Disentangled Contrastive Learning on Graphs

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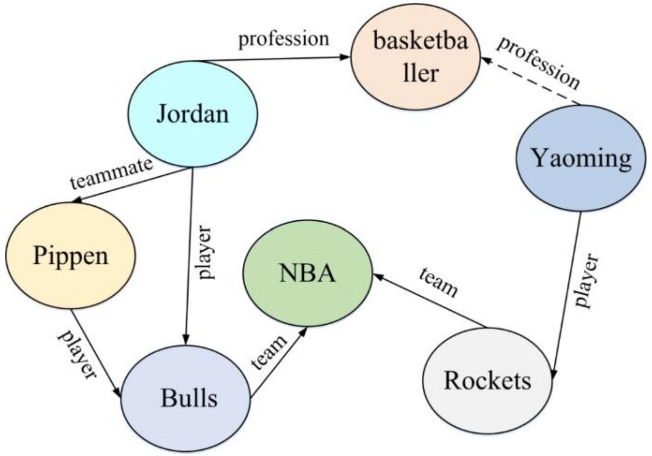
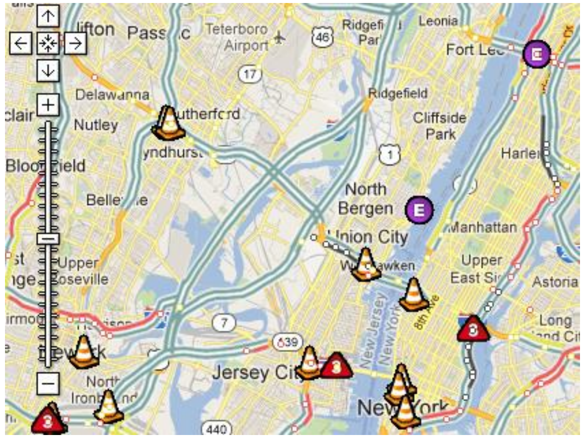
Graph Structured Data is Ubiquitous

Social Network

Knowledge Graph

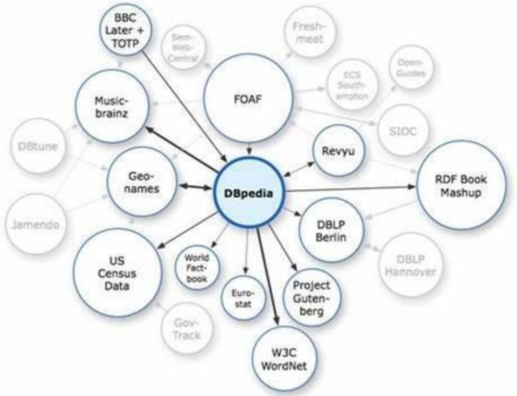


Traffic Network

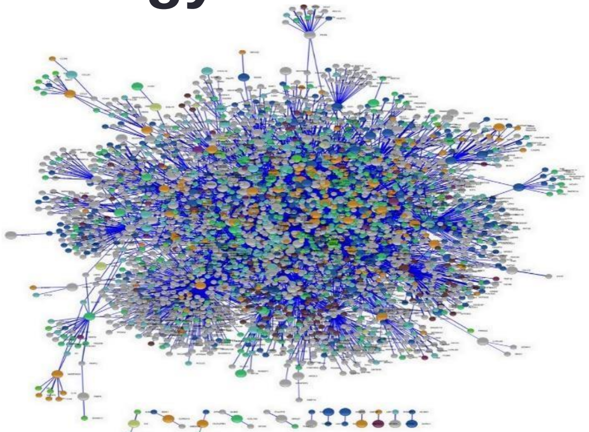


Internet of Things

Information Network

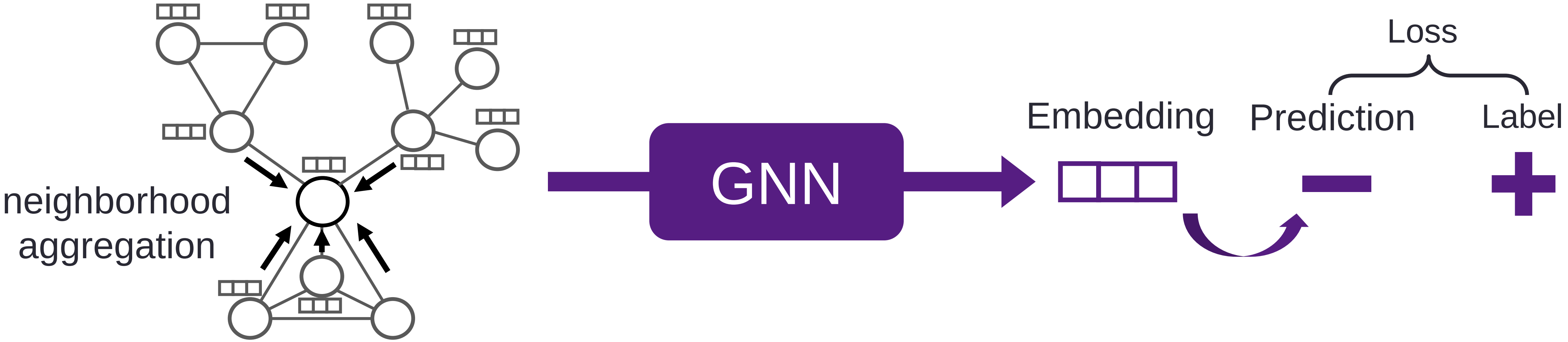


Biology Network



Graph Neural Networks

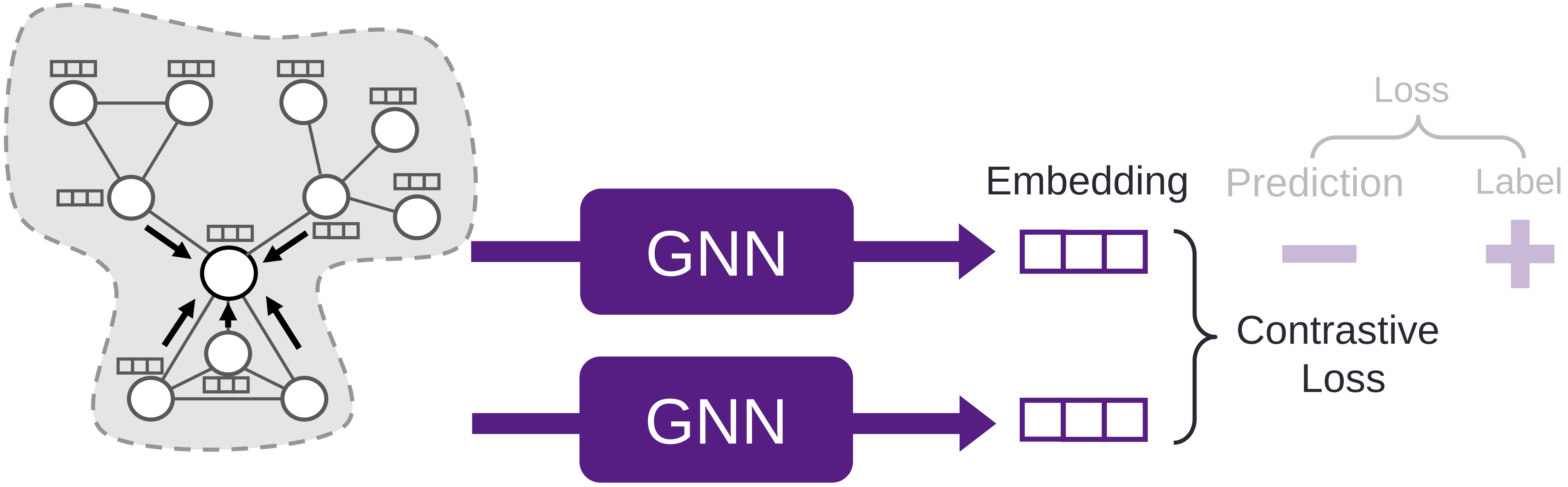
- GNNs generally adopt a neighborhood aggregation paradigm.



- Most famous GNNs are trained end-to-end with task-specific labels, which could be extremely scarce for some graph datasets.

Self-supervised Learning on Graphs

- Graph Contrastive Learning



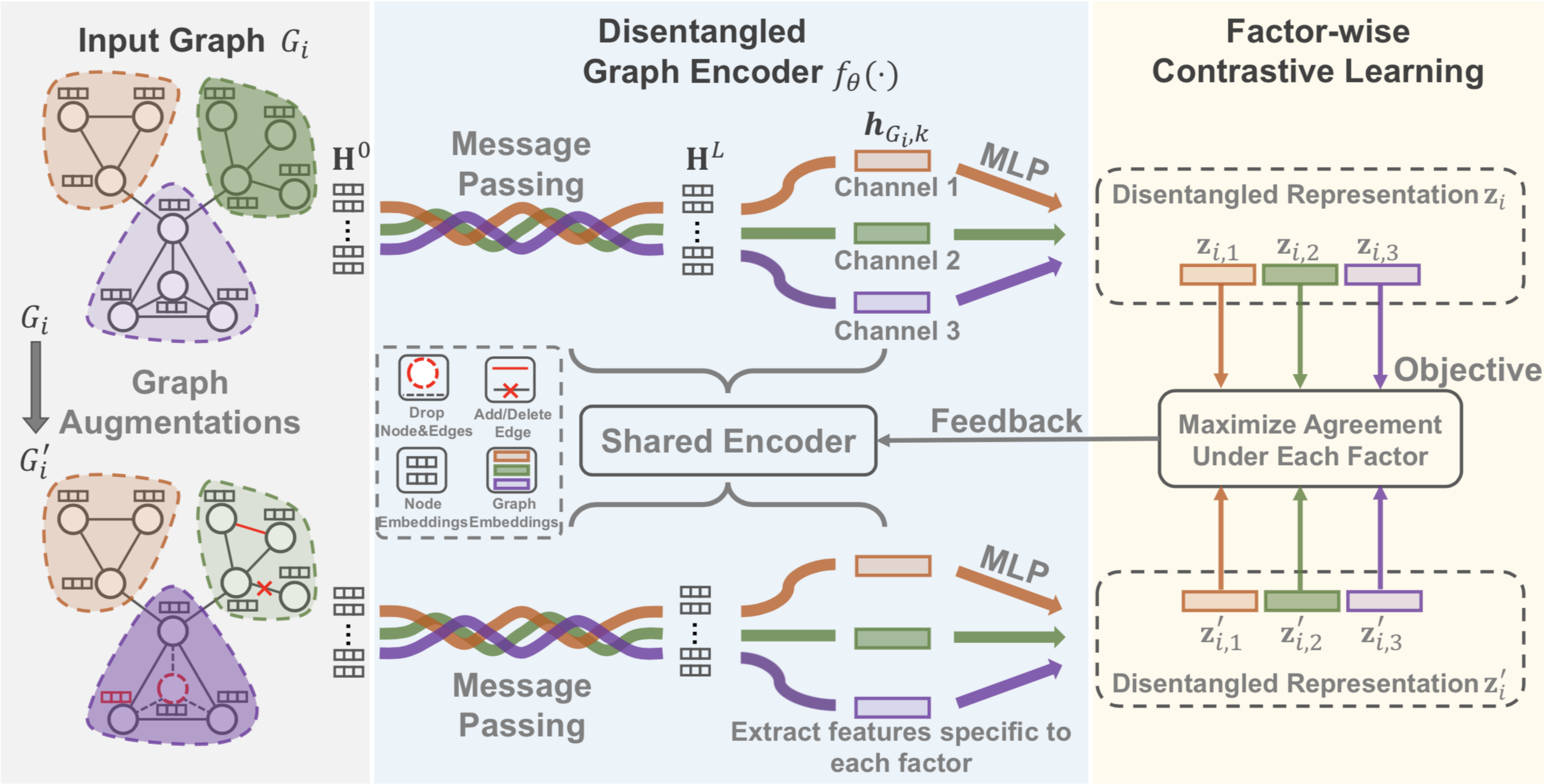
holistic scheme

Disentangled Graph Contrastive Learning

- The formation of a graph is typically driven by ***many latent factors***.

- Existing methods characterize graphs as a perceptual whole.
  - The learned representations contain a mixture of entangled factors.
  - They may lead to suboptimal performance and harm the explainability.

Model Framework

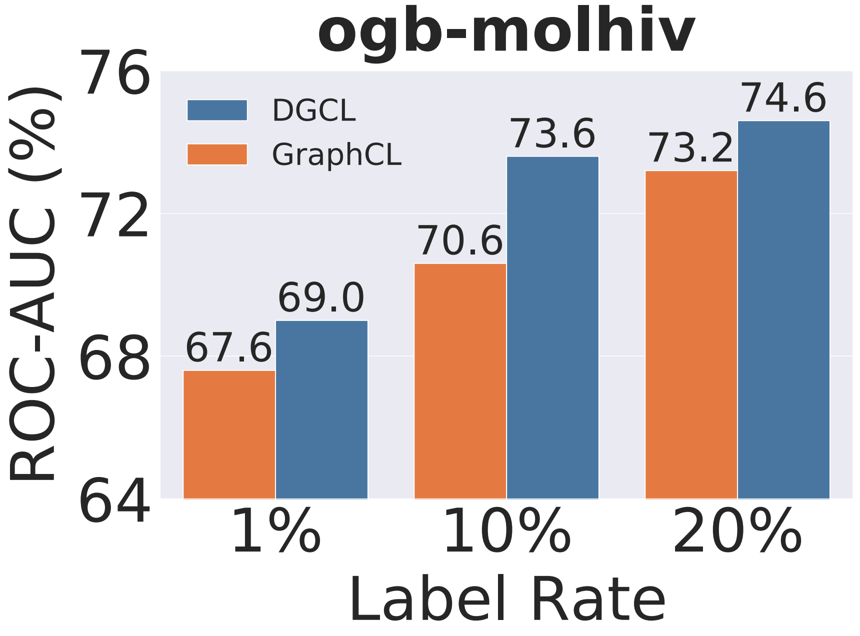


Experimental Results

- Graph classification performance

	MUTAG	PTC-MR	PROTEINS	NCI1	IMDB-B	IMDB-M	RDT-B	RDT-M5K	COLLAB
SP	85.2±2.4	58.2±2.4	75.1±0.5	73.0±0.2	55.6±0.2	38.0±0.3	64.1±0.1	39.6±0.2	–
GK	81.7±2.1	57.3±1.4	71.7±0.6	62.3±0.3	65.9±1.0	43.9±0.4	77.3±0.2	41.0±0.2	72.8±0.3
WL	80.7±3.0	58.0±0.5	72.9±0.6	80.0±0.5	72.3±3.4	47.0±0.5	68.8±0.4	46.1±0.2	–
DGK	87.4±2.7	60.1±2.6	73.3±0.8	80.3±0.5	67.0±0.6	44.6±0.5	78.0±0.4	41.3±0.2	73.1±0.3
MLG	87.9±1.6	63.3±1.5	76.1±2.0	80.8±1.3	66.6±0.3	41.2±0.0	–	–	–
node2vec	72.6±10.2	58.6±8.0	57.5±3.6	54.9±1.6	–	–	–	–	–
sub2vec	61.1±15.8	60.0±6.4	53.0±5.6	52.8±1.5	55.3±1.5	36.7±0.8	71.5±0.4	36.7±0.4	–
graph2vec	83.2±9.3	60.2±6.9	73.3±2.1	73.2±1.8	71.1±0.5	50.4±0.9	75.8±1.0	47.9±0.3	–
GVAE	87.7±0.7	61.2±1.8	–	–	70.7±0.7	49.3±0.4	87.1±0.1	52.8±0.2	–
InfoGraph	89.0±1.1	61.7±1.4	74.4±0.3	76.2±1.1	73.0±0.9	49.7±0.5	82.5±1.4	53.5±1.0	70.7±1.1
GCC	–	–	–	–	72.0	49.4	89.8	53.7	78.9
MVGRL	89.7±1.1	62.5±1.7	–	–	74.2±0.7	51.2±0.5	84.5±0.6	–	–
GraphCL	86.8±1.3	63.6±1.8	74.4±0.5	77.9±0.4	71.1±0.4	50.7±0.4	89.5±0.8	56.0±0.3	71.4±1.2
DGCL	**92.1±0.2**	**65.8±1.5**	**76.4±0.5**	**81.9±0.2**	**75.9±0.7**	**51.9±0.4**	**92.7±0.2**	**56.1±0.2**	**81.2±0.3**

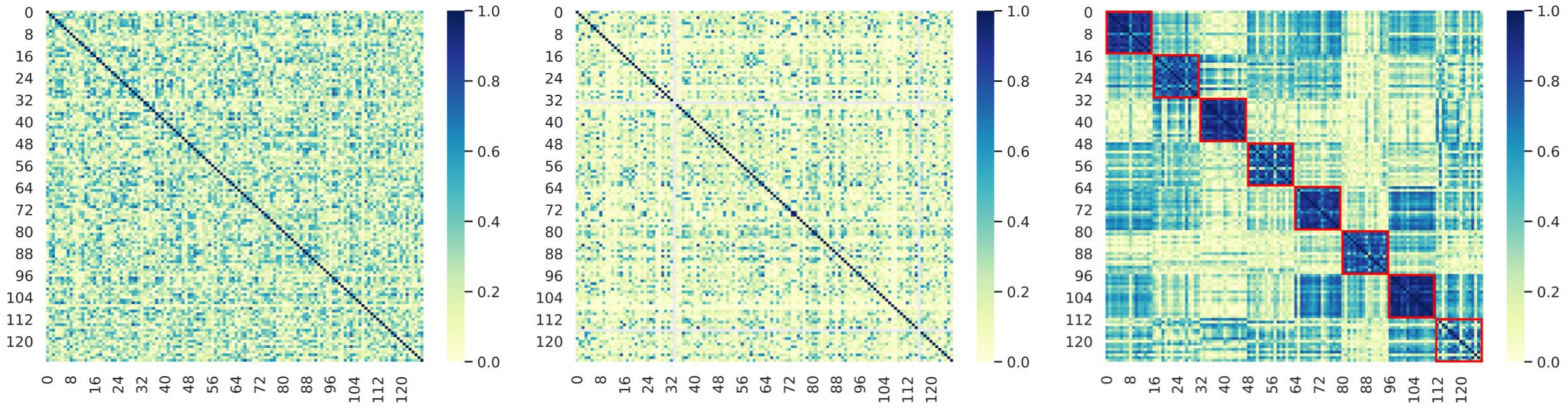
unsupervised setting



semi-supervised setting

Experimental Results

- Feature correlation analysis



(a) MVGRL (b) GraphCL (c) **DGCL**

Conclusions

- This paper proposes a disentangled graph contrastive learning method.
- This paper proposes a disentangled graph encoder and factor-wise contrastive learning approach.
- Extensive experiments demonstrate the superiority of the method.

Thanks!

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