HGPROMPT: Bridging Homogeneous and Heterogeneous Graphs for Few-shot Prompt Learning

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Motivation

Problem

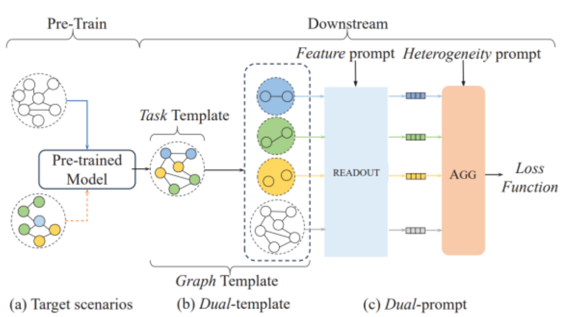


Figure 1: Illustration of HGPROMPT. Black-and-white graphs are homogeneous; colored graphs are heterogeneous, where colors indicate different types of nodes.

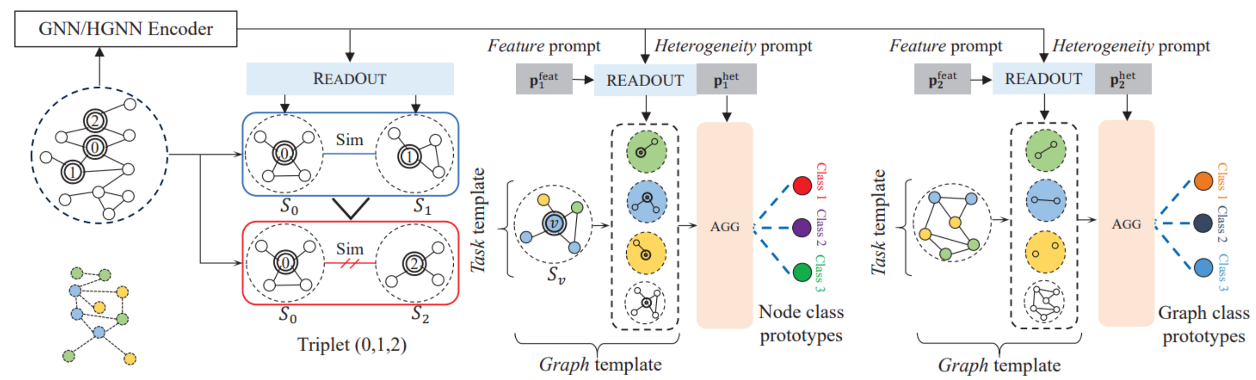
- "Pre-train, prompting" paradigm [1,2] hasn't been explored on heterogeneous graphs.
- Divergence between pre-training and downstream tasks not only lies in different objectives of tasks, but also diverse types of graphs.

Challenges

1. How to unify heterogeneous graphs with homogeneous graphs?
2. How to design a prompt to narrow the gaps caused by feature and heterogeneity?

The proposed model: HGPrompt

Overall framework



(a) Pre-training graphs (b) Pre-training (link prediction) (c) Downstream node classification (d) Downstream graph classification

Figure 2: Overall framework of HGPROMPT. (a) Pre-training graphs can be either homogeneous or heterogeneous. (b) Pre-training task with link prediction on a homogeneous graph[1]. (c) Downstream node classification and (d) graph classification on heterogeneous graphs. Black-and-white graphs are homogeneous; colored graphs are heterogeneous, where colors indicate different types of nodes.

Comparison with GraphPrompt

	GraphPrompt [1]	HGPrompt
Pre-train	Homogeneous	Homogeneous/ Heterogeneous
Template	Task only	Task & Graph
Prompt	Feature only	Feature & Heterogeneity
Downstream	Homogeneous	Heterogeneous

Dual Template & Dual Prompt

Unified graph template

$$\mathcal{GT}(G) = \{G^0\} \cup \{G^i : i \in A\}$$

Unified task template

$$\mathbf{s}_v = \text{AGG}(\{\text{READOUT}(S_v^i) \mid S_v^i \in \mathcal{GT}(S_v)\})$$

Feature prompt

$$\text{READOUT}(\{\mathbf{p}^{\text{feat}} \odot \mathbf{h}_v \mid v \in V(S)\})$$

Heterogeneity prompt

$$\text{AGG}(\{(1 + p_i^{\text{het}}) \odot \text{READOUT}(S^i) \mid S^i \in \mathcal{GT}(S)\})$$

Experiments

Datasets

Table 1: Summary of datasets.

	# Nodes	# Node Types	# Edges	# Edge Types	Target Type	# Classes
ACM	10,942	4	547,872	8	paper	3
DBLP	26,128	4	239,566	6	author	4
Freebase	180,098	8	1,057,688	36	book	7

Baselines

Homogenous GNNs: GCN , GAT **Heterogeneous GNNs**: Simple-HGN[3], HAT

Homogenous graph pre-training & fine-tuning: DGI, InfoGraph, GraphCL

Heterogeneous graph pre-training & fine-tuning: CPT-HG, HeCo

Homogenous graph pre-training & prompting: GPPT[4], GraphPrompt

Performance with different shots

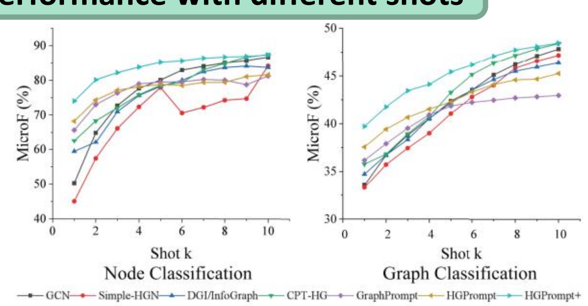


Figure 3: Impact of shots on NC and GC tasks on *ACM*.

Main results

Table 2: Evaluation of node and graph classification. The best method is bolded and the runner-up is underlined.

Methods	Node classification ACM MicroF (%)	ACM MacroF (%)	DBLP MicroF (%)	DBLP MacroF (%)	Freebase MicroF (%)	Freebase MacroF (%)	Graph classification ACM MicroF (%)	ACM MacroF (%)	DBLP MicroF (%)	DBLP MacroF (%)	Freebase MicroF (%)	Freebase MacroF (%)
GCN	50.26±12.17	44.21±16.62	51.36±15.40	48.62±17.27	17.11±11.80	15.35±9.54	33.56± 1.05	17.72± 2.78	38.12±15.02	35.01±16.24	17.38±2.94	16.50±2.54
GAT	38.50± 7.86	28.01±12.44	65.04±11.68	62.83±13.21	17.93± 8.50	16.51±6.81	33.52± 1.05	17.25± 1.53	46.47±14.51	40.33±16.84	16.30±2.69	16.01±2.14
SIMPLE-HGN	45.57±10.64	40.58±14.21	59.74±15.22	57.34±16.29	17.85± 9.12	16.00±7.88	33.30±10.87	16.83± 6.88	44.56±15.80	39.52±17.12	17.83±2.81	16.71±2.49
HAN	62.22± 9.11	57.19±11.79	62.46±18.92	60.64±19.73	18.73±12.40	16.81±8.16	35.35± 8.93	22.27± 5.60	47.09 ±16.52	42.01±17.92	18.47±3.11	17.36±2.65
DGI/INFOGRAPH	59.42±18.82	56.24±24.58	68.24±15.11	65.35±16.16	18.30± 9.23	16.84±6.74	34.73±16.38	20.67±16.65	51.01±15.60	45.13±16.04	18.20±2.85	17.39±2.44
GRAPHCL	58.53±16.64	55.46±21.30	66.59±15.12	64.67±15.25	18.40± 9.23	16.93±6.24	33.17±13.49	21.75±12.03	50.62±15.78	44.78±16.21	18.32±2.85	17.46±2.38
CPT-HG	62.57±15.40	58.47±20.10	70.63±13.46	67.03±12.58	19.00± 8.55	17.46±5.51	35.78±19.57	27.06±18.89	53.67±14.98	46.98±15.52	18.95±2.74	17.94±2.13
HECO	63.32±15.14	59.13±17.46	70.74±11.60	67.63±12.35	19.42± 8.13	18.17±6.18	35.42±15.96	27.37±14.45	53.78±13.21	47.51±15.28	19.30±2.68	18.54±2.38
GPPT	54.89±10.89	51.67±12.24	61.47± 9.23	63.23±10.67	17.58± 7.67	16.57±5.19	-	-	-	-	-	-
GRAPHPROMPT	65.67±13.69	61.10±14.85	73.73± 9.94	69.26±10.63	19.86± 6.07	18.18±4.43	36.18±15.76	27.70±15.41	56.68±11.62	49.08±13.69	19.77±2.44	18.55±1.81
HGPROMPT	<u>68.23</u>±11.35	<u>63.57</u>±13.09	<u>77.69</u>± 9.70	<u>73.22</u>±10.95	<u>21.26</u>± 7.00	<u>19.81</u>±4.83	<u>37.57</u>±15.08	<u>28.90</u>±14.88	<u>58.49</u>±10.68	<u>47.75</u>± 8.80	<u>20.91</u>±2.82	<u>19.86</u>±2.14
HGPROMPT+	**74.04**±12.49	**74.47**±14.28	**82.31**±10.67	**77.44**±12.05	**22.64**± 7.94	**21.08**±5.72	**39.72**±15.08	**32.96**±18.07	**60.53**±11.40	**52.02**±13.95	**21.70**±3.32	**20.91**±3.29

Ablation study

Table 3: Variants used in ablation study, and corresponding results in MicroF (%) on node and graph classification.

Methods	Graph template (pre-training)	Heterogeneity prompt	Graph template (downstream)	Feature prompt	Node classification ACM	DBLP	Freebase	Graph classification ACM	DBLP	Freebase
VARIANT 1	×	×	×	×	55.92	56.49	17.43	33.92	40.47	16.78
VARIANT 2	×	×	×	✓	61.10	69.26	18.18	35.18	56.68	19.77
VARIANT 3	×	×	✓	✓	62.34	70.77	18.63	35.70	56.23	19.03
HGPROMPT	×	✓	✓	✓	**63.57**	**73.22**	**19.81**	**37.57**	**58.49**	**20.91**
VARIANT 1+	✓	×	×	×	61.79	60.71	18.09	35.48	48.56	17.81
VARIANT 2+	✓	×	×	✓	68.47	72.05	19.88	36.85	58.24	20.85
VARIANT 3+	✓	×	✓	✓	71.37	74.36	20.73	37.60	59.08	20.32
HGPROMPT+	✓	✓	✓	✓	**74.47**	**77.44**	**21.08**	**39.72**	**60.53**	**21.70**

Conclusion

- **Problem**
  - Prompting on heterogeneous graphs
- **Motivation**
  - Transfer pre-trained knowledge from homogeneous/heterogeneous graph to downstream heterogeneous tasks
- **Proposed model: HGPrompt**
  - Dual templates unify not only pre-training and downstream tasks, but also various graph types
  - Dual prompts narrow the gap caused by not only feature variations but also heterogeneity differences.

References

[1] Liu, Z., et al. 2023. GraphPrompt: Unifying pre-training and downstream tasks for graph neural networks. In *WWW*.

[2] Sun, X., et al. 2023. All in one: Multi-task prompting for graph neural networks. In *SIGKDD*.

[3] Lv, Q., et al. 2021. Are we really making much progress? Revisiting, benchmarking and refining heterogeneous graph neural networks. In *SIGKDD*.

[4] Sun, M., et al. 2022. GPPT: Graph pre-training and prompt tuning to generalize graph neural networks. In *SIGKDD*.