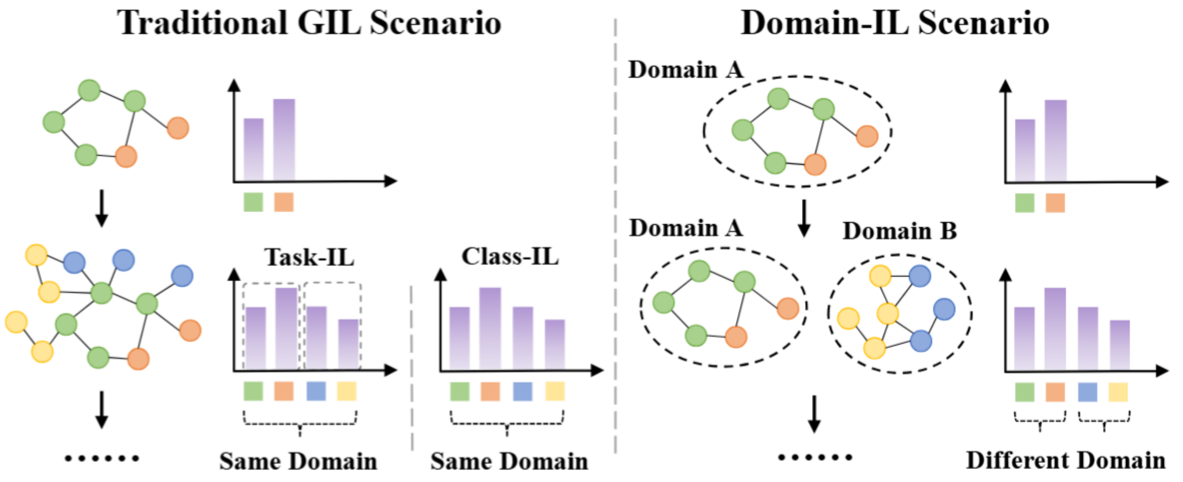
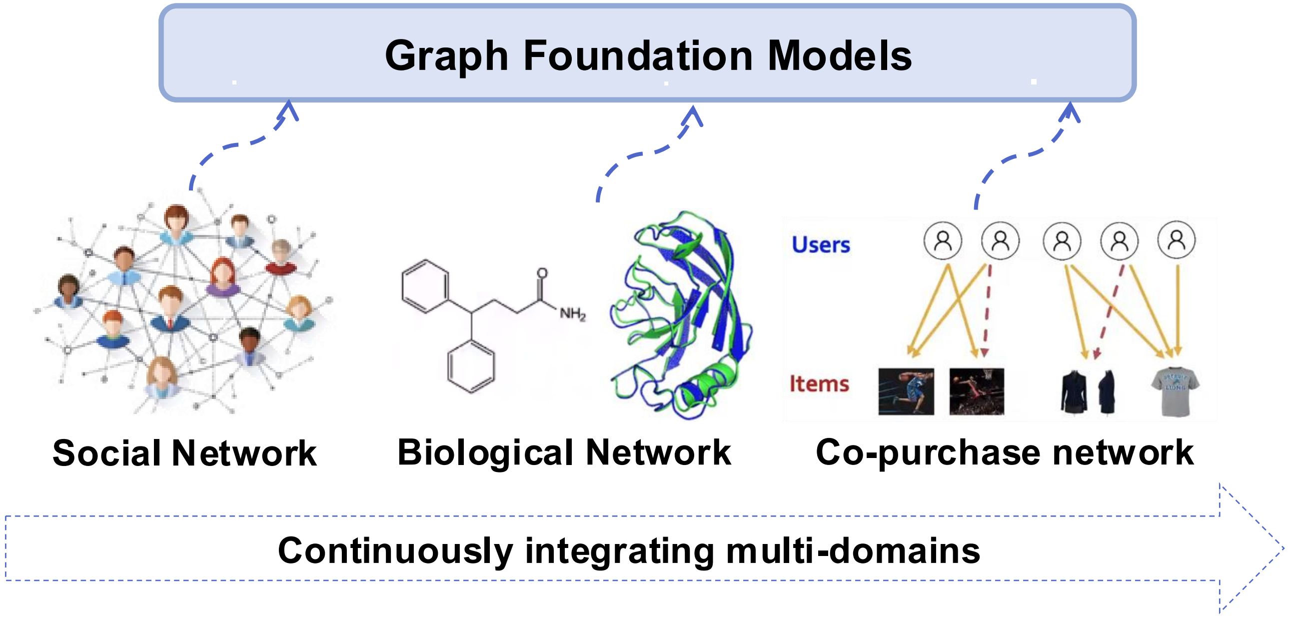
GraphKeeper: Towards Multi-Domain Graph Incremental Learning

■ Background: Graph Domain Incremental Learning (Graph Domain-IL)

- **Traditional scenarios focus on** new tasks or classes emerge **within a single domain.**
- As newly added graphs come from different domains, the **Domain-IL becomes essential**, **especially for graph foundation models (GFMs).**





Zihao Guo, Qingyun Sun, et al. GraphKeeper: Graph Domain-Incremental Learning via Knowledge Disentanglement and Preservation, NeurIPS 2025.

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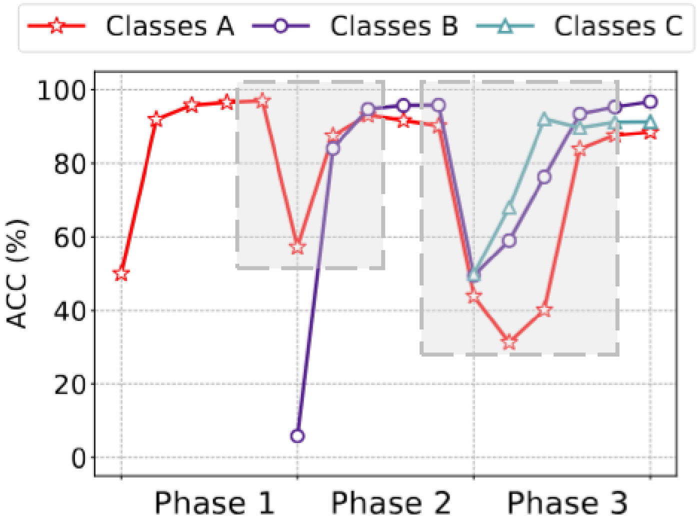
Challenge: Catastrophic Forgetting in Graph Domain-IL Scenario

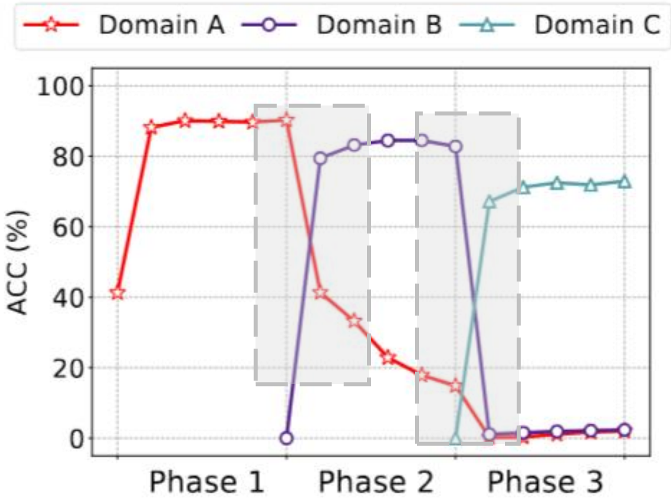
- **Existing GIL methods are designed** for Task-IL and Class-IL **within a single-domain.**
- The representative GIL method performs well under traditional incremental scenario but **fails in the more challenging Domain-IL scenario.**



AA: 92.18%

AF: 2.96%

Traditional Scenario



AA: 25.79%

AF: 56.20%

Domain-IL Scenario

Catastrophic Forgetting !

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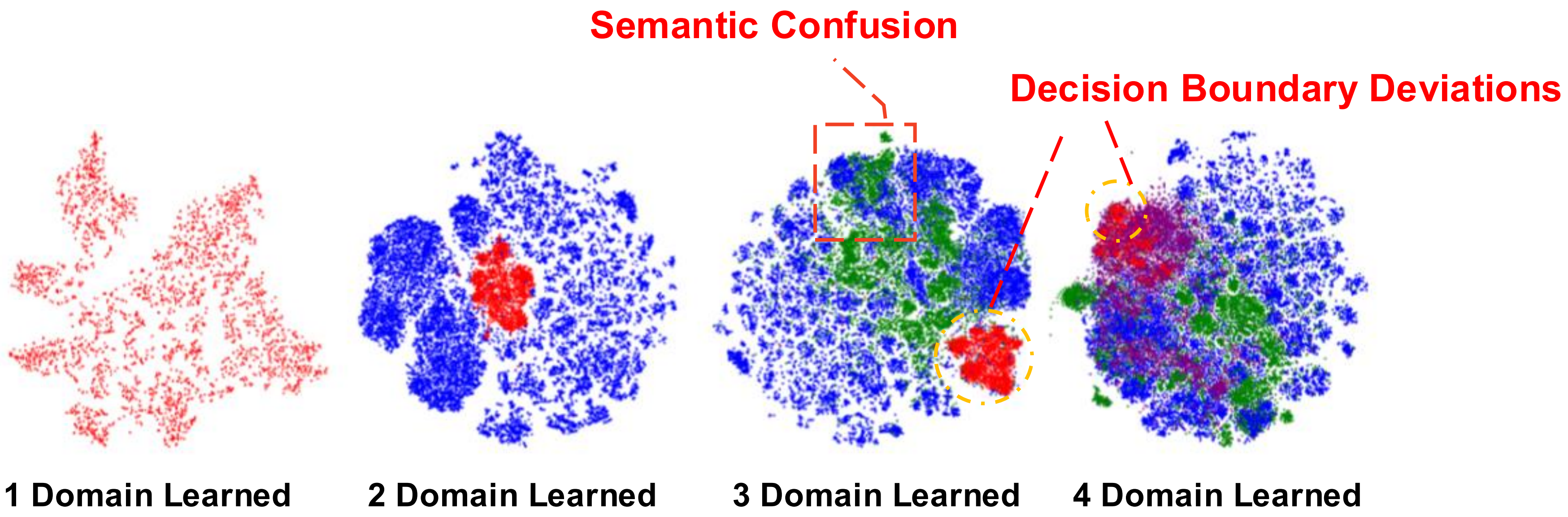
What's the Underlying Cause of Catastrophic Forgetting in Domain-IL?

Embedding shifts

- **The embedding shifts** introduced by drastic model parameter changes when adapting to new domains, bring the risk of **semantic confusion between incremental graphs**.

Decision boundary deviations

- The drastic parameter changes cause **decision boundary deviations. Previous methods,** which treat embedding learning and prediction as an integrated process, **struggle to constrain the decision boundary effectively.**



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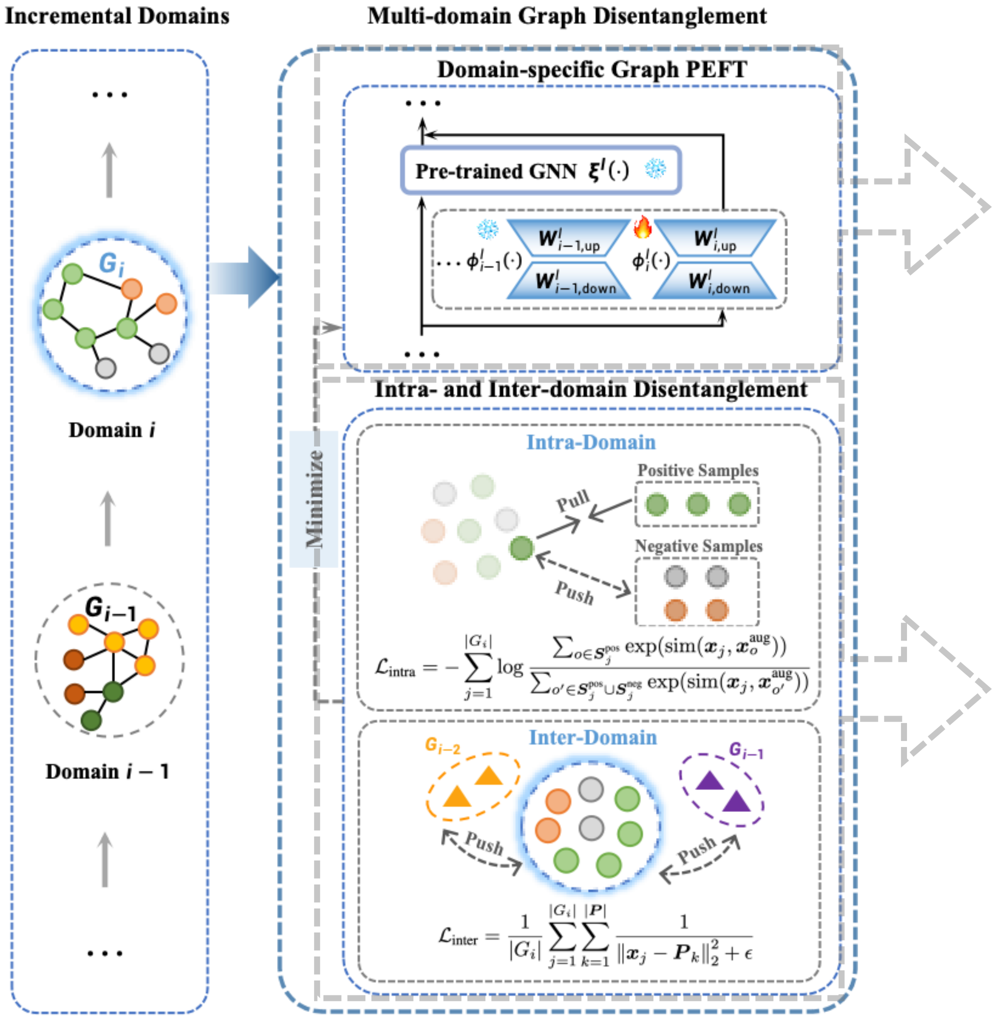
Method: Multi-domain Graph Disentanglement

- **RQ1.** How to learn stable and disentangled representations for different graph domains in GIL?



- **Domain-specific Graph PEFT.** We equip the pre-trained GNN with a LoRA module for each incremental domain, to **prevent potential catastrophic forgetting of previous domains** due to drastic parameter changes.

- **Intra- and Inter domain Disentanglement.** To enhance **the discriminability of node embeddings across different classes within a single domain**, and **prevent catastrophic forgetting caused by confusion between domains**, we intra- and inter domain Disentanglement objective, respectively.

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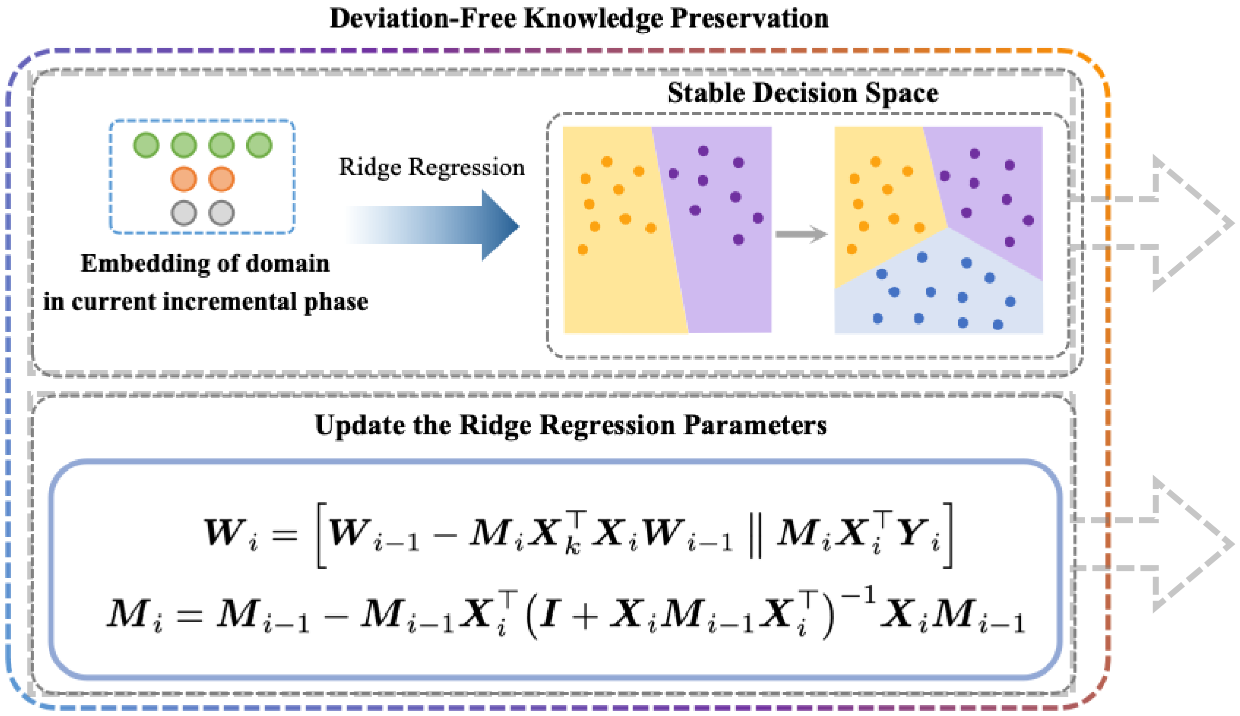
Method: Deviation-Free Knowledge Preservation

- **RQ2.** How to effectively retain knowledge from previously learned graph domains?



- **Ridge Regression for Stable Classifier Updates.** We fit the classes **through ridge regression rather than end-to-end classifiers** through backpropagation, to **constrain the decision boundary effectively**.

- **Recursive Update without Historical Data Access.** To adapt to the GIL process, we **recursively update the parameter matrix** only using data from the current graph domain, cause **the historical domains are not accessible**.

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Performance on Domain-IL Scenario

	Method	Group 1		Group 2		Group 3		Group 4		Group 5		Group 6	
		AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑
Self-designed Baselines	Fine-Tune	23.9±0.1	-72.7±0.3	17.1±0.4	-74.4±0.7	20.9±0.1	-81.3±0.2	21.6±0.6	-77.8±1.1	19.7±0.1	-77.8±0.3	18.6±0.6	-77.9±0.6
	Joint	66.6±0.8	-	67.6±0.4	-	78.0±0.3	-	75.7±0.8	-	74.5±0.3	-	71.5±0.5	-
General IL Methods	EWC	23.3±0.1	-72.0±0.3	17.3±0.4	-74.8±1.0	20.8±0.3	-80.9±0.2	22.4±0.6	-76.1±0.8	20.6±0.2	-77.9±0.6	18.0±0.3	-76.6±0.9
	MAS	24.0±2.4	-70.5±4.3	16.8±5.1	-69.8±5.0	18.9±2.5	-77.4±3.0	21.1±5.0	-75.5±7.7	18.9±3.4	-74.0±3.2	19.8±2.3	-71.5±1.1
	GEM	23.3±3.2	-71.7±5.6	20.1±3.4	-69.2±2.8	21.7±2.3	-80.6±2.1	21.1±4.2	-77.4±4.3	20.0±2.5	-77.4±2.1	19.4±1.8	-76.1±0.7
	LWF	23.7±2.9	-72.5±1.3	17.0±0.7	-73.8±0.7	20.2±0.2	-80.7±0.2	20.1±0.2	-78.6±0.6	19.8±0.2	-77.9±0.4	18.8±0.3	-76.0±0.7
Graph IL Methods	TWP	23.5±0.1	-71.0±0.5	16.0±3.3	-71.0±1.6	20.0±2.2	-79.0±0.7	20.2±2.0	-79.0±1.0	18.8±3.4	-74.4±1.2	18.2±2.1	-75.2±1.0
	ER-GNN	23.3±1.4	-64.8±3.8	22.7±2.2	-66.3±2.9	28.7±3.0	-66.3±3.7	23.9±1.7	-72.9±2.8	24.8±2.7	-68.8±3.9	24.7±4.7	-67.9±5.8
	SSM	24.1±7.8	-36.4±13.1	22.1±3.6	-35.7±5.8	15.6±3.3	-31.0±4.1	25.3±2.6	-45.7±3.8	25.7±2.8	-39.3±3.3	16.1±5.7	-33.9±4.8
	TPP	52.6±1.8	0.0±0.0	49.7±1.5	0.0±0.0	57.1±2.5	0.0±0.0	53.0±2.9	0.0±0.0	56.7±1.0	0.0±0.0	48.3±2.4	0.0±0.0
	DeLoMe	49.3±0.1	-7.7±0.1	58.2±5.1	-9.6±8.5	70.2±4.1	-1.0±0.1	73.4±4.3	-1.1±0.2	63.2±5.7	-3.3±7.1	64.2±2.2	-4.8±5.9
	PDGNNs	52.4±0.5	-15.8±0.6	53.5±0.3	-7.4±0.3	65.5±0.6	-11.4±0.7	65.5±0.5	-7.2±0.8	64.3±0.3	-8.2±0.3	60.2±0.2	-7.2±0.4
	GraphKeeper	**69.2±0.3**	-0.4±0.2	**73.1±1.1**	-2.8±0.7	**80.6±0.4**	0.0±0.1	**79.9±0.5**	1.0±0.5	**75.5±0.9**	0.1±0.5	**77.5±0.7**	-0.1±0.5

- Compared to 12 baselines, GraphKeeper achieves state-of-the-art results with **6.5%~16.6% improvement over the runner-up** and with **negligible forgetting**.
- The **Joint baseline underperforms GraphKeeper** even with full access to historical domains, indicating that **a single GNN struggles to effectively integrate knowledge from multi-domains**.

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Studies of Integration with GFMs in Few-Shot Domain-IL

Method	Group 1		Group 2		Group 3		Group 4		Group 5		Group 6	
	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑	AA ↑	AF ↑
GCOPE	20.6±0.9	-53.5±2.1	10.5±0.7	-36.7±1.0	13.2±1.2	-47.7±2.9	12.6±1.1	-51.0±1.8	13.6±1.4	-41.7±2.9	12.6±0.9	-43.7±1.1
GCOPE+Ours	**56.8±1.9**	0.2±0.3	**36.6±1.4**	0.3±0.3	**47.4±4.1**	-1.6±2.8	**51.6±1.6**	-0.4±0.6	**44.3±4.0**	0.8±0.5	**44.9±0.9**	-0.8±0.8
MDGPT	19.9±1.3	-59.4±2.1	10.7±0.5	-42.7±2.2	12.1±1.5	-50.4±2.1	12.8±1.4	-52.9±3.1	12.8±1.3	-47.6±5.9	12.3±0.5	-48.8±3.3
MDGPT+Ours	**59.7±1.2**	-1.5±0.7	**32.7±1.0**	-0.4±0.7	**49.5±2.1**	-2.8±1.1	**62.7±1.7**	-1.4±1.2	**50.9±1.6**	-0.7±0.4	**43.9±1.1**	-0.2±1.0

- The original GFMs exhibit low average accuracy (AA) and high average forgetting (AF). After **integrating the GraphKeeper**, GFMs show **significantly higher AA with negligible forgetting**.

Longer Incremental Learning Sequence

Method	Group 7 (11 Domains)		Group 8 (12 Domains)	
	AA ↑	AF ↑	AA ↑	AF ↑
TPP	50.2±0.9	0.0±0.0	52.8±2.5	0.0±0.0
DeLoMe	> 1 day		> 1 day	
PDGNNs	37.7±0.1	-13.1±0.4	45.0±0.2	-13.6±0.3
GraphKeeper	**73.0±1.1**	-0.7±0.5	**76.5±0.9**	-0.8±0.2

- The advanced baselines suffer performance drops, while **GraphKeeper still maintains strong performance** and outperforms the runner-up by 22.8%~23.7%.

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