0.8884	0.8182	0.8000	0.8514	0.8258	0.8223	0.8898
DGCPL (Ours)	**0.8564**	**0.8557**	**0.9053**	**0.8347**	**0.8246**	0.8795	**0.8756**	**0.8718**	**0.9236**
Improve rate	1.98% ↑	3.41% ↑	0.55% ↑	1.65% ↑	1.10% ↑	0.08% ↓	2.06% ↑	2.21% ↑	2.22% ↑

On three publicly available benchmark datasets, we compare DGCPL with *eight graph-based* baseline methods and *five traditional classification* baseline methods. The experimental results demonstrate that DGCPL achieves *state-of-the-art performance*.

03 Experimental Results

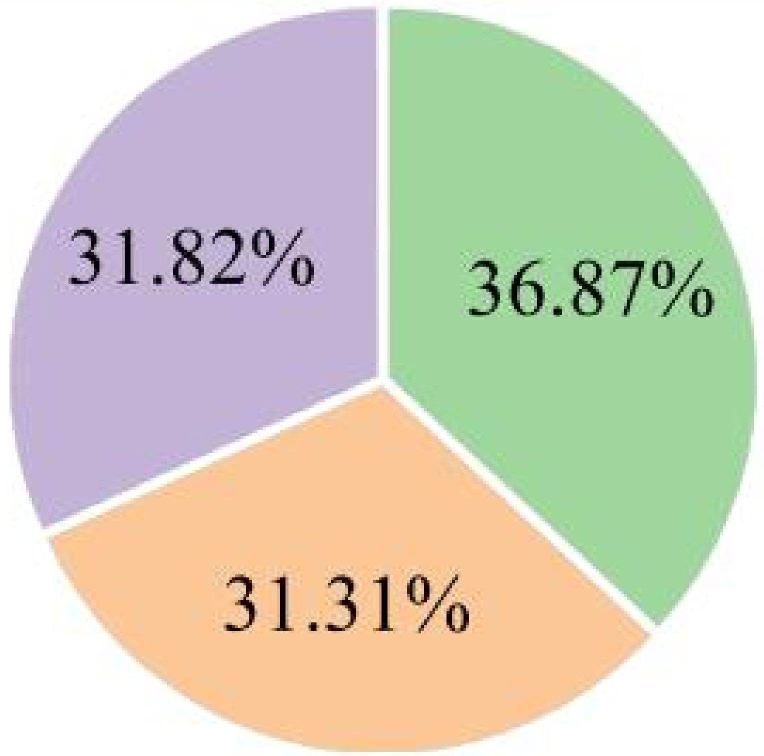
RQ2. Ablation Experiment

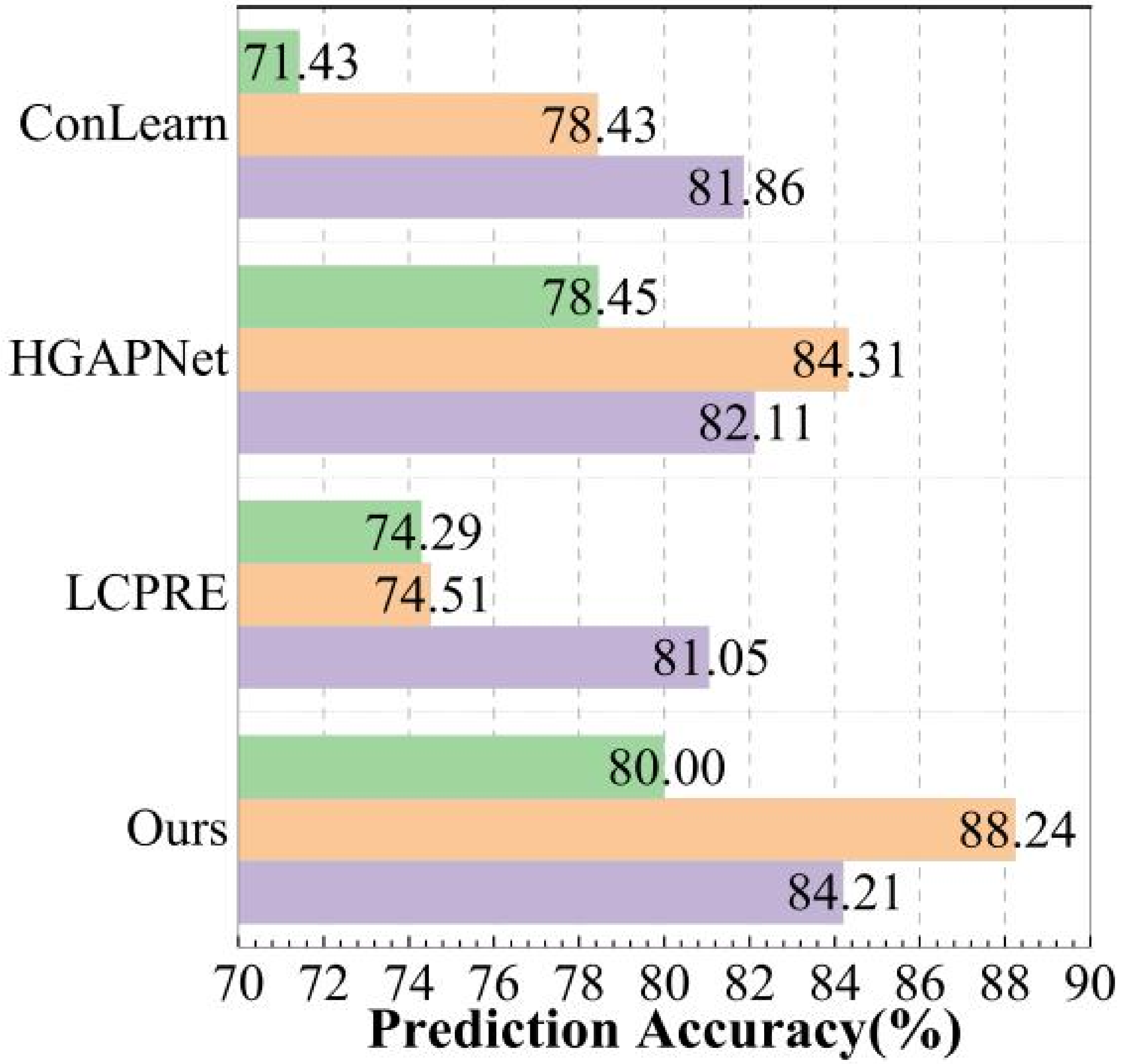
Method	UCD	LectureBank	MOOC
Ours DGCPL	**0.8557**	**0.8246**	**0.8718**
Ours w/o GKD	0.8374	0.8226	0.8528
Ours w/o CRHG	0.8177	0.8160	0.8168
Ours w/o LBG	0.8235	0.8130	0.8469

- ✓ **w/o GKD**: Removing the Gated Knowledge Distillation.
- ✓ **w/o CRHG**: Removing the Concept Resource Hypergraph.
- ✓ **w/o LBG**: Removing the Learning Behavior Graph.

RQ3. Quality Analysis

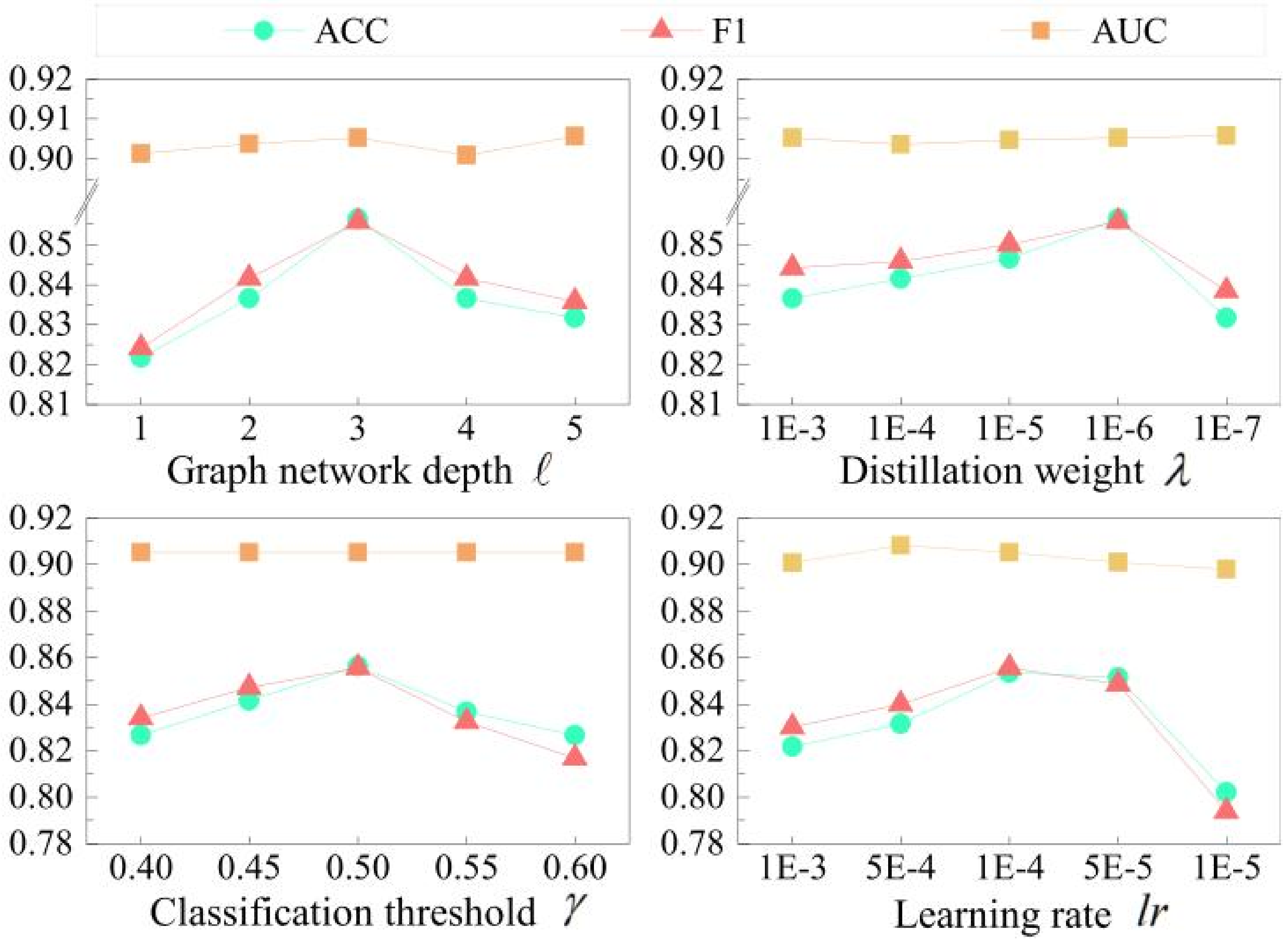
Degree Level	Degree Range
Low Degree	0<Degree<=3
Medium Degree	3<Degree<=6
High Degree	6<Degree



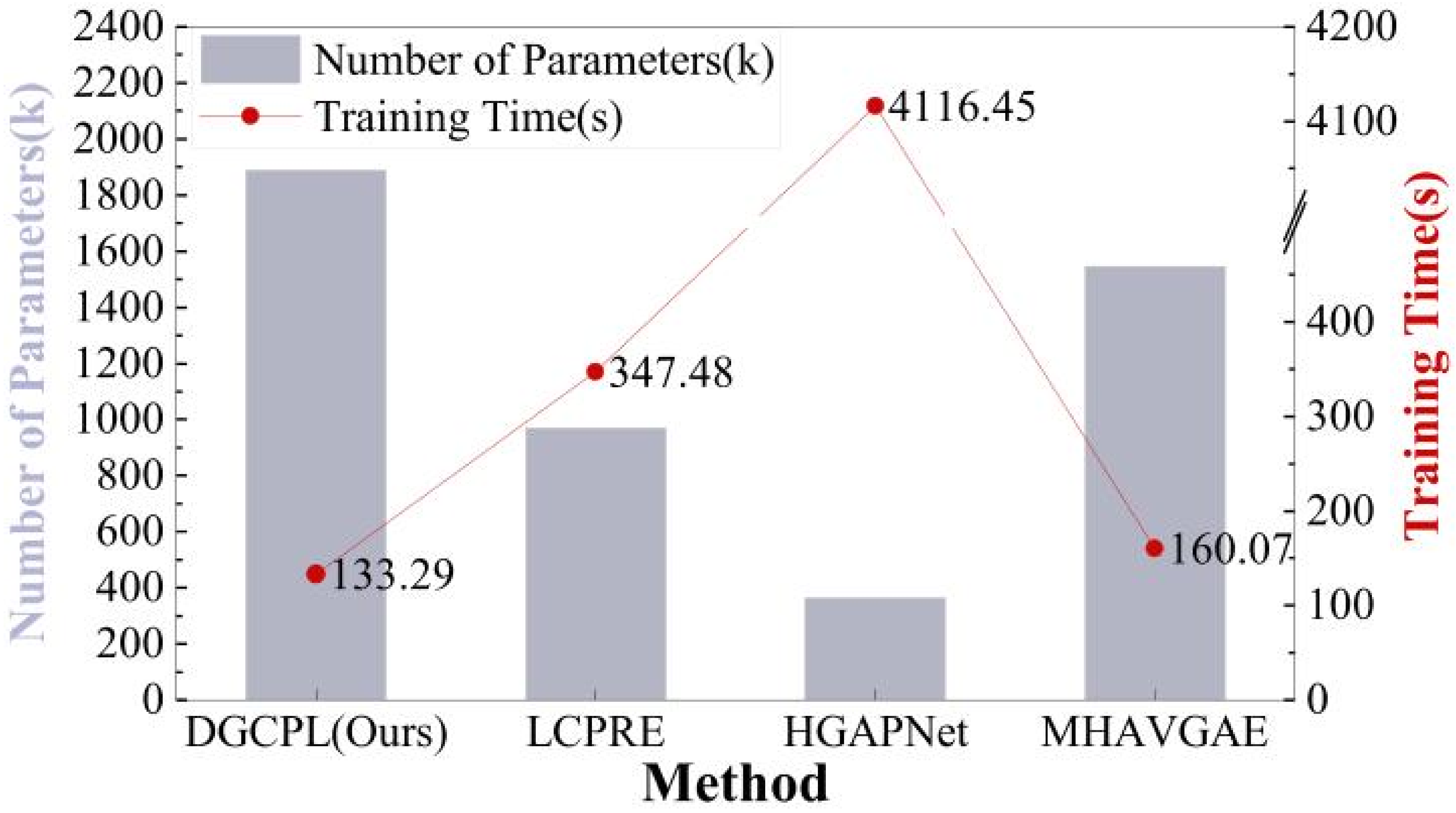


03 Experimental Results

RQ4. Hyperparameter Analysis



RQ5. Training Overhead Analysis



Dual Graph Structure + Gated Knowledge Distillation
-> more efficient and effective concept embedding learning

03 Experimental Results

RQ6 (Appendix). Impact of Directed Graph Feature Fusion Methods

Operation	UCD			LectureBank			MOOC		
	ACC	F1	AUC	ACC	F1	AUC	ACC	F1	AUC
Addition (Ours)	**0.8564**	**0.8557**	0.9053	**0.8347**	**0.8246**	0.8795	**0.8756**	**0.8718**	**0.9236**
Concat+MLP	0.8416	0.8416	**0.9074**	0.8099	0.8099	0.8776	0.8557	0.8497	0.9211
Maximum	0.8515	0.8515	0.9048	0.8264	0.8205	0.8724	0.8657	0.8601	0.9190
Average	0.8416	0.8384	0.9011	0.8017	0.7778	**0.8842**	0.8657	0.8643	0.9214
Minimum	0.8515	0.8469	0.9058	0.7851	0.7636	0.8727	0.8507	0.8485	0.9134

RQ7 (Appendix). Impact of pre-training language model

Method	UCD			LectureBank			MOOC		
	ACC	F1	AUC	ACC	F1	AUC	ACC	F1	AUC
DGCPL (Ours)	**0.8564**	**0.8557**	**0.9053**	**0.8347**	**0.8246**	**0.8795**	**0.8756**	**0.8718**	**0.9236**
LCPRE	0.8366	0.8216	0.8884	0.8182	0.8000	0.8514	0.8258	0.8223	0.8898
HGAPNet	0.8400	0.8333	0.9044	0.7833	0.7759	0.8672	0.7900	0.7835	0.8573
ConLearn	0.7822	0.7684	0.8529	0.8017	0.7931	0.8541	0.7562	0.7200	0.8472

04 Conclusion and Acknowledgement

Conclusion

- ***Dual Graph Structure.*** We propose a Dual Graph Distillation Method for Concept Prerequisite Relation Learning (DGCPL), which predicts concept prerequisite relations by constructing a dual graph.

- ***Gated Knowledge Distillation.*** We introduce gated knowledge distillation that adaptively integrates higher-order knowledge relations and learning behavior features information.

- ***Experiments and Performance.*** The experimental results demonstrate that DGCPL achieves state-of-the-art performance.

Acknowledgement

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Codes available at

https://github.com/wisejw/GKROM

Code and Appendix

If any question, please contact

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Thank you!