A Graph Foundation Model with Cross-Modal Alignment and Modality-Aware Expert Fusion for Multi-Modal Graphs

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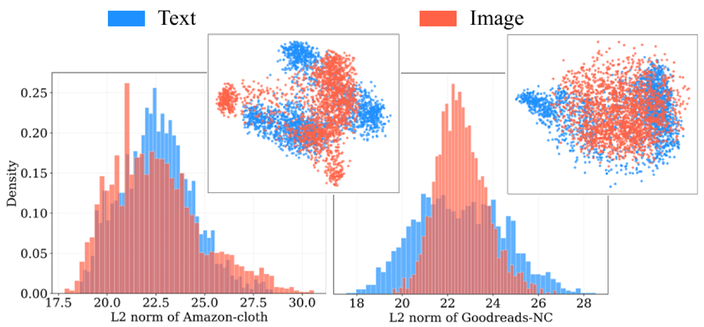
Motivation

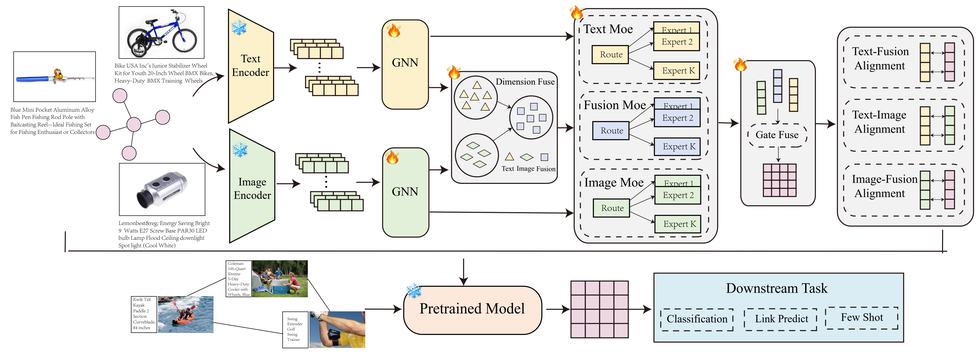
Text and image embeddings remain distributionally different across multi-modal graph datasets, even after CLIP encoding.



Naive early fusion:
Text features + Image features → Average / Concatenate → Shared GNN

Limitations:
Dilute modality-specific information
One modality may dominate graph propagation
Cross-modal alignment remains insufficient

Methodology



CLIP-based modality encoding:

$$\mathbf{x}_i^{(t)} = f_{\text{CLIP}}^{(t)}(\mathbf{s}_i^{(t)}), \qquad \mathbf{x}_i^{(v)} = f_{\text{CLIP}}^{(v)}(\mathbf{s}_i^{(v)}),$$

Modality-specific graph propagation:

$$\mathbf{z}_i^{(t)} = f_{\text{GNN}}^{(t)}\left(\mathcal{G},\ \{\mathbf{x}_j^{(t)}\}_{j\in\mathcal{V}}\right), \quad \mathbf{z}_i^{(v)} = f_{\text{GNN}}^{(v)}\left(\mathcal{G},\ \{\mathbf{x}_j^{(v)}\}_{j\in\mathcal{V}}\right),$$

Modality-Aware MoE

Intra-group routing: selects top-k experts within each modality group

$$\mathbf{e}_i^{(s)} = \sum_{j\in\mathcal{S}_i^{(s)}} \alpha_{i,j}^{(s)}\ \phi_j^{(s)}(\mathbf{z}_i^{(s)}).$$

Inter-modal routing: balances text, image, and fused expert

$$\mathbf{z}_i^{(f)} = \pi_i^{(t)}\mathbf{e}_i^{(t)} + \pi_i^{(v)}\mathbf{e}_i^{(v)} + \pi_i^{(g)}\mathbf{e}_i^{(g)}.$$

Cross-Modal Contrastive Loss

$$\mathcal{L}_{a,b} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{\exp(\text{sim}(\mathbf{z}_i^{(a)},\mathbf{z}_i^{(b)}))}{\sum_{j=1}^{N}\exp(\text{sim}(\mathbf{z}_i^{(a)},\mathbf{z}_j^{(b)}))}, \quad \mathcal{L} = w_{tv}\mathcal{L}_{t,v} + w_{vf}\mathcal{L}_{v,f} + w_{tf}\mathcal{L}_{t,f},$$

Experiments

Self-Supervised Pre-training Evaluation

	In-distribution			In-domain Generalization			Out-of-domain Generalization			
	Products	Goodreads-LP	Amazon-cloth	Amazon-sports	Goodreads-NC	Ele-fashion	Arxiv	Wiki-CS	FB15K237	WN18RR
Use CLIP to encode raw multimodal data as input features.										
BGRL	72.57±0.05	6.49±0.02	17.35±0.03	23.66±0.05	69.28±0.10	74.92±0.03	65.07±0.04	71.35±0.02	90.12±0.15	75.02±0.14
DGI	71.91±0.06	7.23±0.07	18.39±0.04	24.07±0.11	70.39±0.08	83.72±0.02	61.07±0.02	69.79±0.16	91.43±0.17	73.26±0.11
GraphMAE2	70.46±0.15	7.77±0.12	16.25±0.11	27.44±0.14	72.49±0.05	80.23±0.04	64.15±0.18	74.82±0.19	89.96±0.14	73.97±0.14
GRACE	73.44±0.08	4.77±0.02	18.15±0.05	25.59±0.05	67.47±0.12	79.70±0.02	58.11±0.04	67.28±0.02	90.12±0.15	73.02±0.19
GCOPE	76.87±0.14	8.91±0.11	17.49±0.12	24.24±0.13	75.43±0.15	77.61±0.14	63.92±0.09	75.94±0.18	91.03±0.16	75.61±0.13
SAMGPT	78.53±0.11	9.13±0.06	19.14±0.06	28.24±0.13	79.02±0.09	83.82±0.07	69.79±0.17	74.63±0.18	91.76±0.10	74.96±0.15
FUG	74.34±0.17	7.94±0.10	20.49±0.11	25.33±0.12	74.62±0.14	81.29±0.01	68.11±0.05	73.31±0.12	91.49±0.12	74.35±0.10
Use raw multimodal data as input features.										
CLIP-text	64.83±0.09	3.71±0.09	13.77±0.09	25.13±0.06	69.45±0.07	83.53±0.02	62.75±0.03	64.32±0.19	89.72±0.21	74.86±0.13
CLIP-image	–	2.77±0.07	13.09±0.07	16.33±0.02	64.29±0.12	80.26±0.05	–	–	–	–
UniGraph2	80.82±0.08	8.76±0.06	24.25±0.12	29.52±0.14	79.78±0.07	84.83±0.11	70.54±0.04	77.07±0.06	92.30±0.03	75.20±0.09
CAME	**81.84**±0.17	**15.42**±0.08	**28.88**±0.12	**37.68**±0.19	**83.21**±0.11	**85.13**±0.03	**71.66**±0.05	**78.57**±0.13	**94.59**±0.07	**81.97**±0.11

Fewshot Evaluation

	In-distribution			Out-of-domain Generalization					
	Goodreads-NC-5-way			Arxiv-5-way			Wiki-CS-5-way		
	1-shot	3-shot	5-shot	1-shot	3-shot	5-shot	1-shot	3-shot	5-shot
Use CLIP to encode raw multimodal data as input features.									
BGRL	28.73±9.16	39.32±11.45	44.19±11.88	38.93±11.02	54.79±12.26	59.57±12.28	33.98±10.40	44.75±11.22	49.86±11.98
DGI	26.34±8.65	33.67±10.28	38.00±10.63	40.49±11.26	55.23±11.91	61.93±11.44	31.55±9.23	45.04±10.60	51.65±10.96
GraphMAE2	25.21±7.94	32.11±9.68	37.22±10.64	37.48±10.67	56.67±12.14	64.31±11.74	31.92±12.72	43.39±11.71	50.78±11.13
GRACE	38.95±11.22	48.71±11.73	52.48±11.66	41.02±11.14	54.69±12.56	61.17±12.17	36.14±12.43	48.38±11.50	53.79±10.39
GCOPE	37.60±11.35	48.88±10.17	54.34±9.91	47.50±12.89	56.10±12.35	59.91±12.46	39.04±12.96	53.26±11.04	59.53±10.77
SAMGPT	29.95±10.09	34.96±10.36	37.65±10.63	48.37±12.43	59.57±11.34	64.26±11.26	39.52±11.73	49.38±11.28	54.02±10.78
FUG	42.76±12.61	50.49±12.86	53.09±12.68	47.20±13.06	56.77±12.88	60.27±12.46	32.32±10.15	46.83±11.16	49.40±11.48
Use raw multimodal data as input features.									
CLIP-text	34.94±10.75	45.73±11.22	49.26±12.19	42.30±11.25	58.72±12.12	65.03±11.27	32.81±9.70	46.95±10.87	54.31±10.63
CLIP-image	27.33±8.65	35.55±10.29	39.95±11.32	–	–	–	–	–	–
UniGraph2	39.66±11.33	53.06±11.77	58.00±11.65	43.11±11.90	60.74±11.96	66.96±11.13	35.56±10.04	50.95±11.04	58.12±10.54
CAME	**48.03**±12.54	**60.26**±12.30	**60.47**±11.01	**49.38**±13.18	**63.78**±12.17	**67.10**±11.67	**47.65**±12.86	**55.30**±11.92	**61.89**±12.95

Ablation on key components

Setting	Ele-fashion	Goodreads-NC	Amazon-cloth	Amazon-sports
CAME	**85.13**±0.03	**83.21**±0.11	**28.88**±0.12	**37.68**±0.19
w/o $L_{t,v}$	84.67±0.04	82.46±0.09	20.64±0.15	34.30±0.12
w/o $L_{t,f}$	85.04±0.03	83.13±0.07	27.27±0.10	37.24±0.16
w/o $L_{v,f}$	82.44±0.07	82.58±0.11	24.62±0.14	36.26±0.10
only $L_{t,v}$	83.95±0.05	82.20±0.09	21.66±0.17	32.99±0.13
only $L_{t,f}$	80.74±0.11	80.70±0.12	19.19±0.11	34.82±0.18
only $L_{v,f}$	84.35±0.04	81.48±0.08	22.03±0.10	35.12±0.14
w/o Moe	84.39±0.03	82.55±0.06	26.37±0.12	36.36±0.10
w/o dim-gate	84.75±0.06	82.26±0.07	27.90±0.13	37.41±0.09
w/o m-GNN	84.52±0.04	81.92±0.06	21.19±0.13	26.83±0.11