

JAMN-GNN: Jointly-adversarial graph neural network for noisy labels and missing attributes

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Problems & Ideas

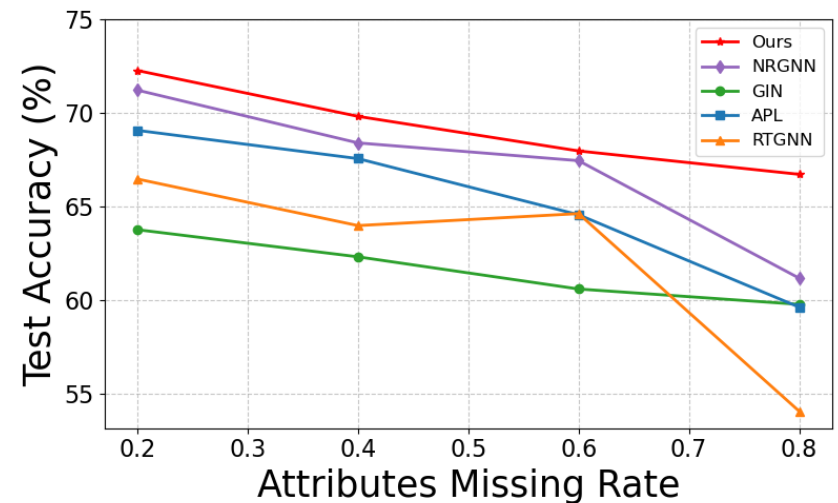
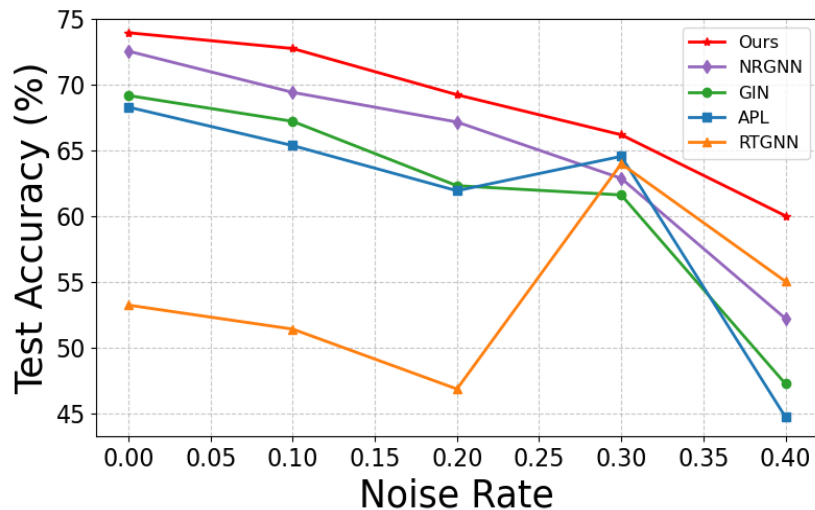
- Problems of conventional stereo matching approaches:
 - Label noise and attribute missing are regarded as independent issues.
 - Under the dual challenges of missing attributes and noisy labels, model performance typically experiences significant degradation.
- Ideas: A graph neural network model capable of simultaneously handling missing attributes and noisy labels.

Method	Cora	CiteSeer	PubMed	DBLP	Amazon-Comp
GCN	49.30 ± 4.56	45.40 ± 4.58	54.18 ± 2.42	56.03 ± 3.10	61.00 ± 4.94
GIN	53.75 ± 7.58	45.68 ± 5.27	54.52 ± 1.52	62.35 ± 1.66	37.66 ± 2.23
S-mode	49.21 ± 4.79	43.60 ± 4.93	53.38 ± 2.75	56.00 ± 3.36	64.96 ± 2.95
JoCoR	45.26 ± 4.63	42.16 ± 6.44	49.06 ± 3.51	58.50 ± 4.11	57.16 ± 10.73
Coteaching	41.93 ± 8.07	39.22 ± 8.52	52.06 ± 7.05	57.56 ± 2.66	62.50 ± 7.69
APL	51.07 ± 6.74	42.34 ± 5.91	53.30 ± 2.80	<u>64.46 ± 1.73</u>	58.72 ± 8.46
SCE	47.86 ± 6.88	44.52 ± 4.44	50.30 ± 5.39	<u>49.92 ± 4.91</u>	64.42 ± 0.76
Forward	49.63 ± 6.24	45.32 ± 6.64	53.88 ± 2.31	56.84 ± 3.79	55.34 ± 6.41
Backward	48.92 ± 7.26	45.64 ± 6.44	53.44 ± 2.69	56.84 ± 3.79	36.22 ± 8.71
RTGNN	38.59 ± 8.49	37.15 ± 6.29	44.34 ± 4.18	61.07 ± 6.27	54.72 ± 11.47
CLNode	50.16 ± 5.44	44.44 ± 5.21	49.66 ± 1.83	58.30 ± 2.18	<u>64.98 ± 2.40</u>
RNCGLN	23.76 ± 7.61	29.88 ± 11.93	43.16 ± 11.72	48.17 ± 0.75	<u>46.56 ± 8.17</u>
NRGNN	52.87 ± 5.56	47.70 ± 4.48	44.56 ± 1.91	62.86 ± 1.72	49.24 ± 6.05
CRGNN	52.06 ± 2.77	<u>43.51 ± 5.17</u>	<u>56.10 ± 2.71</u>	57.74 ± 7.23	60.26 ± 2.54
ITR	52.36 ± 3.18	40.56 ± 4.64	39.46 ± 3.20	53.50 ± 2.56	55.69 ± 2.94
AIAE	<u>55.36 ± 3.64</u>	43.46 ± 3.58	56.50 ± 3.56	56.56 ± 2.10	59.48 ± 2.65
Ours	57.70 ± 2.41	48.16 ± 3.81	60.28 ± 4.71	66.46 ± 1.27	66.32 ± 1.97

Node classification performance on graphs with coexisting noisy labels and missing attributes. Bold indicates the best results, while underlining indicates the second-best results.

Main Contributions

- Contributions:
 - This study introduces a novel graph learning problem aimed at performing node classification on graphs with coexisting label noise and missing attributes;
 - A novel graph neural network framework is proposed to jointly address missing attributes and noisy labels.



Comparative results of different methods under varying label noise rates and attribute missing rates. Left: Different levels of label noise; Right: Different levels of missing attributes.