GLAD: Bidirectional Structure-Attribute Alignment via Latent Graph Diffusion Models

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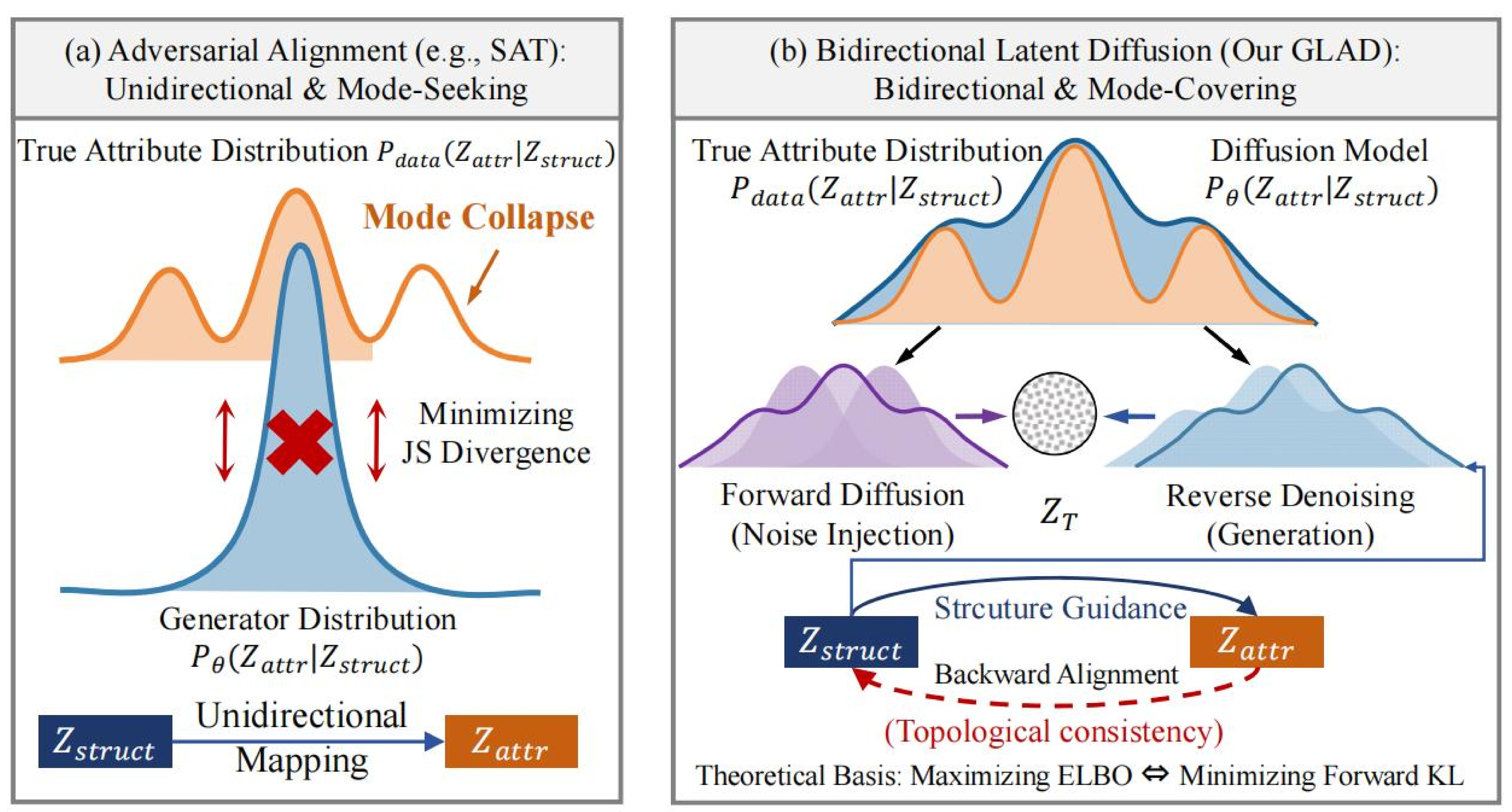
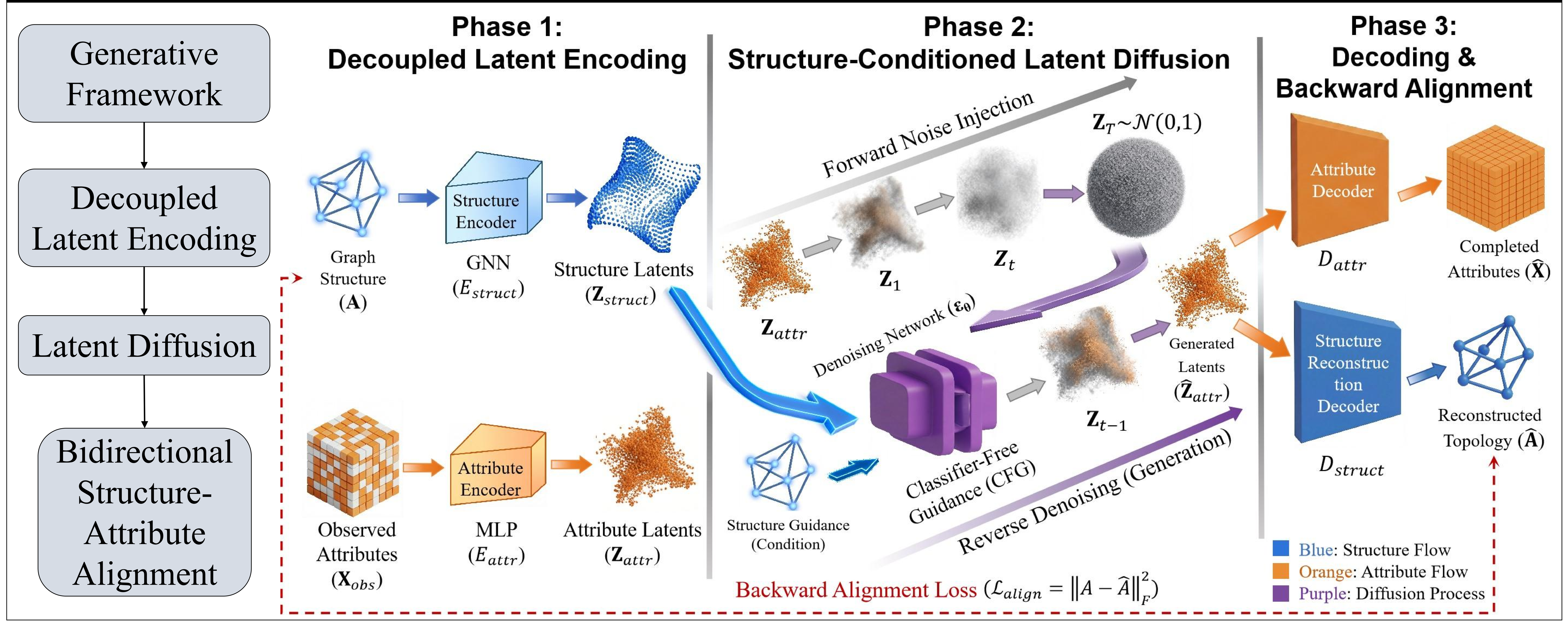
Problem & Motivation

- Real-world graphs often suffer from **missing node attributes**, severely degrading GNN performance.



- Existing GAN-based methods (e.g., SAT) suffer from **training instability** and **mode collapse**.
- Most approaches only use **unidirectional structure-to-attribute mapping**, ignoring topological consistency.
- Heterogeneity between structure and attributes makes direct generation inefficient.

Core Idea: GLAD (Graph Latent Attribute Diffusion)



Experiments & Results (Standard Benchmarks; Real-World Traffic Networks; Quantitative Validation)

Table 1. Profiling of the attribute-level evaluation for node attribute reconstruction on the Cora and Citeseer dataset.

Method	Cora						Citeseer					
	R@10	R@20	R@50	N@10	N@20	N@50	R@10	R@20	R@50	N@10	N@20	N@50
VAE	8.87	12.33	20.97	12.23	14.56	19.16	3.82	6.69	12.94	6.01	8.40	12.50
GCN	12.56	17.85	29.73	17.21	20.76	27.04	6.28	10.97	20.49	10.31	14.21	20.44
GAT	12.67	17.93	29.70	17.30	20.87	27.10	5.62	10.12	19.56	8.79	12.53	18.71
NEIGHAGGR	9.06	14.13	19.61	12.17	15.48	18.50	5.11	9.08	15.01	8.23	11.55	15.60
GRAPHSAGE	12.91	18.10	30.24	17.97	21.45	27.86	5.60	10.63	19.90	9.78	13.56	19.97
GRAPHMAE	3.69	4.39	7.48	5.74	7.25	10.79	1.27	3.54	8.35	2.23	4.91	7.51
ARWMF	12.99	18.03	29.80	18.64	22.14	27.96	5.56	10.18	19.59	8.46	12.25	18.29
T2-GNN	12.26	15.35	22.15	17.20	19.28	22.81	5.27	8.59	15.54	9.46	12.24	16.79
GINN	13.12	18.67	28.87	18.28	21.66	27.78	6.07	10.53	20.22	9.31	13.46	19.89
SAT	14.75	21.30	33.24	20.71	24.98	31.71	7.55	12.61	23.38	13.05	17.26	24.25
AMER	14.48	20.22	31.89	20.01	23.92	30.61	7.45	11.82	21.94	12.23	16.47	22.75
WGNN	15.21	22.34	33.20	21.22	24.83	31.62	8.00	12.25	22.33	13.15	17.59	24.02
GLAD	17.32	24.55	37.03	23.91	28.83	36.12	9.77	15.52	26.86	17.65	20.15	27.22

Note: The highest performance is shaded in green, and the second-highest performance is shaded in blue.

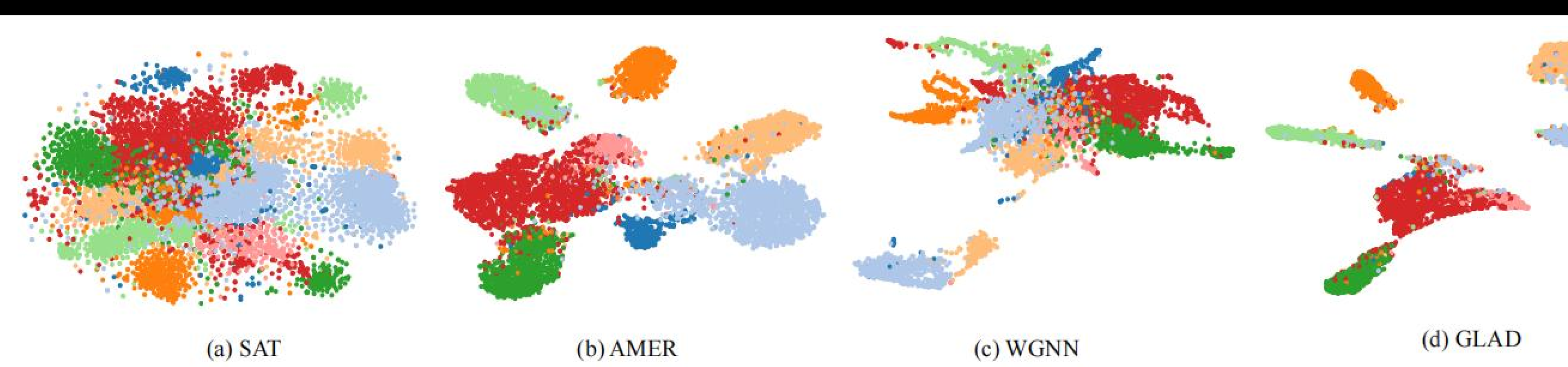


Figure 3. Visualization of node representations generated by four methods on the Amazon-Photo dataset.

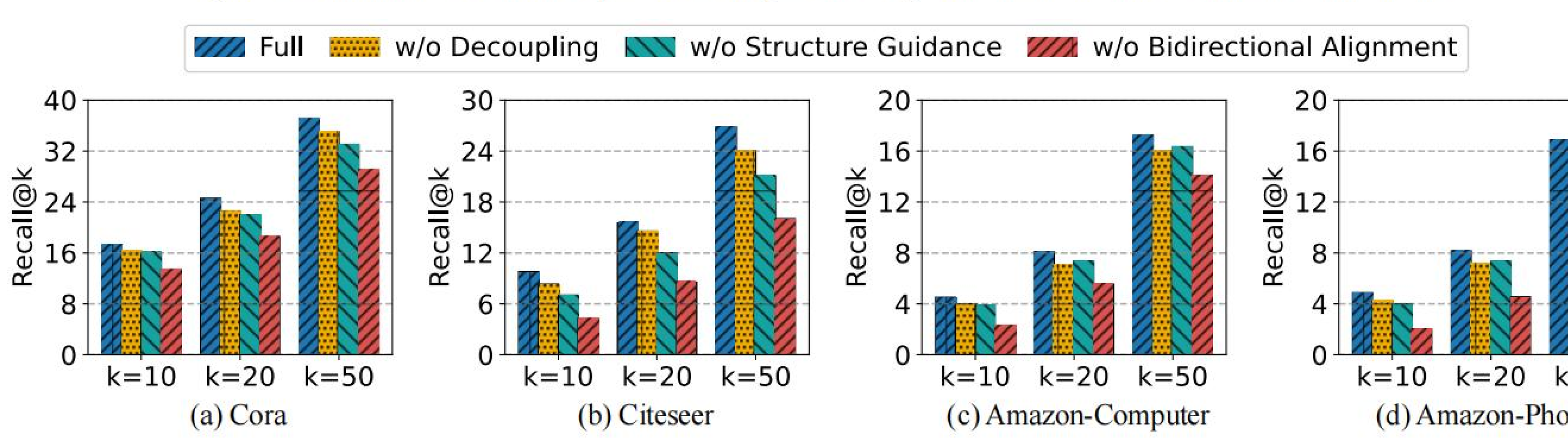


Figure 4. Ablation results of the proposed GLAD model across four graph datasets in term of the Recall@k evaluation metric.

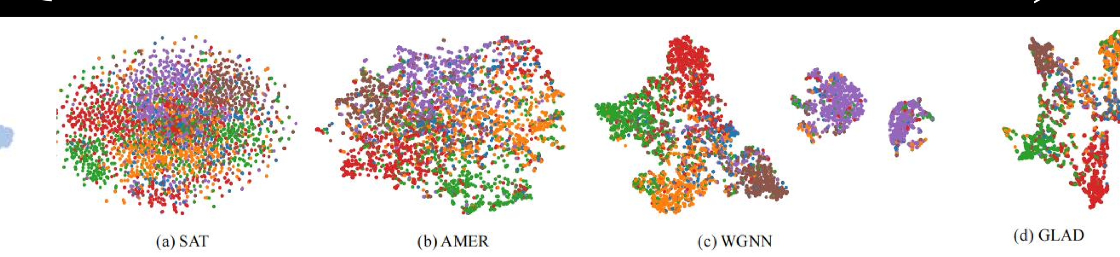


Figure 11. Visualization of node representations generated by four methods on the Citeseer dataset.

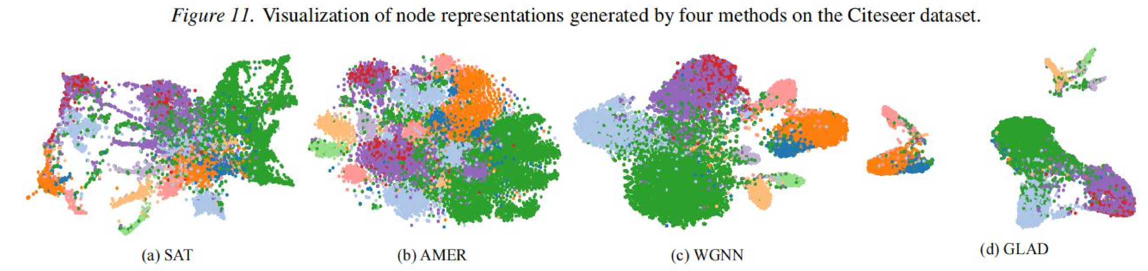


Figure 12. Visualization of node representations generated by four methods on the Amazon-Computer dataset.

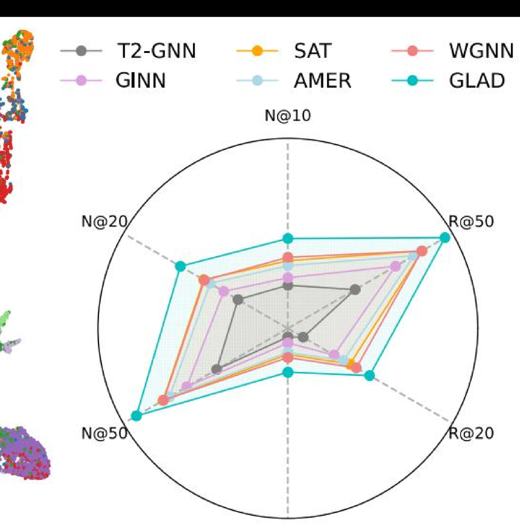


Table 5. Comparison of diversity & topological consistency.

Method	Diversity: APD (↑)	Topology: AUC (↑)
Ground Truth	1.18	92.5%
SAT	0.18	79.2%
AMER	0.20	78.6%
WGNN	0.24	81.5%
GLAD	1.12	88.4%

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