

Relation-Aware Diffusion for Heterogeneous Graphs with Partially Observed Features

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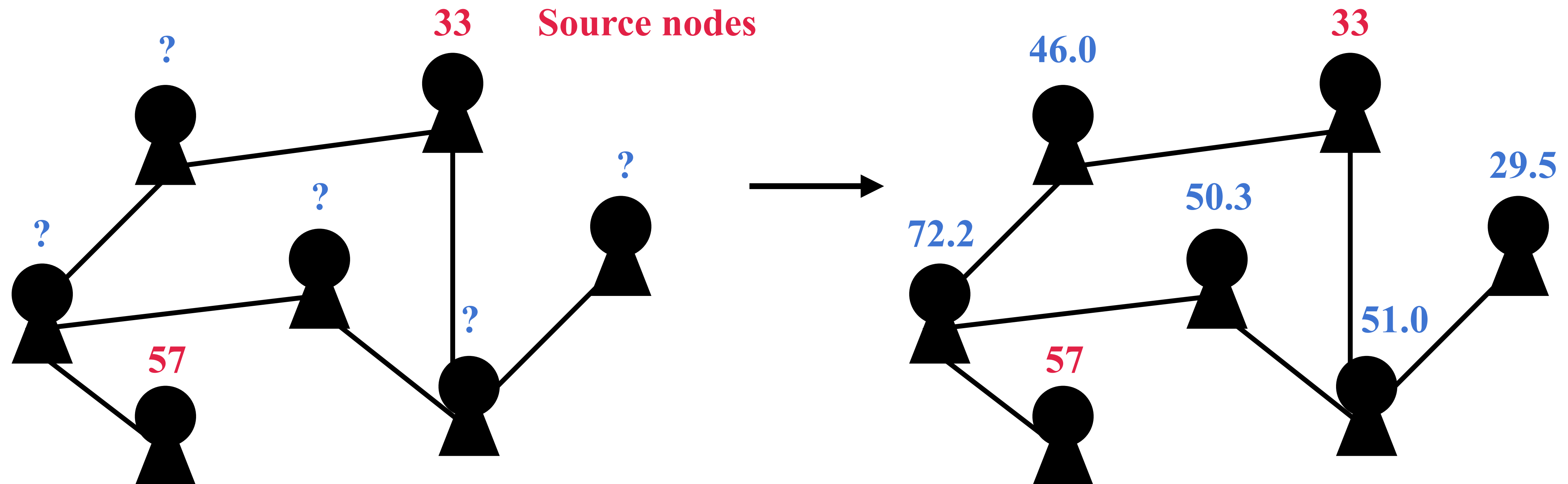
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Background

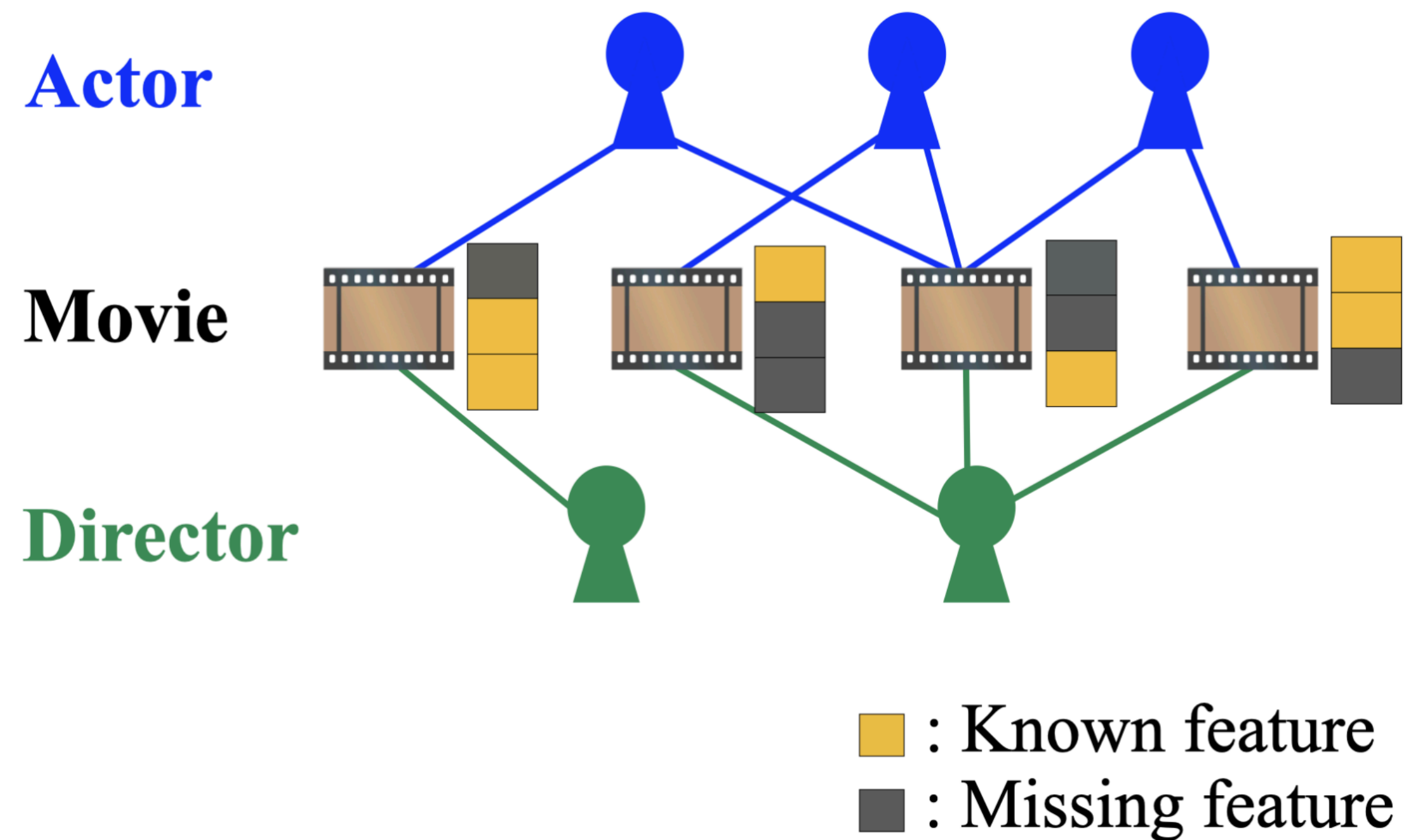
Diffusion-based feature imputation for graphs

- Diffusion-based feature imputation methods iteratively propagate known features along edges.
- At each step, each unknown feature updates its value by aggregating features from its neighboring nodes.



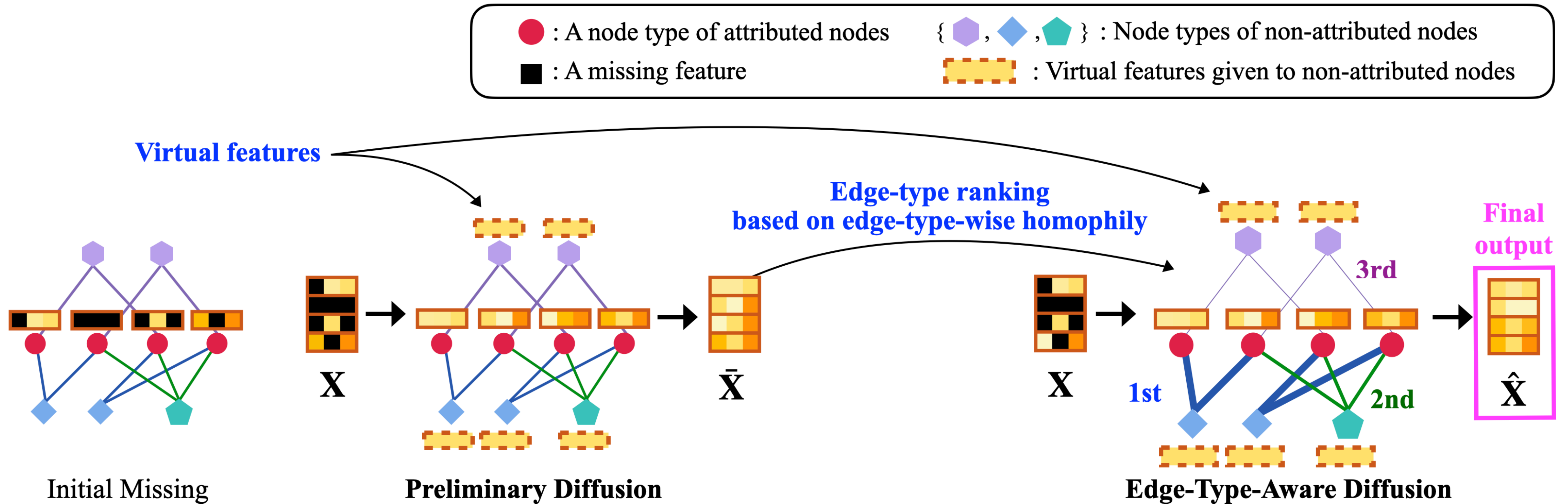
Motivation

- Heterogeneous graph
 - two challenges
 - 1) Node types without features block diffusion
 - 2) Multiple types of edges



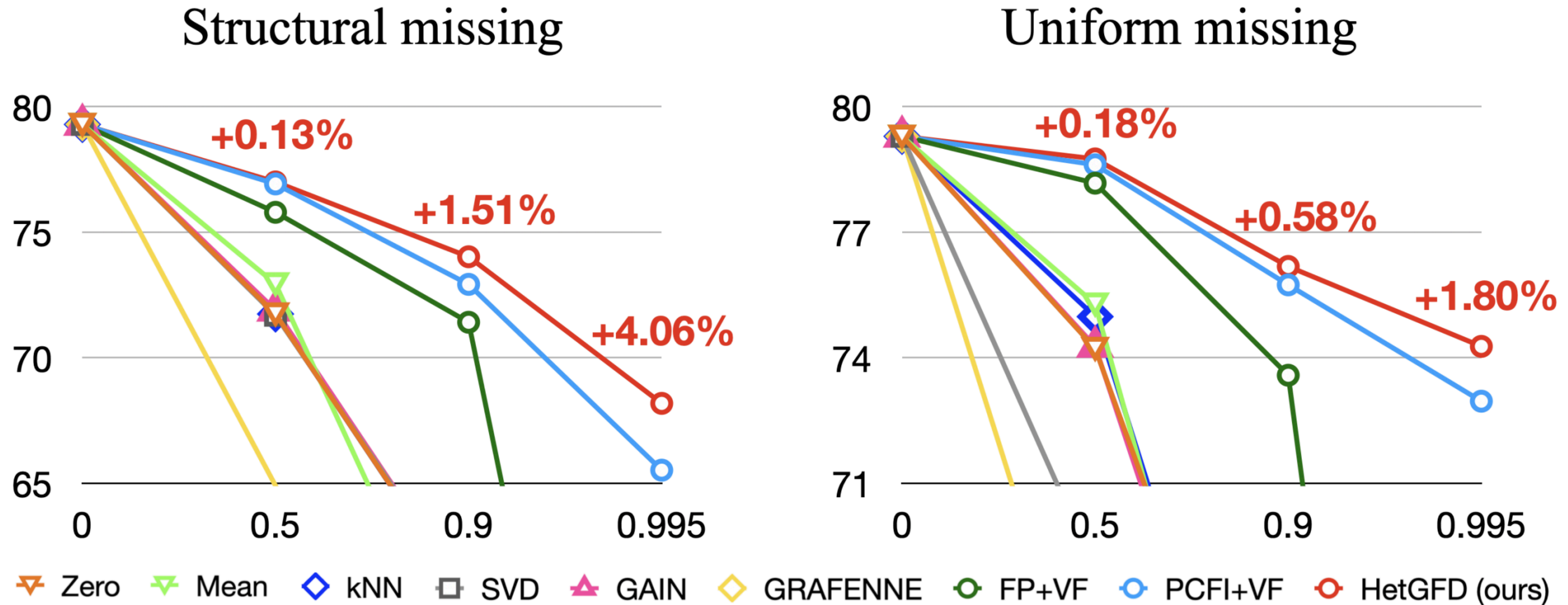
HetGFD

(Heterogeneous graph feature diffusion)



Experiments

Semi-supervised node classification



Experiments

Link prediction

Missing type	Method	ACM		DBLP		IMDB	
		AUC	AP	AUC	AP	AUC	AP
	Full features	76.25 \pm 1.20	77.64 \pm 1.07	71.52 \pm 0.51	66.92 \pm 0.66	92.47 \pm 1.06	86.94 \pm 1.61
Structural missing	Zero	71.65 \pm 2.16	71.74 \pm 3.55	72.49 \pm 0.63	74.21 \pm 0.60	92.48 \pm 1.06	86.95 \pm 1.60
	Mean	71.64 \pm 1.30	71.66 \pm 1.33	72.49 \pm 0.63	74.20 \pm 0.60	91.78 \pm 1.13	85.80 \pm 2.12
	kNN	72.04 \pm 1.66	72.55 \pm 2.11	71.96 \pm 1.37	69.86 \pm 1.89	91.10 \pm 1.07	84.44 \pm 1.97
	SVD	71.49 \pm 1.77	72.29 \pm 2.13	72.49 \pm 0.63	74.21 \pm 0.60	92.48 \pm 1.06	86.95 \pm 1.60
	GAIN	72.22 \pm 1.19	73.21 \pm 1.10	72.49 \pm 0.63	74.20 \pm 0.61	92.48 \pm 1.06	86.95 \pm 1.60
	GRAFENNE	74.87 \pm 6.71	67.60 \pm 5.87	90.14 \pm 7.26	76.53 \pm 7.12	82.38 \pm 5.75	69.72 \pm 4.60
	FP+VF	73.40 \pm 0.75	74.03 \pm 0.84	71.58 \pm 0.85	70.01 \pm 1.43	92.50 \pm 1.04	86.99 \pm 1.58
	PCFI+VF	73.41 \pm 1.16	73.22 \pm 1.18	71.37 \pm 0.55	66.78 \pm 0.74	91.71 \pm 1.33	85.37 \pm 2.08
	HetGFD (ours)	78.25 \pm 1.34	78.62 \pm 2.12	91.94 \pm 0.67	91.88 \pm 0.91	92.50 \pm 1.04	86.99 \pm 1.58
Uniform missing	Zero	70.69 \pm 1.48	70.17 \pm 3.07	72.48 \pm 0.62	74.20 \pm 0.60	92.50 \pm 1.04	86.99 \pm 1.58
	Mean	71.98 \pm 1.02	72.02 \pm 0.96	72.48 \pm 0.62	74.20 \pm 0.60	91.40 \pm 1.14	85.33 \pm 1.93
	kNN	71.02 \pm 1.49	72.49 \pm 2.46	72.72 \pm 1.85	70.29 \pm 3.73	91.15 \pm 1.09	84.50 \pm 2.04
	SVD	70.49 \pm 2.11	70.70 \pm 4.08	72.48 \pm 0.62	74.20 \pm 0.60	92.50 \pm 1.04	86.99 \pm 1.58
	GAIN	71.92 \pm 0.92	73.17 \pm 1.09	72.48 \pm 0.62	74.20 \pm 0.60	92.50 \pm 1.04	86.99 \pm 1.58
	GRAFENNE	74.76 \pm 9.82	72.96 \pm 9.71	63.78 \pm 31.28	61.86 \pm 28.14	80.69 \pm 15.81	73.22 \pm 14.33
	FP+VF	73.18 \pm 0.96	73.77 \pm 0.82	71.86 \pm 1.66	70.03 \pm 1.97	91.52 \pm 1.15	85.67 \pm 2.14
	PCFI+VF	74.94 \pm 1.37	73.80 \pm 1.63	70.76 \pm 3.14	68.97 \pm 3.85	91.54 \pm 1.13	85.70 \pm 2.08
	HetGFD (ours)	76.96 \pm 1.74	77.19 \pm 1.98	92.17 \pm 0.56	92.12 \pm 0.53	91.95 \pm 1.72	86.72 \pm 3.40

Experiments

Applicability to the biomedical domain

r_m	0	0.5	0.9	0.995
Zero	98.49 ± 0.13	78.74 ± 1.01	64.15 ± 1.18	62.20 ± 0.24
Mean	98.49 ± 0.13	64.40 ± 1.97	64.40 ± 1.97	62.14 ± 0.15
kNN	98.49 ± 0.13	78.74 ± 1.01	64.15 ± 1.18	62.20 ± 0.24
SVD	98.49 ± 0.13	79.30 ± 1.15	64.10 ± 1.23	62.23 ± 0.26
GAIN	98.49 ± 0.13	78.85 ± 1.09	64.13 ± 1.09	62.20 ± 0.24
GRAFENNE	83.76 ± 9.15	63.97 ± 1.87	63.15 ± 1.31	62.26 ± 0.00
FP+VF	98.49 ± 0.13	80.44 ± 2.34	64.78 ± 1.51	62.20 ± 0.24
PCFI+VF	98.49 ± 0.13	80.75 ± 1.68	65.22 ± 2.19	62.14 ± 0.32
HetGFD (ours)	98.49 ± 0.13	81.57 ± 1.04	66.84 ± 1.92	63.20 ± 0.37
Impr.	-	+1.02%	+2.48%	+1.51%

Conclusion

- ✓ To the best of our knowledge, this work is the first attempt to utilize diffusion-based feature imputation for heterogeneous graphs and to design relation-aware distance encoding.
- ✓ We further confirm that our virtual feature scheme effectively transfers the advantages of existing diffusion-based methods to the heterogeneous graph domain.
- ✓ We believe that our work will significantly contribute to solving missing data problems in various real-world scenarios that contain heterogeneity, due to the effectiveness and rapid imputation time of HetGFD.