SIGIR-22 Short Paper

GraFN: Semi-Supervised Node Classification on Graph with Few Labels via Non-Parametric Distribution Assignment

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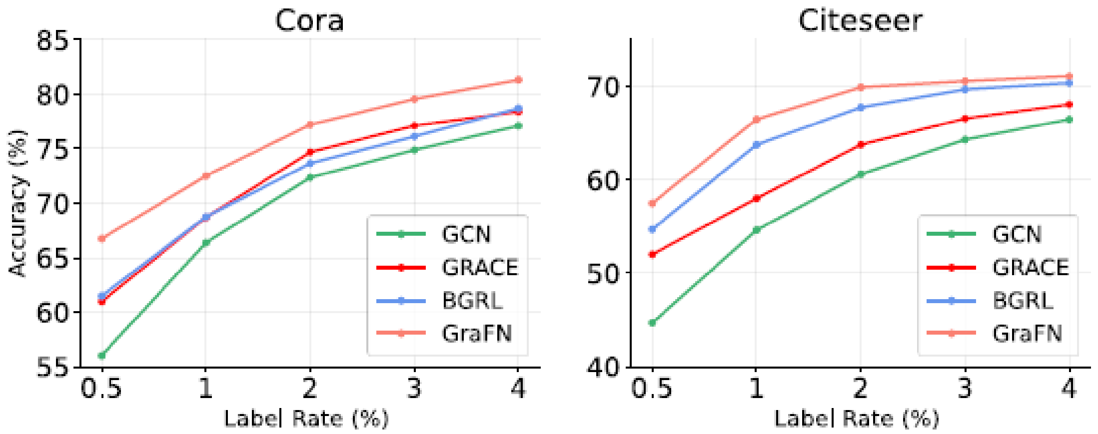
MOTIVATION PERFORMANCE DEGRADATION OF GNN WITH FEW LABELED NODES



Node Classification accuracy over various labeled node rates

Limitation The performance of GCNs on node classification significantly degrades when only few labeled nodes are given

- Suffers from overfitting
- Ineffective propagation of supervisory signal

Related work 1. Pseudo Labeling Technique

Idea Expand the label set by obtaining pseudo-labels

Limitation Incorrect pseudo-labels incur confirmation bias

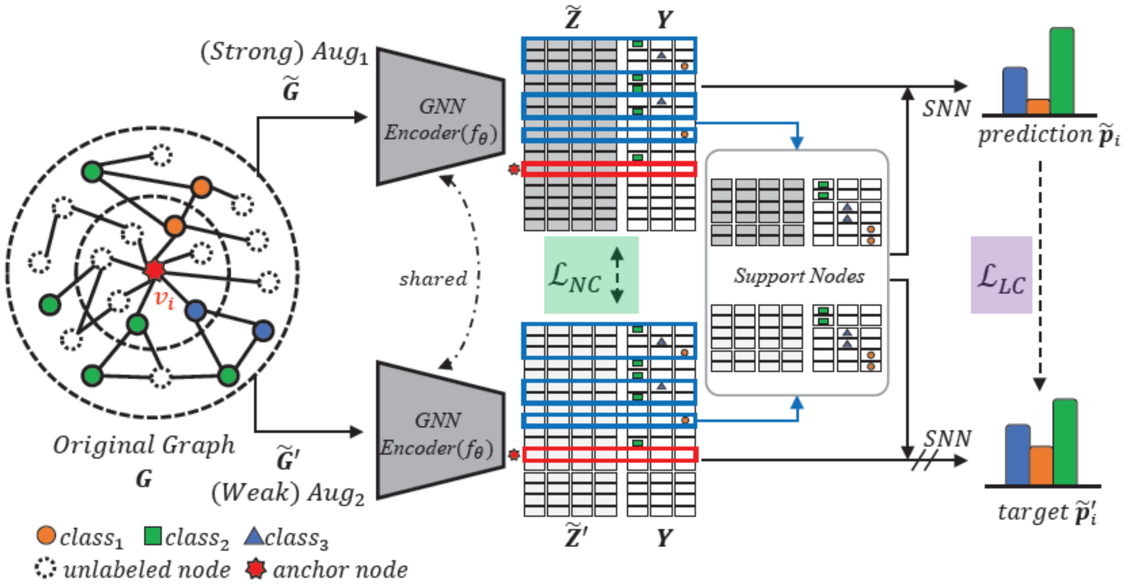
Related work 2. Self-Supervised Learning

Idea Learn node representation without requirements of labeled nodes

Limitation Node label information is not involved in the training process
→ Hard to learn class discriminative node representations

Proposed Method: GraFN

Key Idea GraFN not only exploits the self-supervised loss but also fully leverages a small amount of labeled nodes to ensure the nodes with same class to be grouped together.



• Node-wise Consistency Regularization

Minimize the difference between the node representations obtained from the two differently augmented graphs in a node-wise manner

• Label-guided Consistency Regularization

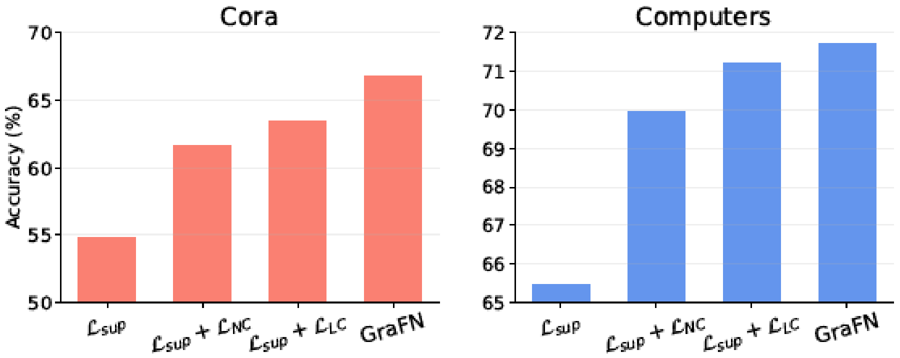
Minimize the difference between two predicted class distributions that are non-parametrically assigned by anchor-supports similarity from two differently augmented graphs

→ Unlabeled nodes can be grouped together according to their classes by enforcing them to be consistently close with a certain class of labeled nodes.

EXPERIMENTS

Methods	Cora			Citeseer			Pubmed			Am. Comp			Am. Photos		
Label Rate	0.5%	1%	2%	0.5%	1%	2%	0.03%	0.06%	0.1%	0.15%	0.2%	0.25%	0.15%	0.2%	0.25%
MLP	31.24	37.74	44.53	32.07	43.07	46.11	52.50	55.80	61.22	40.30	42.22	49.98	29.76	31.64	38.55
LP	50.77	58.28	64.43	31.15	37.95	41.71	50.93	55.83	62.14	60.46	65.90	68.79	63.67	66.38	70.40
GCN	56.00	66.36	72.35	44.67	54.61	60.59	59.28	64.00	73.74	62.71	66.81	71.75	66.70	70.72	75.74
GAT	58.57	67.75	72.74	48.70	58.73	62.71	63.15	64.11	73.19	66.17	70.18	72.82	73.29	74.46	80.12
SGC	49.19	63.60	69.56	44.02	55.89	63.61	58.58	62.50	71.90	59.69	64.24	68.29	55.96	61.64	69.69
APPNP	62.02	71.45	76.89	41.79	54.70	62.86	63.15	64.11	73.19	68.53	72.47	74.27	75.54	78.49	82.75
GRAND	54.51	70.92	74.90	46.76	58.40	65.31	55.87	61.25	72.42	68.00	72.71	75.77	73.80	75.83	82.33
GLP	56.94	68.28	72.97	41.53	54.84	63.08	56.70	60.83	73.46	62.97	68.56	70.70	63.18	67.96	75.19
IGCN	58.81	70.10	74.34	43.28	57.00	64.62	57.50	62.06	73.13	65.48	70.05	71.03	71.27	73.28	77.93
CGPN	64.21	70.54	72.97	53.90	63.70	65.15	64.55	67.58	71.42	65.37	67.98	70.77	74.14	76.89	81.57
GRACE	60.95	68.69	74.68	52.01	58.00	63.76	64.86	68.35	**75.92**	65.25	67.79	71.79	70.19	71.89	77.32
BGRL	61.74	68.74	73.65	54.69	63.75	67.75	65.77	**68.86**	75.91	68.80	73.04	75.11	74.27	78.25	83.12
Co-training	62.75	68.72	74.05	43.76	54.75	61.13	63.01	68.15	74.24	67.06	71.62	71.34	72.85	74.65	79.92
Self-training	57.28	70.73	75.40	46.26	60.36	66.47	57.34	65.13	72.86	61.32	65.95	68.66	61.92	65.24	71.34
M3S	64.46	**72.93**	76.41	55.07	65.74	67.64	61.53	64.60	73.18	61.51	66.30	68.10	63.93	67.62	73.39
GraFN	**66.73**	72.50	**77.20**	**57.48**	**66.47**	**69.89**	**65.91**	68.41	75.74	**71.73**	**74.26**	**77.37**	**79.25**	**80.87**	**85.36**

Test Accuracy on semi-supervised node classification



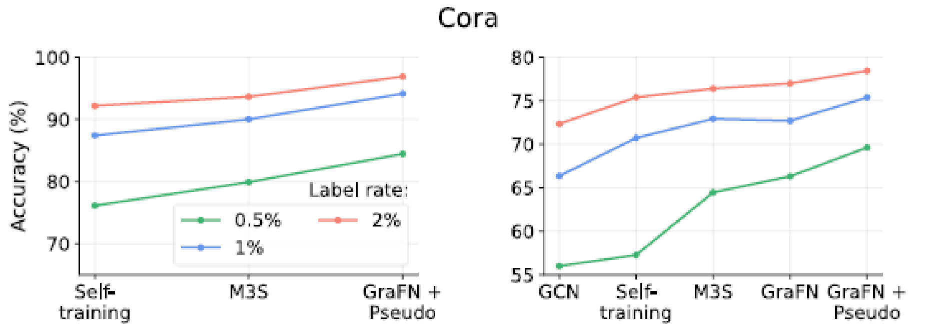
Ablation studies on GraFN

Performance Analysis

- GraFN outperforms both the semi-supervised and self-supervised methods over various label rates
- Note that GraFN uses the simplest structure(no stop gradient and only simple 2-layer encoder)
  → Shows the efficiency of our proposed model
- Ablation studies also show that all the components of GraFN helps to learn class discriminative node representation

EXPERIMENTS

Adopting Pseudo-labeling to GraFN

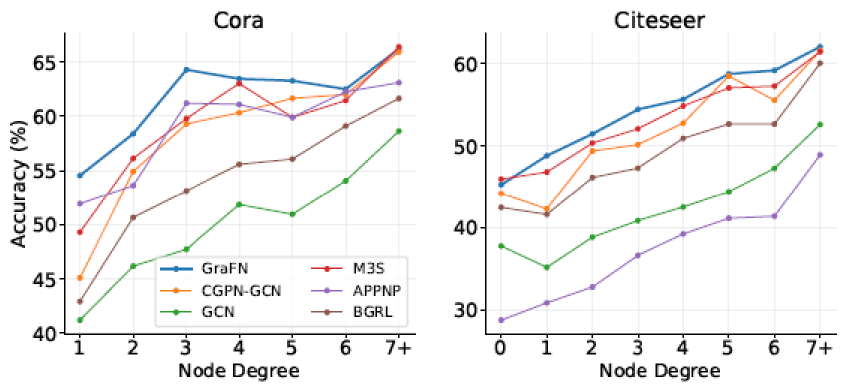


(a) Pseudo-label accuracy (b) Node classification accuracy

Accuracy of pseudo-labeling and node classification

- GraFN also can adopt pseudo-labeling technique
- It shows that GraFN achieves the best pseudo-labeling accuracy
  → Alleviates confirmation bias by learning discriminative node representation

Performance Comparison on Different Node Degree



Node classification results on various node degrees

- GraFN greatly outperforms other methods on low-degree nodes
  → Label guided consistency regularization can evenly spread the supervision information over the unlabeled nodes regardless of their node degree!

  → Effective Propagation of supervisory signal!

SUPPLEMENTARY MATERIALS

[Paper] https://arxiv.org/abs/2204.01303

[Code] https://github.com/Junseok0207/GraFN

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