$\mathcal{G}$-Mixup: Graph Data Augmentation for Graph Classification

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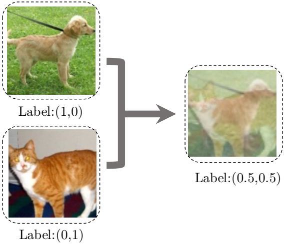
Overview

Overview

1. Background and Motivation
2. Methodology
   - $\mathcal{G}$-Mixup
   - Implementation
3. Experiments
   - Verification Experiments
   - Performance Experiments

Mixup

Mixup is a cross-instance data augmentation method, which linearly interpolates random sample pair to generate more synthetic training data.



$$\mathbf{x}_{new} = \lambda \mathbf{x}_i + (1-\lambda)\mathbf{x}_j,$$
$$\mathbf{y}_{new} = \lambda \mathbf{y}_i + (1-\lambda)\mathbf{y}_j,$$

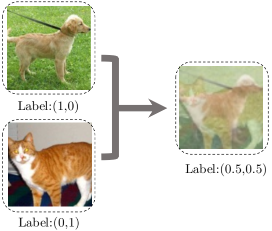
where $(\mathbf{x}_i, \mathbf{y}_i)$, $(\mathbf{x}_j, \mathbf{y}_j)$ are two samples randomly drawn from training data.

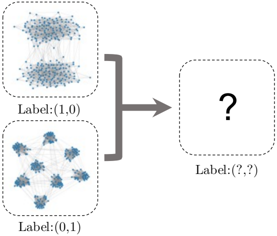
Mixup have been empirically and theoretically shown to improve the generalization and robustness of deep neural networks (H. Zhang et al., 2017; L. Zhang et al., 2021).

Can we mix up input graph pair to improve graph neural networks?

Challenges for Graph Mixup

Graph data is different from image data:





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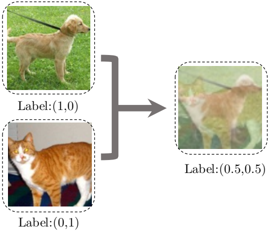

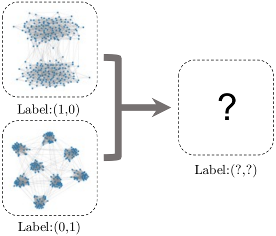

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1. Graph data is irregular (the number of nodes)

Challenges for Graph Mixup

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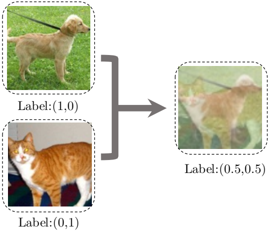

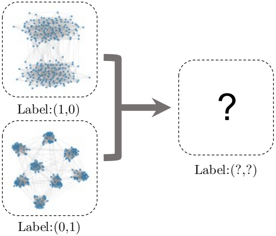

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2. Image data is well-aligned (pixel to pixel correspondence)

1. Graph data is irregular (the number of nodes)
2. Graph data is not well-aligned (nodes not naturally ordered)

Challenges for Graph Mixup

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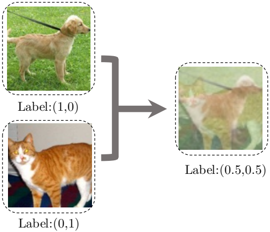

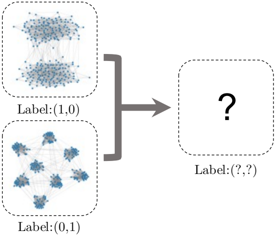

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1. Graph data is irregular (the number of nodes)
2. Graph data is not well-aligned (nodes not naturally ordered)
3. Graph has divergent topology information

Challenges for Graph Mixup

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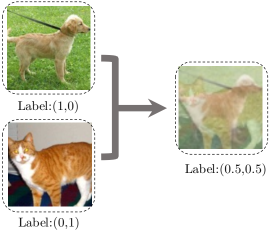

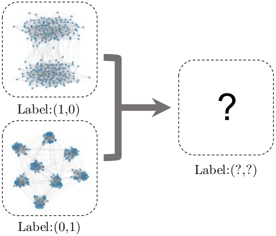

1. Image data is regular (image can be represented as matrix)
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3. Image data is grid-like data

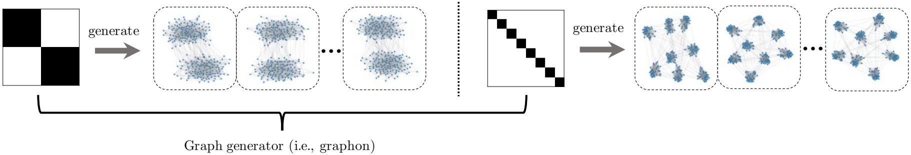
- Image is in Euclidean space

1. Graph data is irregular (the number of nodes)
2. Graph data is not well-aligned (nodes not naturally ordered)
3. Graph has divergent topology information

- Graph is in non-Euclidean space

Graph Generator: Graphon

The real-world graphs can be regarded as generated from generator (i.e., graphon[1]). For example,



The graphons of different graphs are **regular**, **well-aligned**, and **in Euclidean space**.

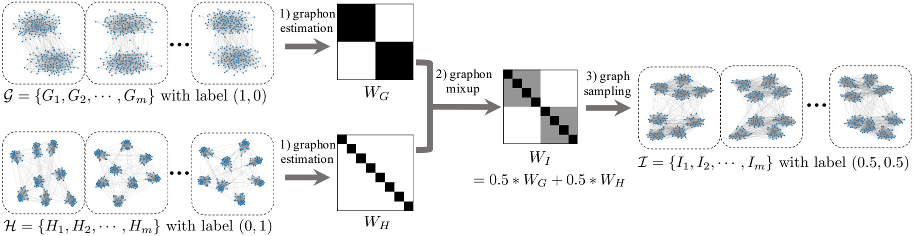
We propose to mix up graph generator (i.e., graphon) to achieve the input graph mixup.

[1] For ease of exposition, we use step function as grpahon in the following.

Overview

$\mathcal{G}$-Mixup

We propose to mixup the generator (i.e., graphon) of graphs, mix up the graphons of different classes, and then generate synthetic graphs.



The formal mathematical expression are as follows:

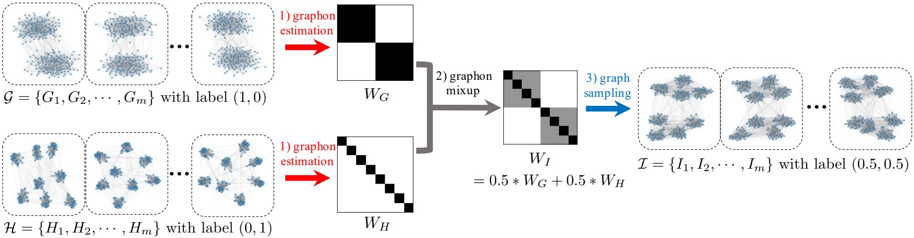
(1) Graphon Estimation: $\mathcal{G} \rightarrow W_{\mathcal{G}}, \mathcal{H} \rightarrow W_{\mathcal{H}}$

(2) Graphon Mixup: $W_{\mathcal{I}} = \lambda W_{\mathcal{G}} + (1-\lambda) W_{\mathcal{H}}$

(3) Graph Generation: $\{I_1, I_2, \cdots, I_m\} \overset{\text{i.i.d}}{\sim} \mathbb{G}(K, W_{\mathcal{I}})$

(4) Label Mixup: $\mathbf{y}_{\mathcal{I}} = \lambda \mathbf{y}_{\mathcal{G}} + (1-\lambda) \mathbf{y}_{\mathcal{H}}$

Implementation

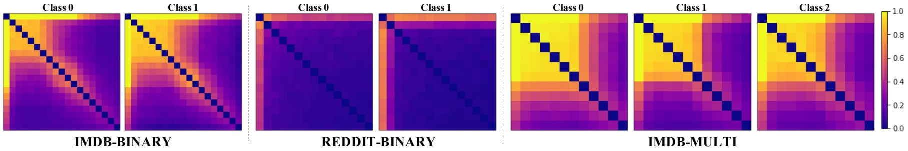


1. **Graphon Estimation.** We use the step function (Lovász, 2012; Xu et al., 2021) to approximate graphons. In general, the *step function* can be seen as a matrix $\mathbf{W} = [w_{kk'}] \in [0, 1]^{K \times K}$, where $\mathbf{W}_{ij}$ is the probability that an edge exists between node i and node j.
2. **Synthetic Graphs Generation.** Generates an adjacency matrix $\boldsymbol{A} = [a_{ij}] \in \{0, 1\}^{K \times K}$, whose element values follow the Bernoulli distributions $(\cdot)$ determined by the step function.

Overview

Do different classes of graphs have different graphons?

We visualize the estimated graphons on IMDB-BINARY, REDDIT-BINARY, and IMDB-MULTI.

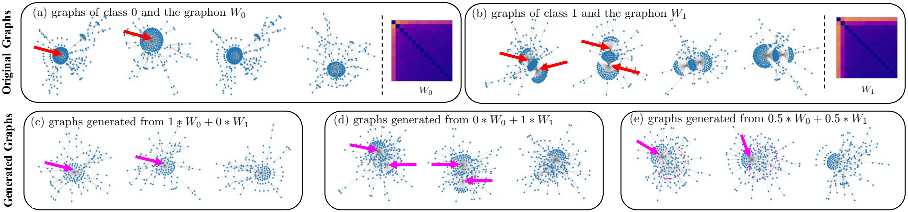


We make the following observations:

1. Real-world graphs of different classes have different graphons.
2. This observation lays a solid foundation for our proposed method.

What is $\mathcal{G}$-Mixup doing? A case study

We visualize the generated synthetic graphs on REDDIT-BINARY dataset.



We make the following observations:

1. The class 0 has one high-degree node while class 1 have two (a)(b).
2. The generated graphs based on
   - $(1 * W_0 + 0 * W_1)$ have one high-degree node (c).
   - $(0 * W_0 + 1 * W_1)$ have two high-degree nodes (d).
   - $(0.5 * W_0 + 0.5 * W_1)$ have a high-degree node and a dense subgraph (e).
3. Graphs generated by $\mathcal{G}$-Mixup are the mixture of original graphs.

Can $\mathcal{G}$-Mixup improve the performance of GNNs?

We use different GNNs for graph classification and report the performance comparisons of $\mathcal{G}$-Mixup.

	Dataset	IMDB-B	IMDB-M	REDD-B	REDD-M5	REDD-M12
	#graphs	1000	1500	2000	4999	11929
	#classes	2	3	2	5	11
	#avg.nodes	19.77	13.00	429.63	508.52	391.41
	#avg.edges	96.53	65.94	497.75	594.87	456.89
GCN	vanilla	72.18	48.79	78.82	45.07	46.90
	w/ Dropedge	72.50	49.08	81.25	51.35	47.08
	w/ DropNode	72.00	48.58	79.25	49.35	47.93
	w/ Subgraph	68.50	49.58	74.33	48.70	47.49
	w/ M-Mixup	72.83	49.50	75.75	49.82	46.92
	w/ $\mathcal{G}$-Mixup	**72.87**	**51.30**	**89.81**	**51.51**	**48.06**
GIN	vanilla	71.55	48.83	92.59	55.19	50.23
	w/ Dropedge	**72.20**	48.83	92.00	55.10	49.77
	w/ DropNode	72.16	48.33	90.25	53.26	49.95
	w/ Subgraph	68.50	47.25	90.33	54.60	49.67
	w/ M-Mixup	70.83	49.88	90.75	54.95	49.81
	w/ $\mathcal{G}$-Mixup	71.94	**50.46**	**92.90**	**55.49**	**50.50**

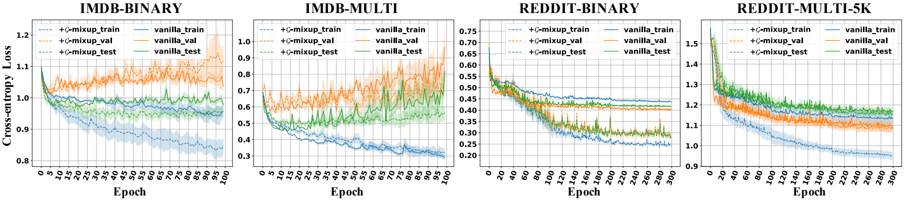
	Method	IMDB-B	IMDB-M	REDD-B	REDD-M5k
TopKPool	vanilla	72.37	50.57	90.30	45.07
	w/ Dropedge	71.75	48.75	88.96	**47.43**
	w/ DropNode	69.16	48.50	81.33	46.15
	w/ Subgraph	67.83	50.83	86.08	45.75
	w/ M-Mixup	71.83	51.22	87.58	45.60
	w/ $\mathcal{G}$-Mixup	**72.80**	**51.30**	**90.40**	46.48
DiffPool	vanilla	71.68	47.75	78.40	31.61
	w/ Dropedge	69.16	49.44	76.00	34.46
	w/ DropNode	70.25	46.83	76.68	33.10
	w/ Subgraph	69.50	46.00	76.06	31.65
	w/ M-Mixup	66.50	45.16	78.37	34.46
	w/ $\mathcal{G}$-Mixup	**73.25**	**50.70**	**78.87**	**38.42**
MincutPool	vanilla	73.25	49.04	84.95	49.32
	w/ Dropedge	69.16	49.66	81.37	47.20
	w/ DropNode	73.50	49.91	85.68	46.82
	w/ Subgraph	70.25	48.18	84.91	49.22
	w/ M-Mixup	70.62	49.96	85.12	47.20
	w/ $\mathcal{G}$-Mixup	**73.93**	**50.29**	**85.87**	**50.12**

We make the following observation:

1. $\mathcal{G}$-Mixup can improve the performance of GNNs on various datasets.

Can $\mathcal{G}$-Mixup improve the performance of GNNs?

We present the training/validation/test curves on IMDB-BINARY, IMDB-MULTI, REDDIT-BINARY and REDDIT-MULTI-5K with GCN.



We make the following observations:

1. The loss curves of $\mathcal{G}$-Mixup are lower than the vanilla model.
2. $\mathcal{G}$-Mixup can improve the generalization of graph neural networks.

References I

Lovász, L. (2012). *Large networks and graph limits* (Vol. 60). American Mathematical Soc.

Xu, H., Luo, D., Carin, L., & Zha, H. (2021). Learning graphons via structured gromov-wasserstein barycenters. *Proceedings of the AAAI Conference on Artificial Intelligence*, 10505–10513.

Zhang, H., Cisse, M., Dauphin, Y. N., & Lopez-Paz, D. (2017). Mixup: Beyond empirical risk minimization. *International Conference on Learning Representations*.

Zhang, L., Deng, Z., Kawaguchi, K., Ghorbani, A., & Zou, J. (2021). How does mixup help with robustness and generalization? *International Conference on Learning Representations*.

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Q&A