Directed Graph Contrastive Learning

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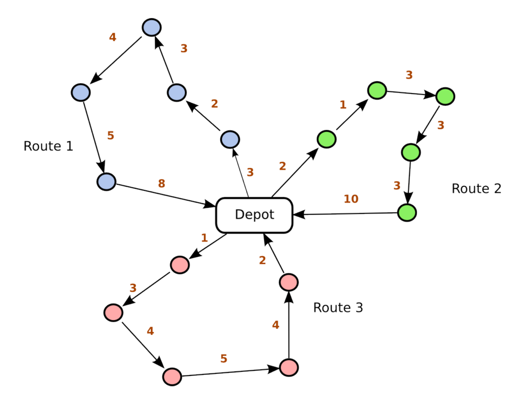
Summary

We present the first contrastive learning framework for learning directed graph representation.

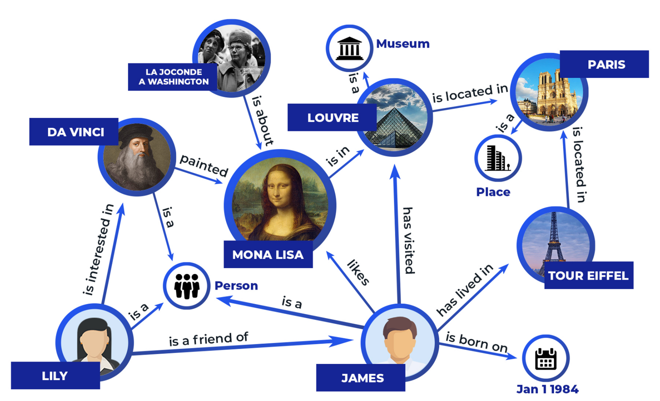
Why we need directed graphs?

Directed structures are everywhere:

- Recommender Systems
- Traffic Forecasting
- Biology (LGT)
- Neuroscience

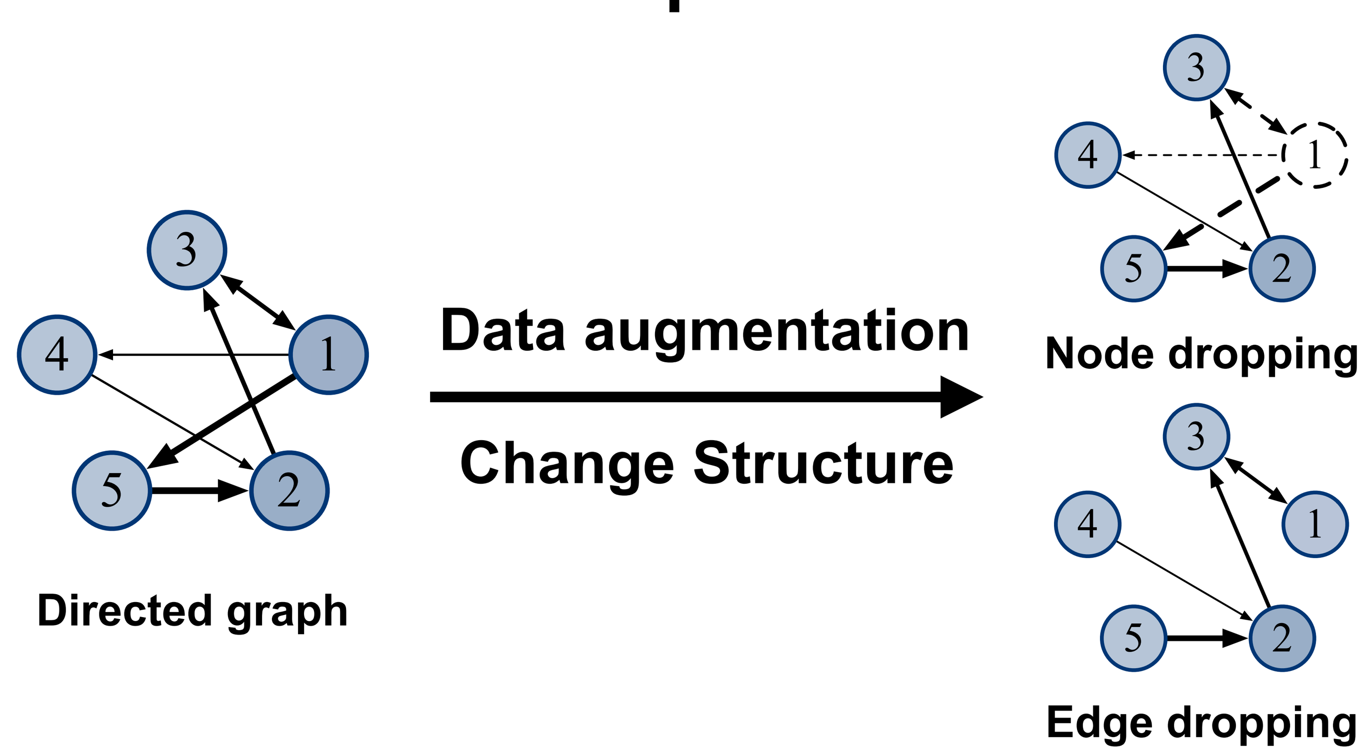


Road network



Knowledge graph

Limitations of Graph Contrastive Learning



Directed graph

Data Augmentation Limits

1. discard distinctive structural information
2. overlooks the discrepancy of nodes and edges

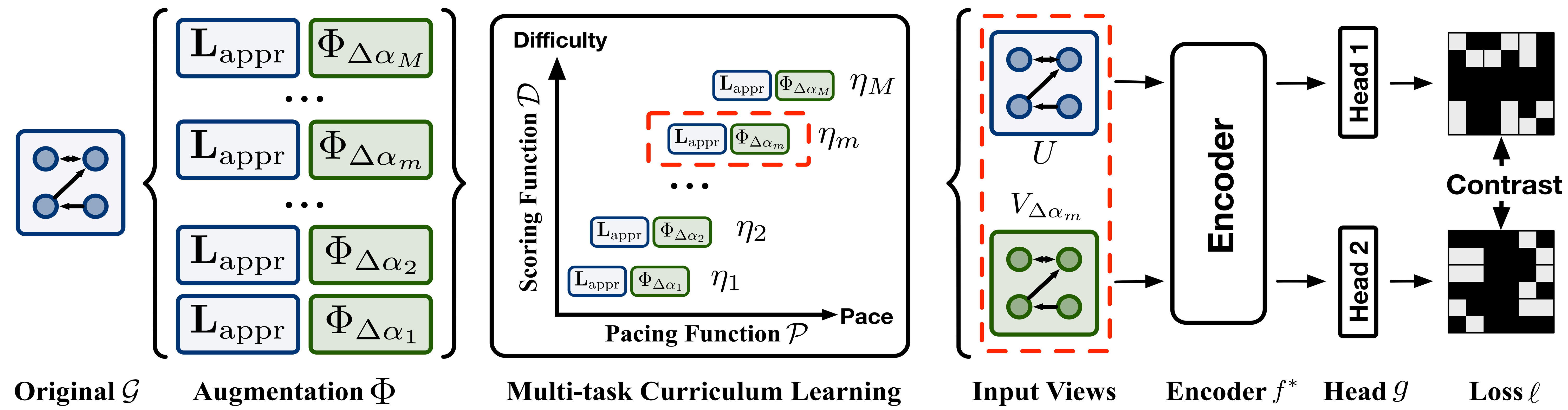
There is a lack of data augmentation methods specifically designed for directed graphs.

Learning Framework Limits

1. inability to take full advantage of data augmentation
2. hand-picking data augmentation parameters

Integrating data augmentation into contrastive learning framework is still at early stage.

Directed Graph Contrastive Learning Framework

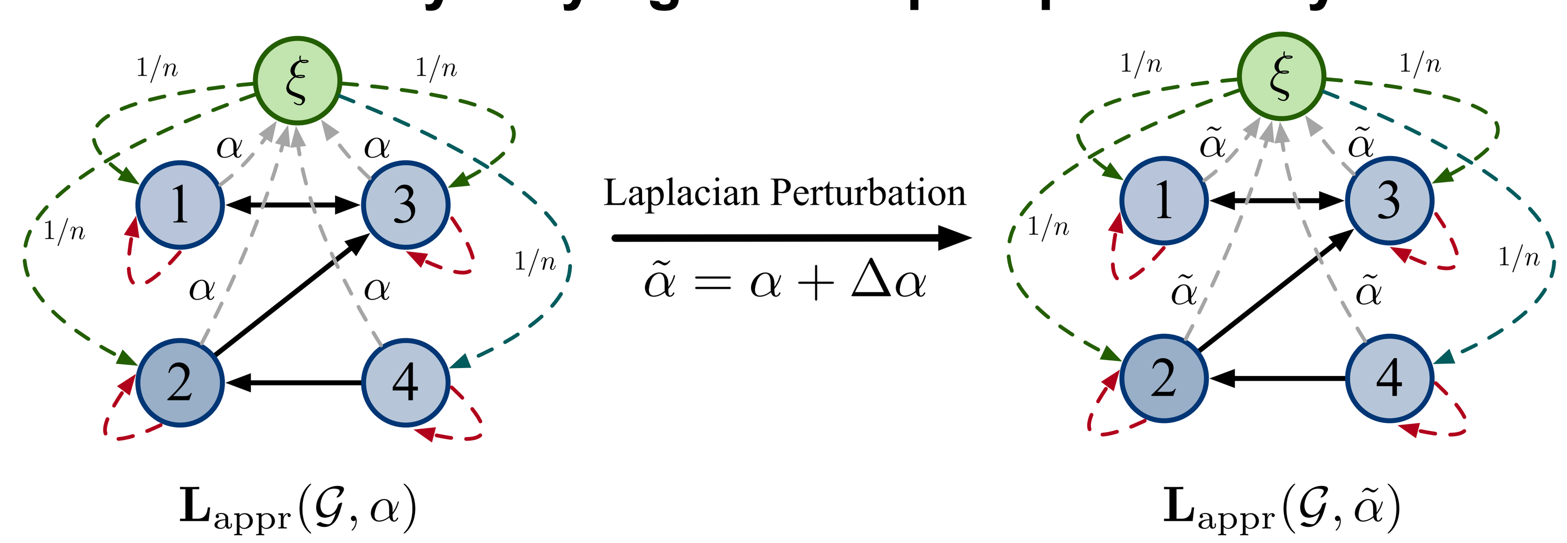


Original $\mathcal{G}$ Augmentation Φ Multi-task Curriculum Learning Input Views Encoder f^* Head g Loss ℓ

1. We first generate M different pairs of contrastive views by **Laplacian perturbation**.
2. The different contrastive view pairs are then scored by a **scoring function** and mapped to different training paces by a **pacing function**.
3. Finally, the arranged contrastive view pairs are input into a **shared encoder** to progressively learn the unsupervised graph representation with contrastive loss.

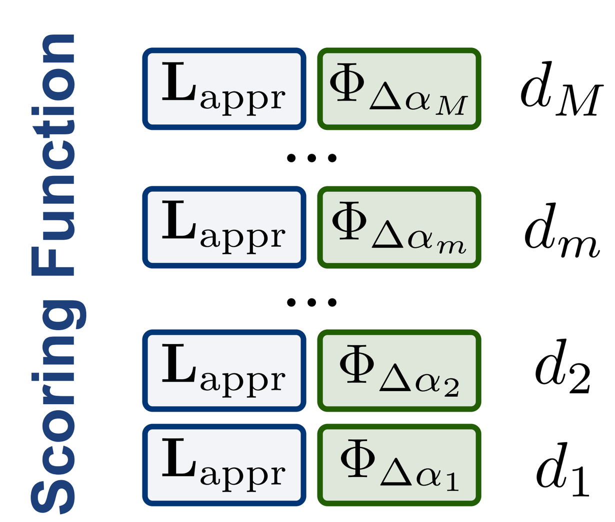
Directed Graph Data Augmentation

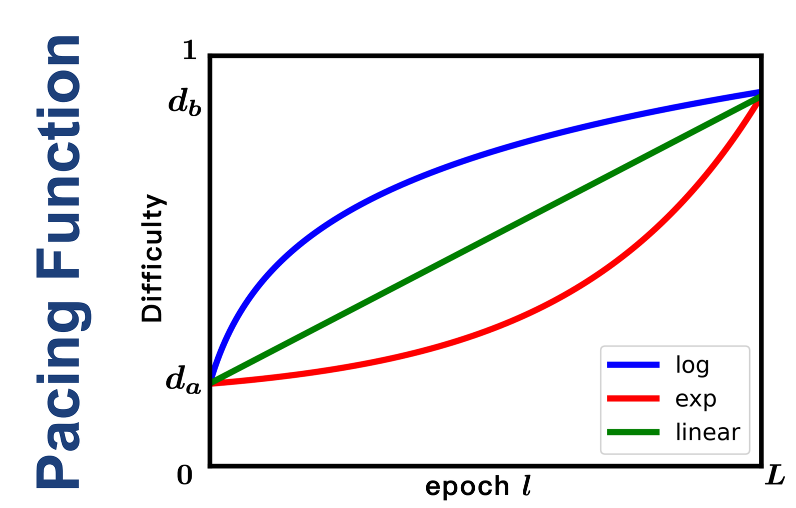
Laplacian Perturbation: changing the Laplacian matrix by varying the teleport probability.



Multi-task Curriculum Learning

Utilizes **prior knowledge** about the difficulty of the learning tasks to learn from **easy-to-difficult** contrastive views.



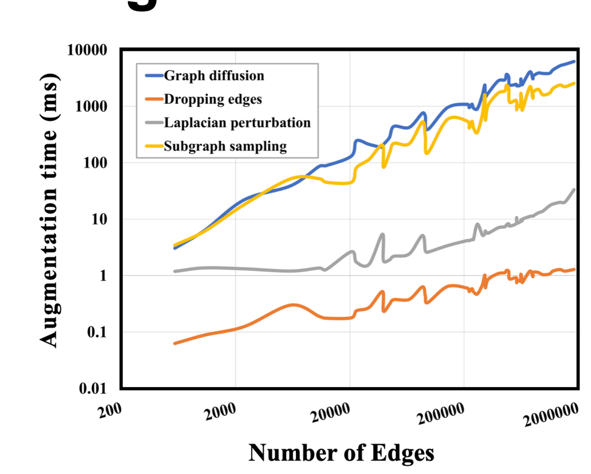


Brief Experimental Results

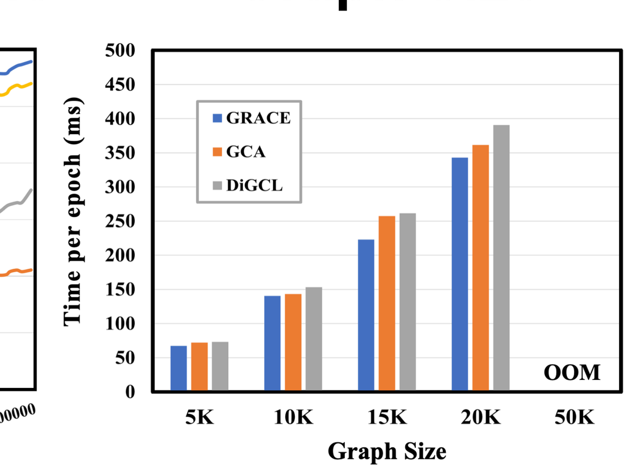
Node classification task in directed graphs

	Method	Directed: Cora-ML	Directed: CiteSeer	Directed: AM-Photo	Undirected: PubMed	Undirected: DBLP
Supervised	GCN [17]	70.92 ± 0.39	63.00 ± 0.45	88.52 ± 0.47	78.78 ± 0.30	73.54 ± 0.77
	GAT [46]	72.22 ± 0.57	63.73 ± 0.57	88.36 ± 1.25	77.49 ± 0.47	76.08 ± 0.54
	APPNP [18]	70.31 ± 0.67	61.63 ± 0.63	87.43 ± 0.98	79.35 ± 0.48	77.92 ± 0.75
	MagNet [64]	76.32 ± 0.10	65.04 ± 0.47	86.80 ± 0.65	74.23 ± 0.46	69.73 ± 0.98
	DiGCN [43]	$\underline{77.03 \pm 0.70}$	64.60 ± 0.60	88.66 ± 0.51	76.79 ± 0.49	73.37 ± 0.72
Unsupervised	DGI[47]	75.21 ± 1.29	64.58 ± 1.78	85.25 ± 0.59	74.11 ± 0.62	76.53 ± 1.24
	GMI[32]	76.59 ± 0.35	63.29 ± 0.70	81.12 ± 0.01	80.27 ± 0.16	76.66 ± 0.48
	MVGRL[13]	76.67 ± 0.12	62.22 ± 0.02	86.15 ± 0.21	79.98 ± 0.04	OOM
	GraphCL [63]	67.34 ± 0.12	57.84 ± 0.11	67.66 ± 0.05	75.29 ± 0.08	77.85 ± 0.22
	GRACE [68]	73.88 ± 0.25	61.20 ± 0.20	87.95 ± 0.32	79.54 ± 0.05	78.03 ± 0.09
	GCA [69]	76.32 ± 0.33	63.25 ± 0.10	87.35 ± 0.27	79.81 ± 0.61	77.83 ± 0.35
	Ours + No Curr	75.86 ± 0.09	66.99 ± 0.54	87.32 ± 0.14	79.57 ± 0.12	78.28 ± 0.05
	Ours + Random	76.52 ± 1.66	$\underline{67.15 \pm 0.82}$	$\underline{89.03 \pm 0.46}$	$\mathbf{80.75 \pm 0.10}$	$\underline{79.58 \pm 0.14}$
	Ours + Anti Curr	76.12 ± 1.04	66.83 ± 1.13	88.83 ± 0.73	80.22 ± 0.37	79.42 ± 0.15
	Ours + Curr	$\mathbf{77.53 \pm 0.14}$	$\mathbf{67.42 \pm 0.14}$	$\mathbf{89.41 \pm 0.11}$	$\underline{80.69 \pm 0.08}$	$\mathbf{79.70 \pm 0.13}$

Augmentation Time



Graph Size



More info