CGMN: A Contrastive Graph Matching Network for Self-Supervised Graph Similarity Learning

Di Jin[1], **Luzhi Wang**[1], **Yizhen Zheng**[2], **Xiang Li**[3], **Fei Jiang**[3], **Wei Lin**[3] and **Shirui Pan**[2]*
[1]College of Intelligence and Computing, Tianjin University, Tianjin, China
[2]Department of Data Science and AI, Faculty of IT, Monash University, Australia
[3]Meituan, Beijing, China
{jindi, wangluzhi}@tju.edu.cn, {yizhen.zheng1, shirui.pan}@monash.edu

IJCAI 2022
Code: None

2022.06.29 • ChongQing

Leibniz-Institut für Sozialwissenschaften

Reported by Chenghong Li

Introduction

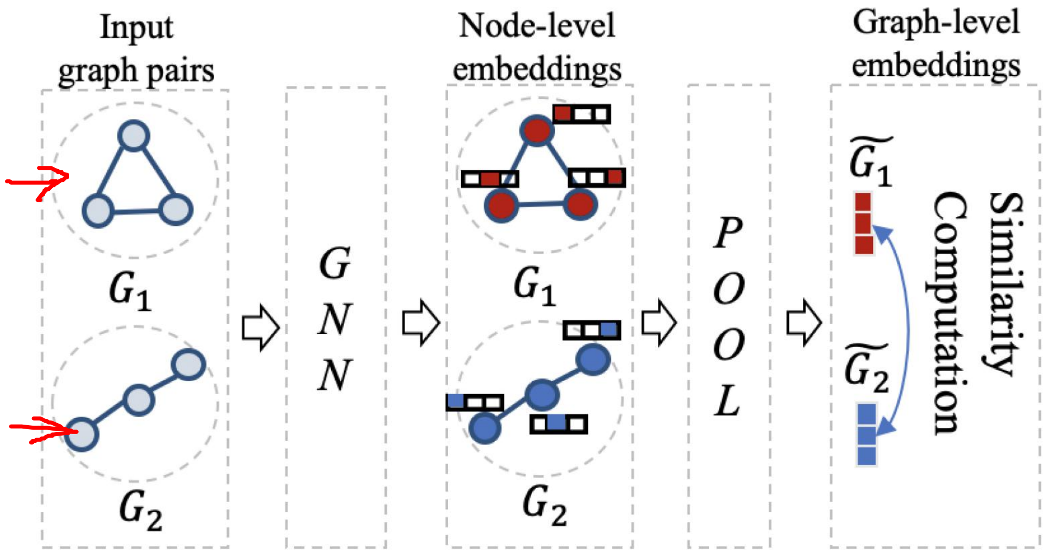


Figure 1: A view of the supervised graph similarity learning model.

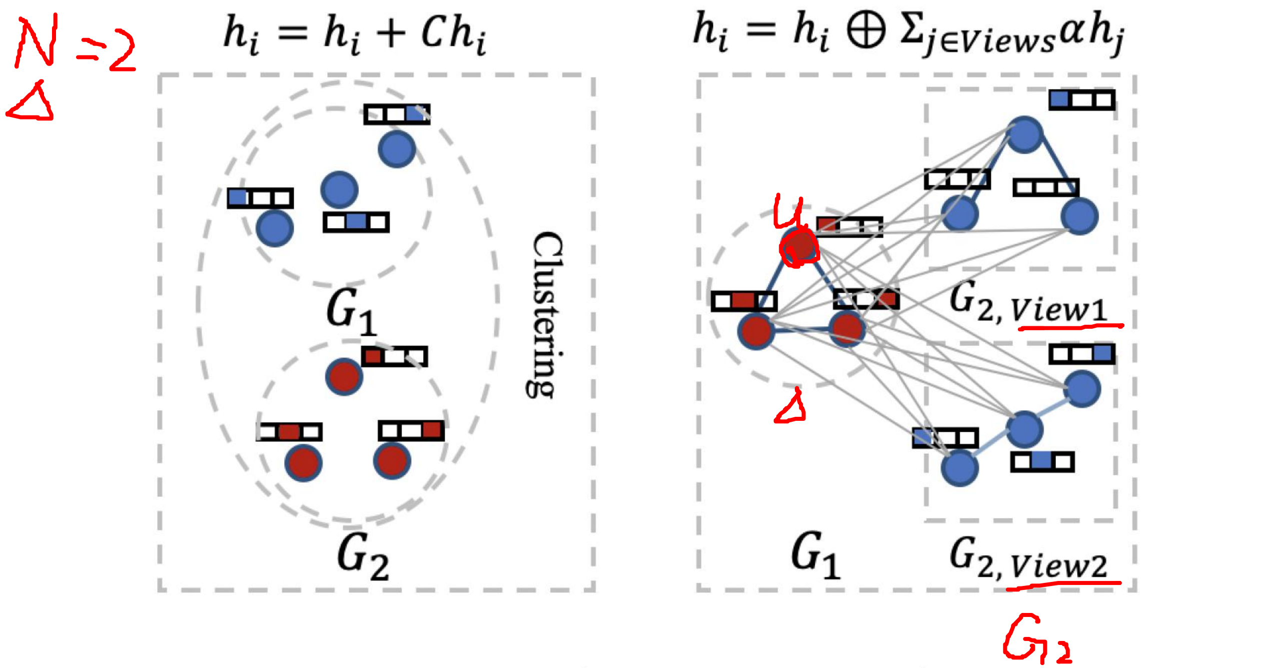


Figure 2: Comparison of node information update process. Left: Clustering-based unsupervised graph similarity learning. Right: Our proposed model CGMN. h_i denotes the embedding of node i, C represents the clustering weight, $\oplus$ is concatenation, and α represents the cross-graph interaction weight.

Method

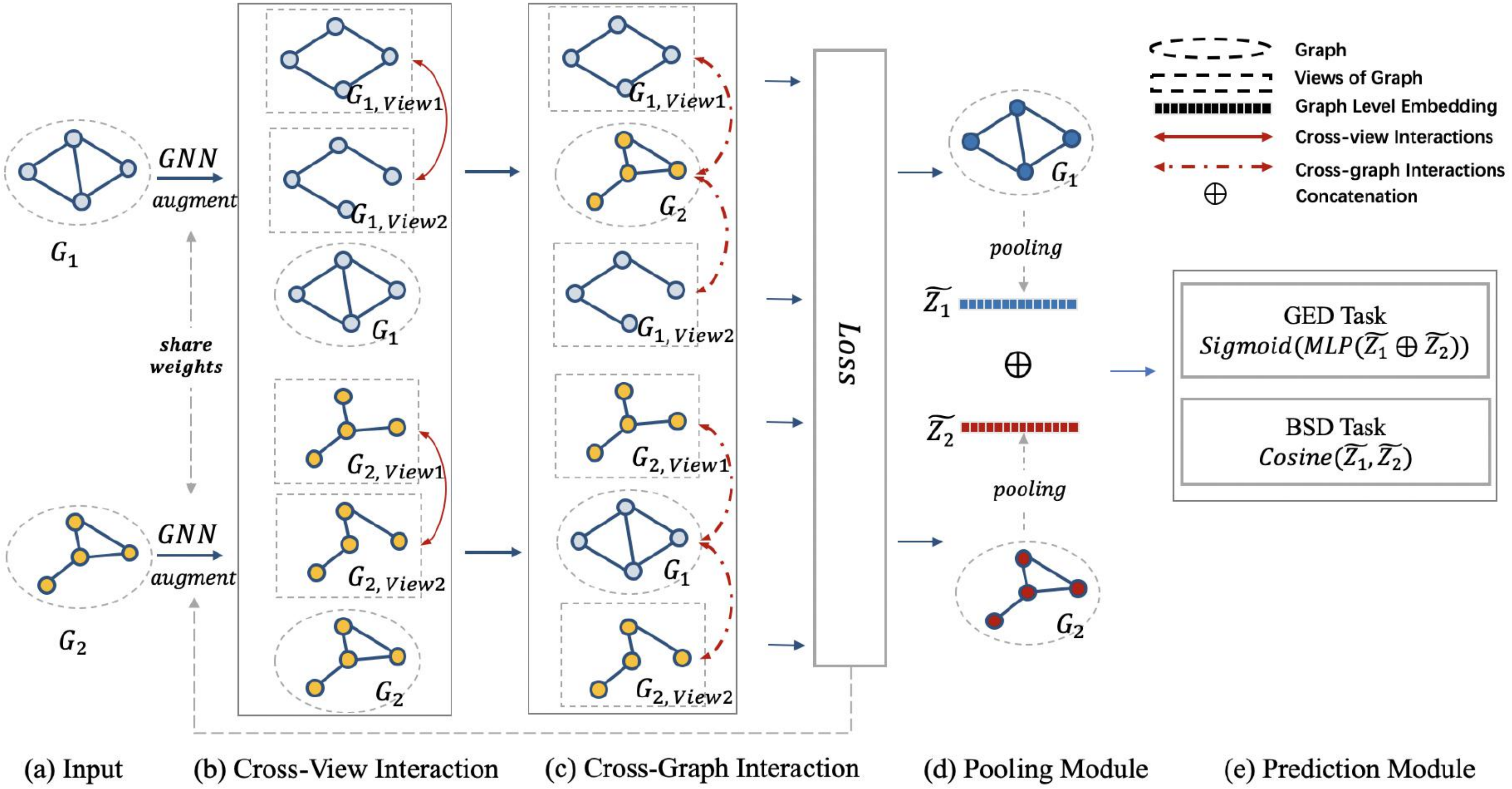
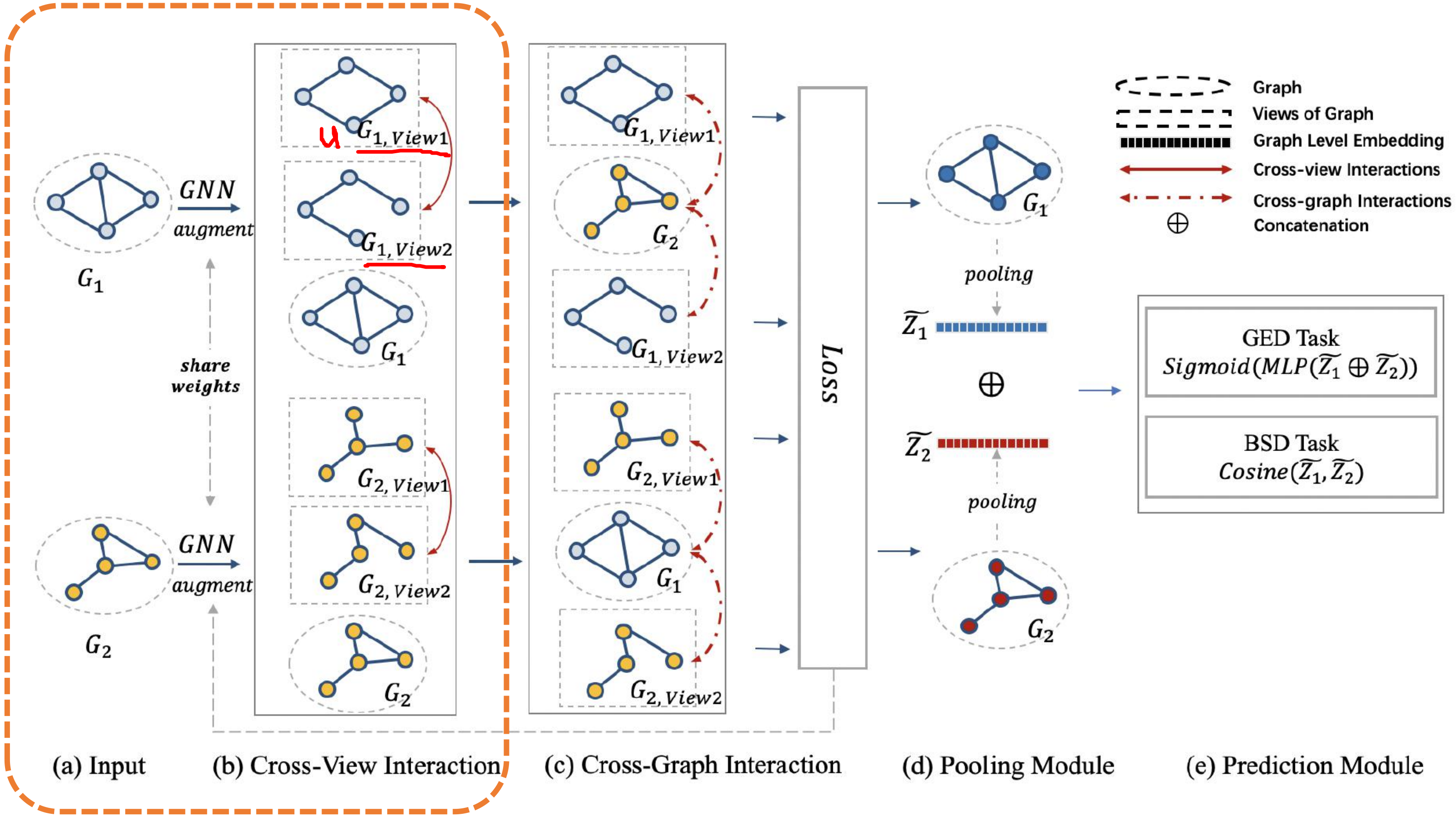


Figure 3: Overview of CGMN. First, we provide a framework to learn the embedding of each node. Second, we propose a cross-graph interaction strategy to match nodes in graph pairs. Third, we aggregate node embeddings to obtain the graph-level representations. Finally, we predict the similarity of graphs for different tasks.

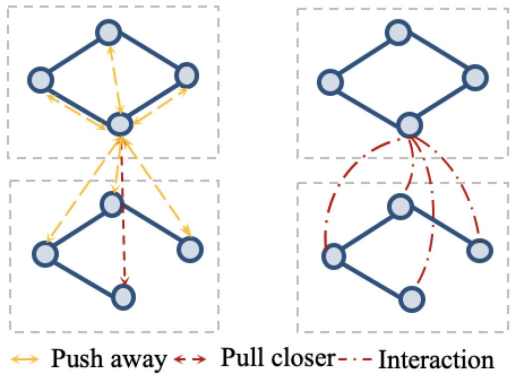
Method



$$H^l = \sigma(\widetilde{A}H^{l-1}W^{l-1}), \tag{1}$$

$$\mathtt{sim}(h_u, h_v) := \exp(\cos(h_u, h_v)/\tau), \tag{2}$$

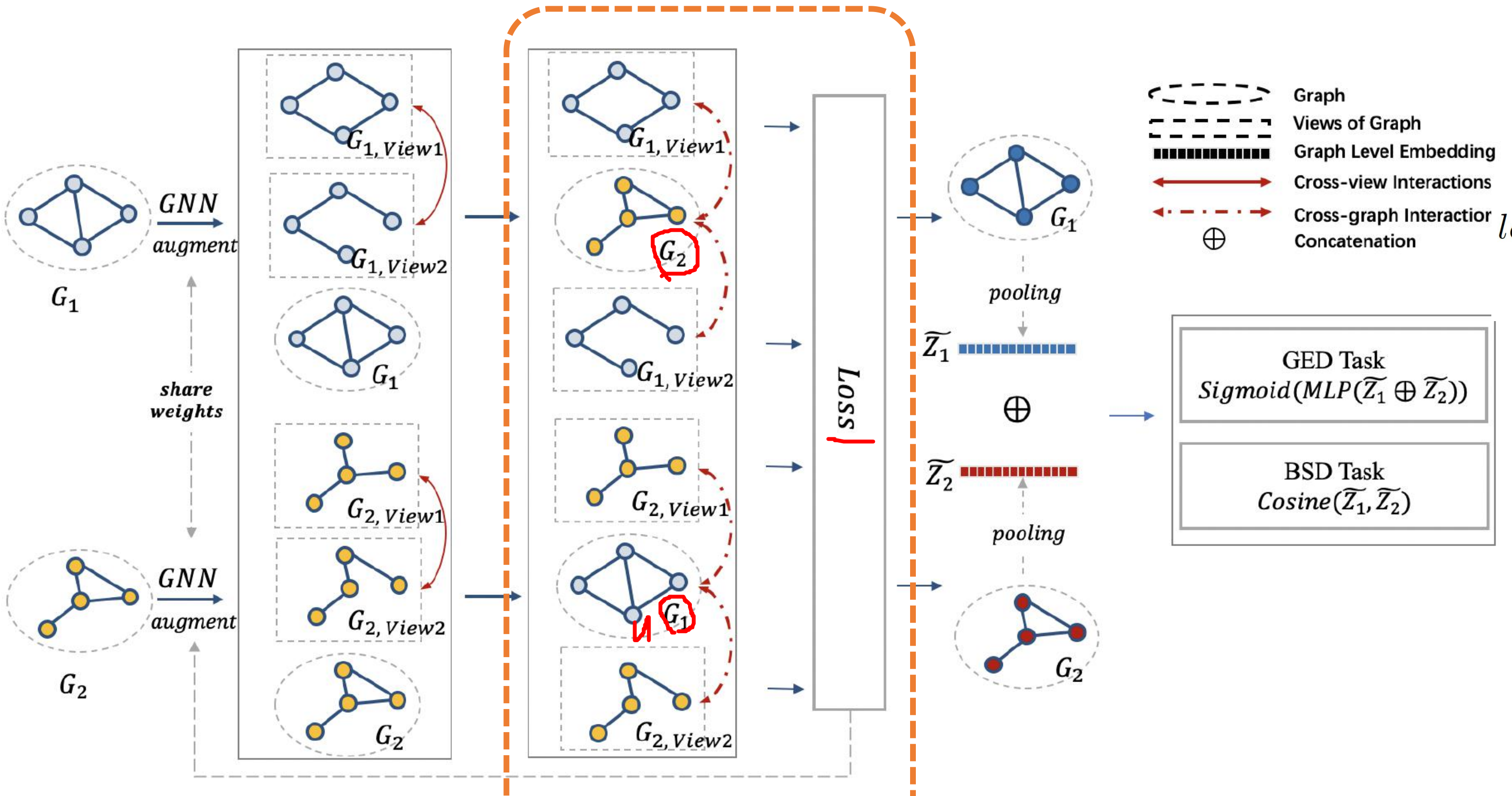
$$\hat{h}_u = h_u \oplus \sum_{v \in G_{1,View2}} \cos(h_u, h_v) h_v, \tag{3}$$



(a) Contrastive learning. (b) Cross-view interaction.

Figure 4: Difference between (a) contrastive learning and (b) cross-view interaction.

Method

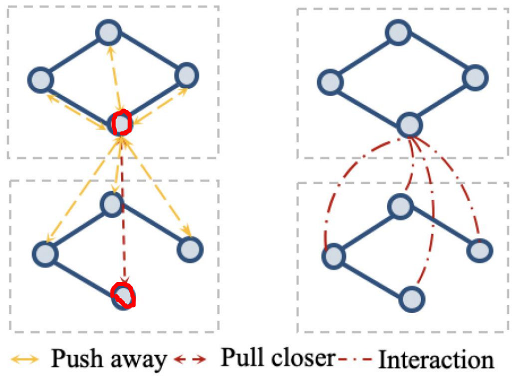


(a) Input (b) Cross-View Interaction (c) Cross-Graph Interaction (d) Pooling Module (e) Prediction Module

$$h_u^* = \hat{h}_u \oplus \sum_{i \in G_{2,View1}} \cos(\hat{h}_u, \hat{h}_i)\, \hat{h}_i \oplus \sum_{j \in G_{2,View2}} \cos(\hat{h}_u, \hat{h}_j)\, \hat{h}_j \tag{4}$$

$$loss(h_u^*, h_v^*) = -\log \frac{\mathrm{sim}(h_u^*, h_v^*)}{\mathrm{sim}(h_u^*, h_v^*) + \sum_{k=1}^{N} \mathrm{sim}(h_u^*, h_k^*)}, \tag{5}$$

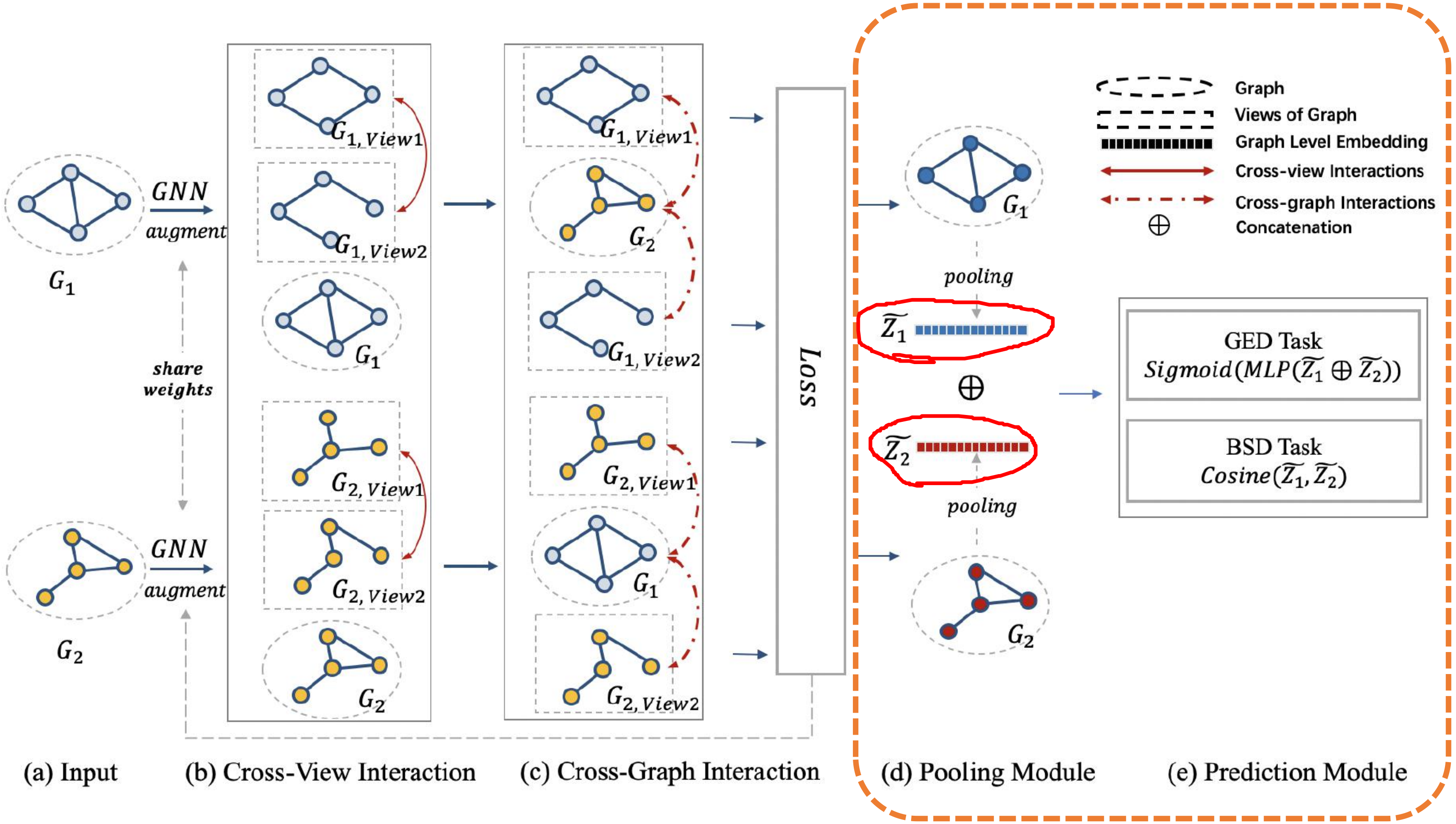
$$\mathcal{L} = \frac{1}{2}\left[loss(h_u^*, h_v^*) + loss(h_v^*, h_u^*)\right]. \tag{6}$$



(a) Contrastive learning. (b) Cross-view interaction.

Figure 4: Difference between (a) contrastive learning and (b) cross-view interaction.

Method



$$\tilde{Z} = \texttt{AVG}(h_u : u \in G), \tag{7}$$

$$y = \texttt{sigmoid}(\texttt{MLP}(\tilde{Z}_1 \oplus \tilde{Z}_2)). \tag{8}$$

$$y = \cos(\tilde{Z}_1, \tilde{Z}_2). \tag{9}$$

Experiments

	Datasets	Graphs	AvgN	AvgE	Classes
	Aids700nef	700	8.90	8.80	-
	Linux1000	1000	7.58	6.94	-
OpenSSL (OS)	OS [3, 200]	73,953	15.73	21.97	4,249
	OS [20, 200]	15,800	44.89	67.15	1,073
	OS [50, 200]	4,308	83.68	127.75	338
FFmpeg (FF)	FF [3, 200]	83,008	18.83	27.02	10,376
	FF [20, 200]	31,696	51.02	75.88	7,668
	FF [50, 200]	10,824	90.93	136.83	3,178

Table 1: Statistics of the datasets.

Experiments

Spearman's Rank Correlation Coefficient (ρ)

Kendall's Rank Correlation Coefficient (τ)

Datasets	Methods	MSE (10^{-3})	ρ	τ	p@10	p@20
Aids700nef	GCN	11.395±1.315	0.577±0.021	0.418±0.018	0.041±0.002	0.077±0.003
	GIN	9.280±0.163	0.629±0.020	0.462±0.016	0.044±0.018	0.096±0.021
	DGI	15.009±0.347	0.231±0.093	0.164±0.061	0.039±0.006	0.076±0.001
	GRACE	12.176±1.693	0.366±0.186	0.261±0.134	0.038±0.004	0.072±0.018
	ScGSLC	13.060±0.193	0.394±0.133	0.281±0.097	0.080±0.026	**0.142±0.044**
	CGMN	**6.641±2.227**	**0.674±0.129**	**0.502±0.107**	**0.084±0.019**	0.140±0.024
Linux1000	GCN	11.986±1.532	0.569±0.033	0.411±0.028	0.043±0.005	0.071±0.001
	GIN	22.188±5.259	0.647±0.112	0.484±0.099	0.081±0.018	0.084±0.025
	DGI	33.854±0.013	0.052±0.018	0.039±0.002	0.035±0.020	0.073±0.016
	GRACE	14.180±2.080	0.852±0.019	0.673±0.025	**0.443±0.155**	**0.452±0.175**
	ScGSLC	13.423±2.038	0.840±0.010	0.658±0.021	0.192±0.095	0.213±0.120
	CGMN	**10.514±1.178**	**0.873±0.013**	**0.700±0.015**	0.307±0.071	0.330±0.091

Table 2: Experimental results on the GED datasets in terms of five evaluation metrics.

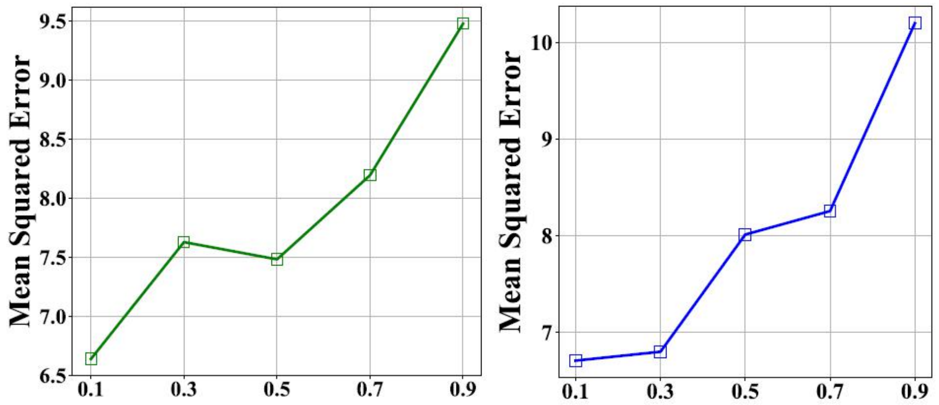
Methods	OS [50, 200]	OS [20, 200]	OS [3, 200]	FF [50, 200]	FF [20, 200]	FF [3, 200]
GCN	67.24±1.14	68.09±1.01	73.51±0.72	78.41±0.49	79.47±0.08	80.88±0.18
GIN	66.60±0.10	63.85±0.56	75.65±0.30	78.38±0.20	81.25±0.57	**81.82±0.25**
DGI	67.55±2.76	63.58±1.96	72.58±2.36	86.10±0.66	80.82±2.22	66.28±0.30
GRACE	68.84±2.45	67.01±0.49	69.86±0.29	85.44±0.27	75.05±0.73	66.95±2.78
ScGSLC	67.43±0.82	61.46±0.33	63.28±0.09	**87.57±0.82**	83.27±0.71	69.80±1.22
CGMN	**80.89±0.20**	**78.15±0.85**	**75.94±1.86**	86.11±0.98	**86.76±0.85**	77.98±2.69

Table 3: Experimental results on the BSD datasets in terms of AUC scores (%).

Experiments

Methods	MSE	ρ	τ	p@10	p@20
CGMN w/o cross-view	8.239	0.614	0.451	0.064	0.114
CGMN w/o cross-graph	8.753	0.537	0.387	0.050	0.091
CGMN	6.641	0.674	0.502	0.084	0.140

Table 4: Ablation study on Aids700nef.



(a) Masking node features. (b) Removing edges.

Figure 5: Influence on parameters.

Thanks