

Quantizing Text-attributed Graphs for Semantic-Structural Integration



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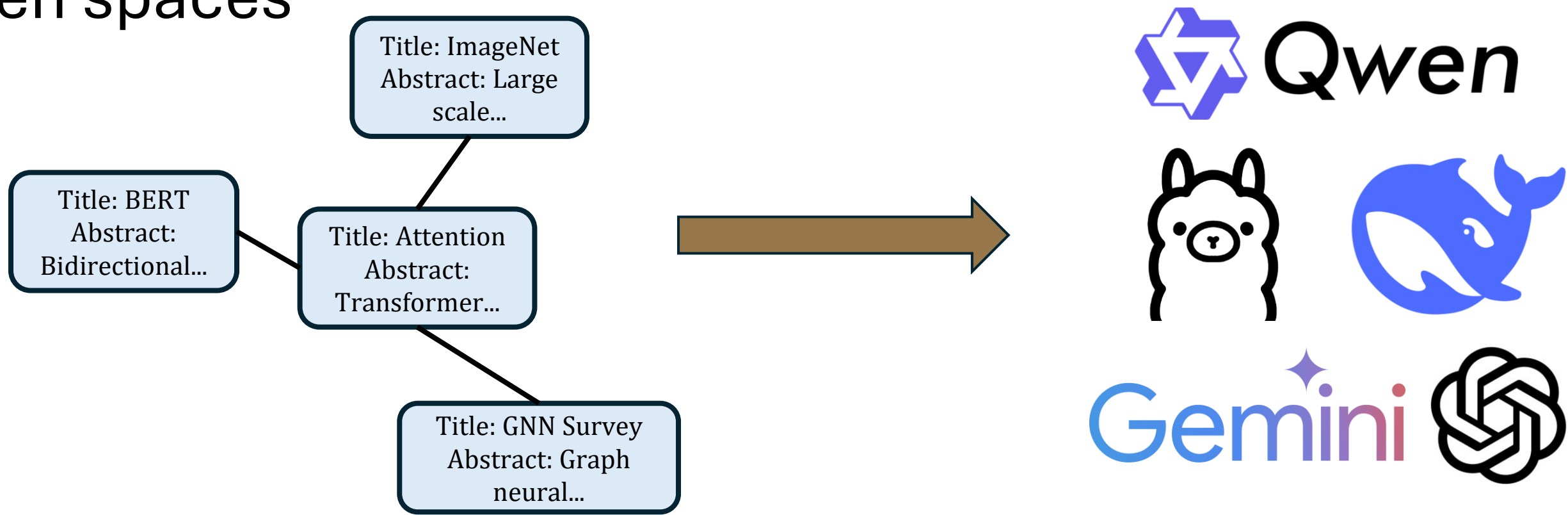


Introduction

Motivation

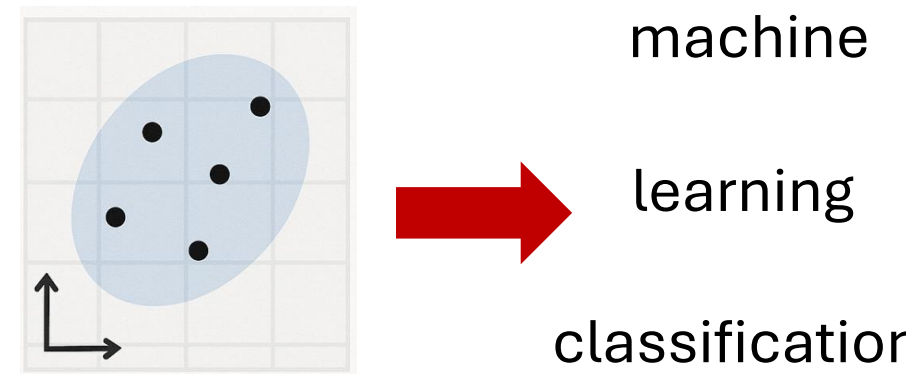
Text-Attributed Graphs (TAGs) + Large Language Models

- TAGs contain rich semantic + structural information
- LLMs excel at semantic understanding but struggle with graph structures
- Need to bridge continuous graph embeddings $\leftrightarrow$ discrete LLM token spaces



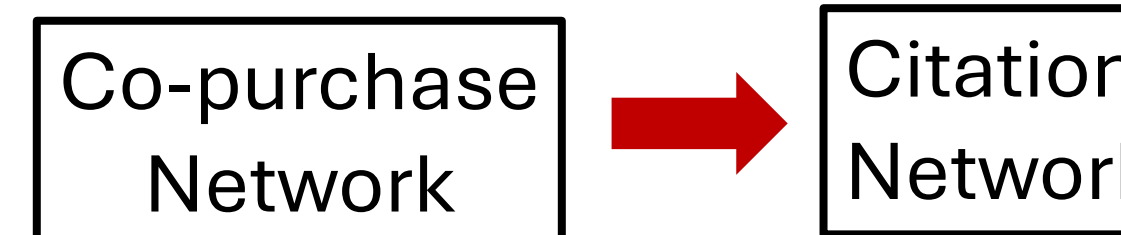
Problem 1: Semantic-Structural Integration

- Graph embeddings are continuous vectors
- LLMs work with discrete tokens



Problem 2: Transfer Learning Requirements

- Need labeled source data
- Limits adaptability across domains

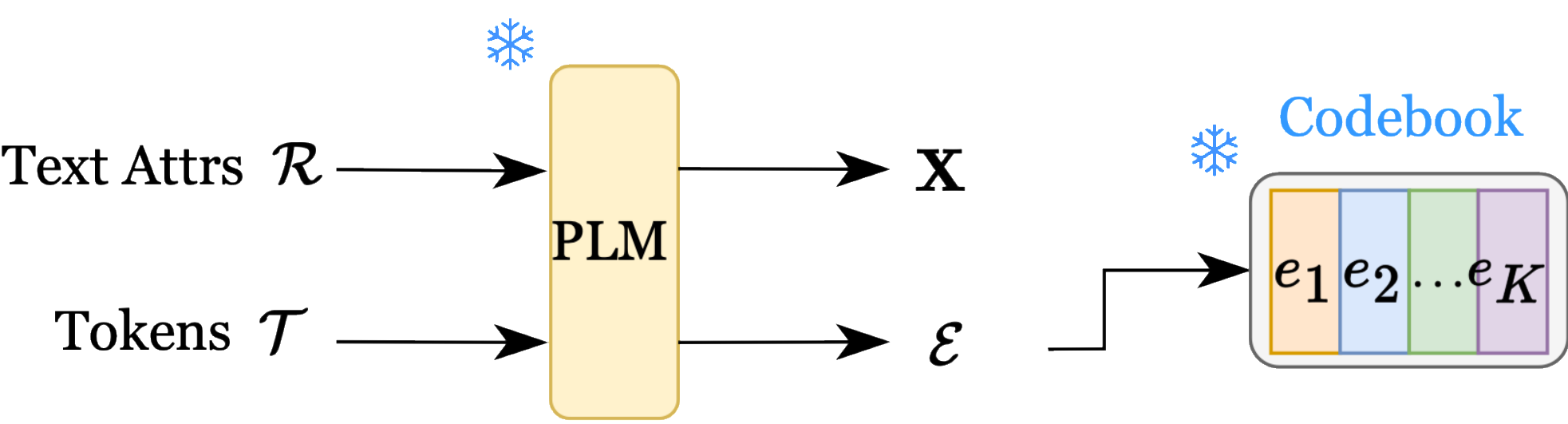


Current Limitations

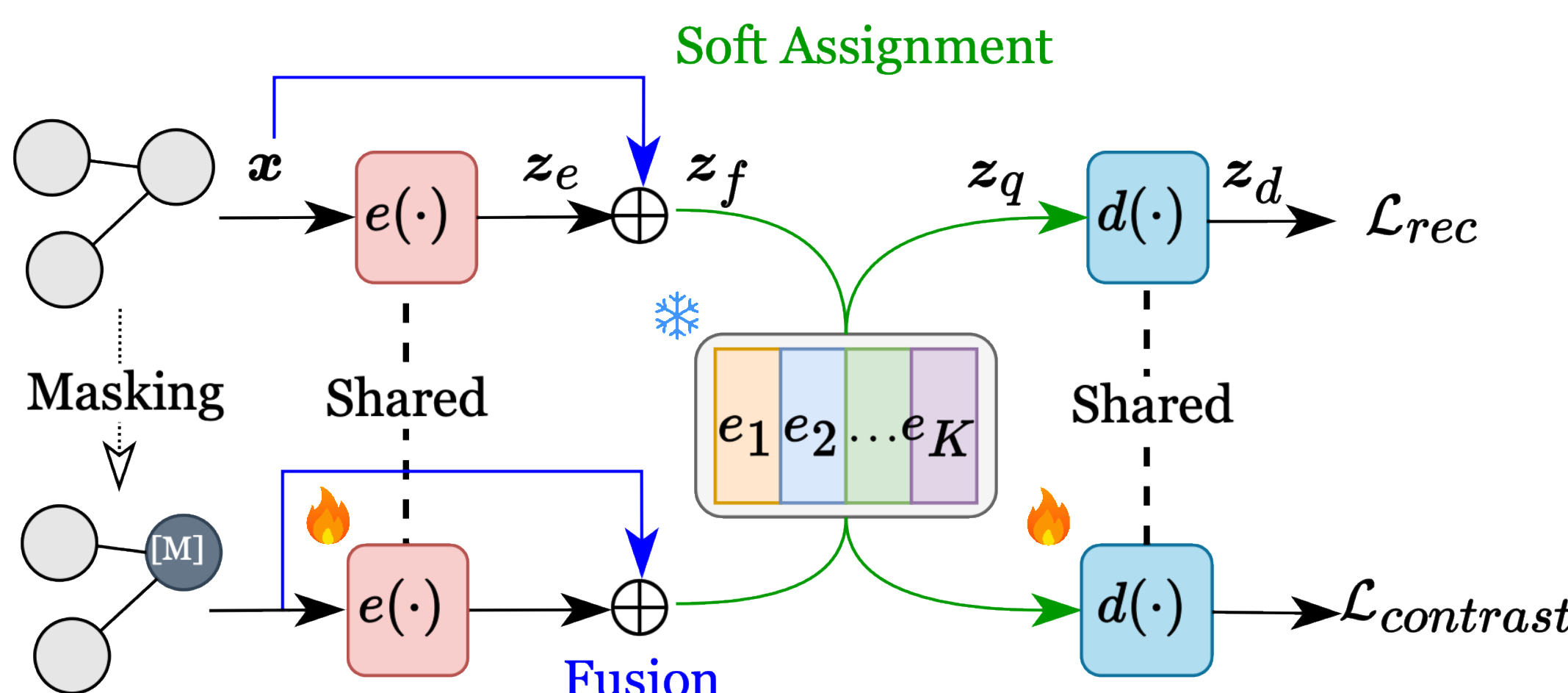
- Expensive alignment mechanisms between GNN and LLM
- Manual graph verbalization loses structural details
- Require labeled data for cross-dataset transfer

Proposed Method: STAG

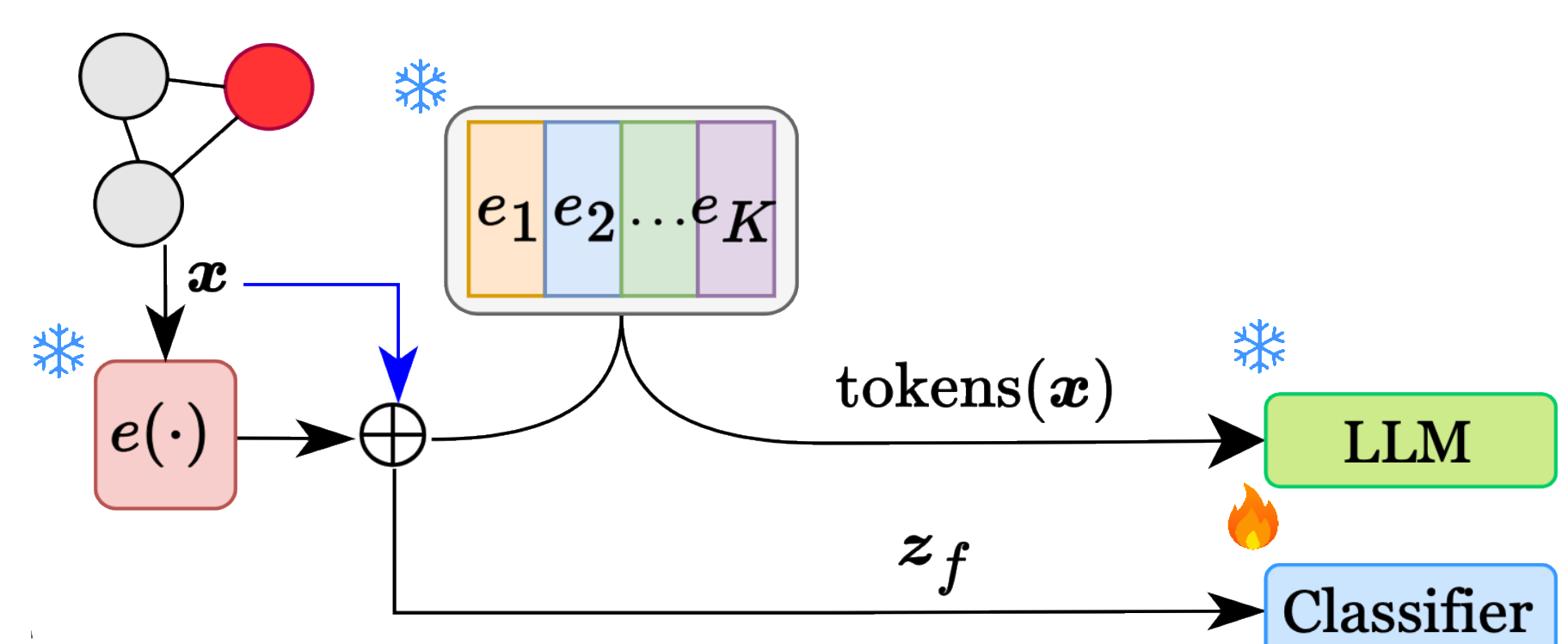
❄️ Frozen 🔥 Training 🔴 Query 🔵 Support 🟡 PLM Sentence Transformer



(a) Codebook Construction



(b) Pre-training



(c) Inference

Method

Experiments

STAG: Soft Tokenization for Text-Attributed Graphs

Three Key Innovations

1 Semantic-Structural Fusion

- Fuse GNN embeddings + original text features

$$z_f = \phi \cdot \frac{\mathbf{W}_f z_e}{\|\mathbf{W}_f z_e\|_2} + \psi \cdot \frac{\mathbf{x}}{\|\mathbf{x}\|_2}$$

2 Soft Assignment Strategy

- Map nodes to token distributions (not single tokens)
- KL divergence guides quantization to semantic tokens
- Prevents overfitting, improves transferability



3 Dual-Branch Training

- Reconstruction branch: preserves semantics
- Contrastive branch: captures neighborhood structure
- No labeled data required!

Inference with LLM

System Prompt: You are a node classifier. Given a list of tokens representing a node's features, predict its class from the following options: [Research Paper, Dataset, Software].

Few-shot examples: Node tokens: [research, methodology, experiment] Class: Research Paper

Node tokens: [benchmark, statistics, collection] Class: Dataset

Node tokens: [implementation, code, library] Class: Software

Test Node: Node tokens: [algorithm, computation, optimization] Predict the class:

Few-shot Node Classification

Pre-train data	Method	LLM	Target data						
			Cora	Cora Full	CiteSeer	PubMed	WikiCS	ogbn-arxiv	ogbn-products
Same as target	GCN	✗	76.10 $\pm$ 4.26	82.81 $\pm$ 7.40	59.95 $\pm$ 6.92	66.35 $\pm$ 6.71	70.55 $\pm$ 8.26	76.61 $\pm$ 7.72	80.08 $\pm$ 7.41
	GAT	✗	79.60 $\pm$ 5.00	84.72 $\pm$ 7.83	60.85 $\pm$ 6.78	67.40 $\pm$ 7.18	77.95 $\pm$ 7.81	80.80 $\pm$ 7.99	81.94 $\pm$ 7.07
No pre-train	Raw Text	✓	63.40 $\pm$ 9.07	71.66 $\pm$ 7.84	62.10 $\pm$ 5.35	85.00 $\pm$ 5.48	77.15 $\pm$ 6.92	54.74 $\pm$ 9.21	87.58 $\pm$ 5.48
	Raw Feat + Quantization	✓	54.85 $\pm$ 6.28	73.74 $\pm$ 8.10	56.40 $\pm$ 5.48	48.30 $\pm$ 7.78	73.40 $\pm$ 8.19	63.75 $\pm$ 9.98	65.84 $\pm$ 9.96
	Raw Feat + Linear Probing	✗	70.25 $\pm$ 7.22	81.29 $\pm$ 7.47	63.00 $\pm$ 6.72	68.30 $\pm$ 6.28	78.05 $\pm$ 7.47	83.05 $\pm$ 7.40	77.53 $\pm$ 7.16
Cora Full	DGI	✗	77.05 $\pm$ 5.12	83.32 $\pm$ 8.12	63.85 $\pm$ 5.39	68.20 $\pm$ 7.57	78.65 $\pm$ 6.90	81.30 $\pm$ 8.51	79.90 $\pm$ 7.20
	GraphMAE2	✗	77.70 $\pm$ 6.92	84.74 $\pm$ 7.42	65.25 $\pm$ 5.84	66.35 $\pm$ 6.09	80.95 $\pm$ 4.96	80.04 $\pm$ 8.15	73.93 $\pm$ 7.57
	GPPT	✗	27.16 $\pm$ 7.61	67.90 $\pm$ 12.72	28.66 $\pm$ 7.60	21.53 $\pm$ 10.91	29.00 $\pm$ 8.08	36.92 $\pm$ 10.32	24.32 $\pm$ 5.13
	G2P2	✗	74.90 $\pm$ 7.47	81.10 $\pm$ 7.44	59.65 $\pm$ 9.68	67.85 $\pm$ 8.02	69.90 $\pm$ 10.52	68.75 $\pm$ 10.14	70.97 $\pm$ 10.03
	Prodigy	✗	39.50 $\pm$ 6.75	60.80 $\pm$ 6.38	42.90 $\pm$ 5.02	43.68 $\pm$ 6.91	43.25 $\pm$ 6.91	47.85 $\pm$ 6.89	30.70 $\pm$ 5.94
	OFA	✗	45.95 $\pm$ 4.52	56.95 $\pm$ 5.31	36.80 $\pm$ 5.50	49.40 $\pm$ 4.75	46.45 $\pm$ 4.67	50.80 $\pm$ 4.73	33.60 $\pm$ 4.26
	STAG	✓	67.60 $\pm$ 6.72	80.95 $\pm$ 8.02	62.45 $\pm$ 7.02	54.50 $\pm$ 7.83	79.20 $\pm$ 8.41	71.56 $\pm$ 10.32	69.34 $\pm$ 9.93
	+ Linear Probing	✗	78.50 $\pm$ 5.62	86.04 $\pm$ 6.70	66.70 $\pm$ 5.36	69.00 $\pm$ 6.31	84.05 $\pm$ 5.78	82.99 $\pm$ 8.10	79.62 $\pm$ 7.12
	+ Prompt Tuning	✓	73.30 $\pm$ 4.77	85.20 $\pm$ 7.59	65.40 $\pm$ 5.98	66.20 $\pm$ 5.70	79.45 $\pm$ 7.53	79.18 $\pm$ 8.28	73.94 $\pm$ 9.67
	+ Prompt Tuning*	✗	78.65 $\pm$ 5.93	86.66 $\pm$ 7.67	65.80 $\pm$ 7.03	68.25 $\pm$ 6.80	83.55 $\pm$ 5.94	83.57 $\pm$ 8.30	80.48 $\pm$ 6.86

Zero-shot Node Classification

Pre-train data	Method	LLM	Target data			
			Cora	Cora Full	WikiCS	ogbn-arxiv
No pre-train	Raw Feat + Q	✓	47.10 $\pm$ 5.98	60.33 $\pm$ 10.88	70.40 $\pm$ 8.88	25.48 $\pm$ 5.54
	Raw Feat + C	✗	62.20 $\pm$ 8.45	77.23 $\pm$ 8.96	73.85 $\pm$ 8.02	72.85 $\pm$ 10.43
Cora Full	G2P2	✗	60.45 $\pm$ 7.58	64.29 $\pm$ 11.56	50.25 $\pm$ 8.43	19.66 $\pm$ 6.38
	OFA	✗	20.30 $\pm$ 2.93	23.85 $\pm$ 3.58	21.45 $\pm$ 3.99	17.60 $\pm$ 3.74
	STAG	✓	48.05 $\pm$ 6.15	62.63 $\pm$ 11.70	76.25 $\pm$ 8.48	26.01 $\pm$ 7.52
	STAG + C	✗	66.55 $\pm$ 7.48	82.90 $\pm$ 9.52	75.15 $\pm$ 7.81	74.23 $\pm$ 9.35

Task Generalization

Zero-shot Binary Link Prediction

Method	Cora	ogbn-products
LLaGA	87.35	92.99
STAG	63.00	92.65
STAG (non LLM)	93.20	96.85

N-way 5-shot Edge Classification

Method	WN18RR	FB15K237
OFA	34.35	19.55
STAG	41.75	56.60
STAG + Linear Probing	58.30	74.80