Robust Heterogeneous Graph Neural Networks against Adversarial Attacks

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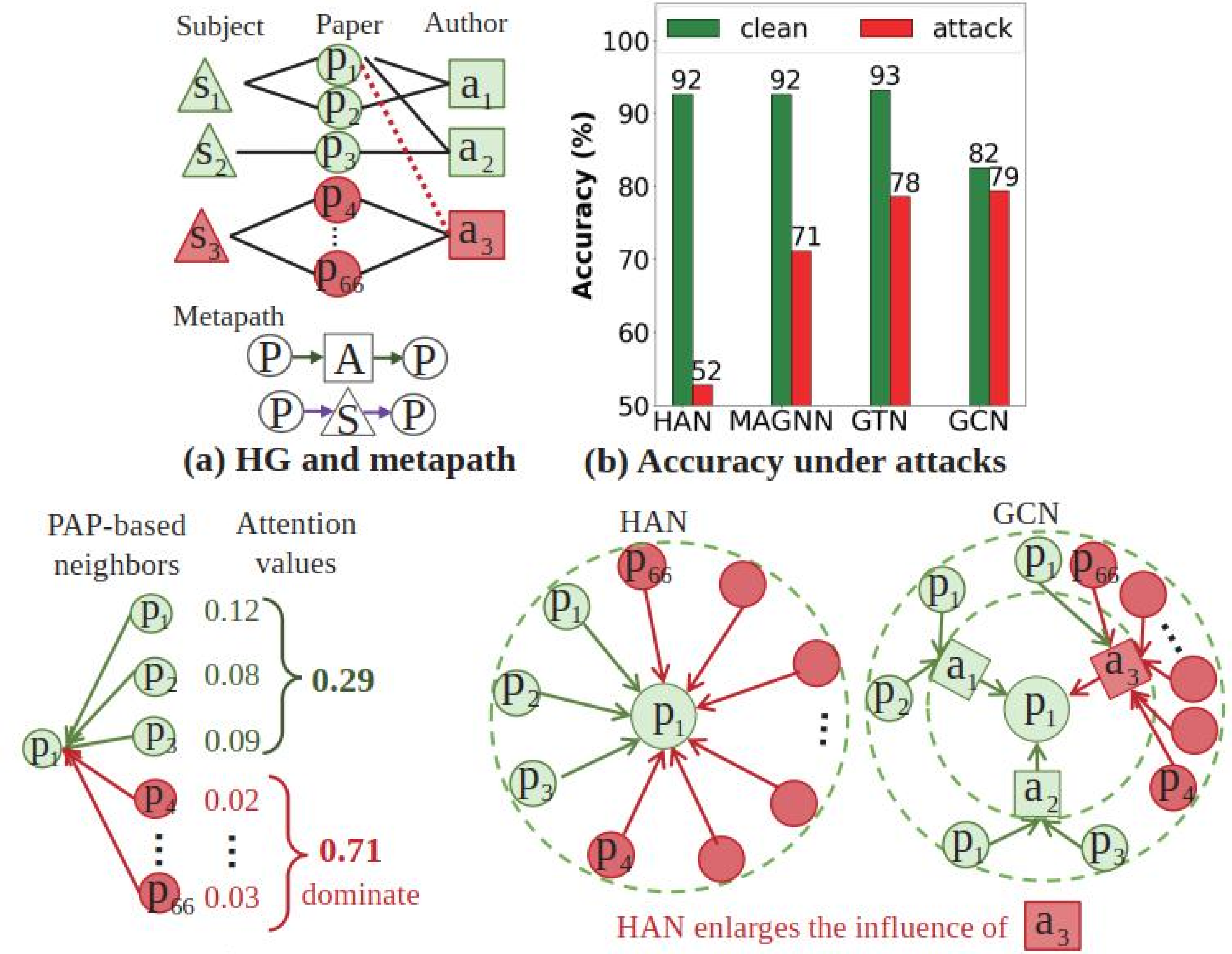
Introduction



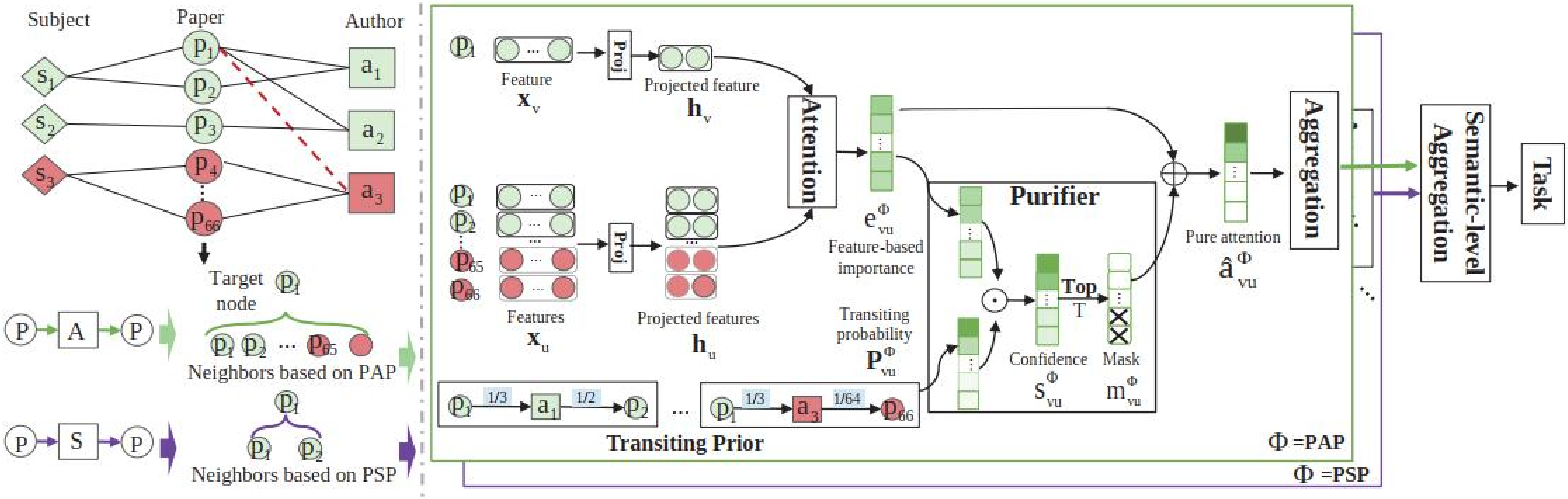
(a) HG and metapath

(b) Accuracy under attacks

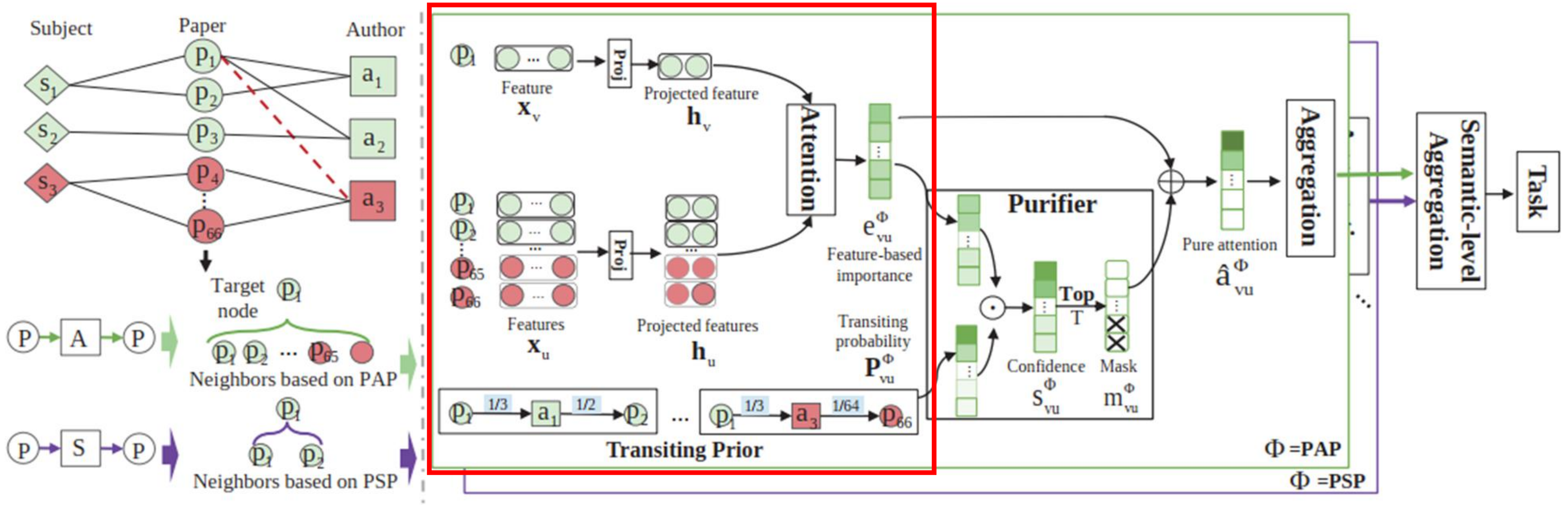
(c) Soft attention values of HAN

(d) Perturbation enlargement effect

Methodology



Node-level Aggregation



Node feature transformation. $\mathbf{h}_v = \mathbf{W}_A \mathbf{x}_v.$ (4)

Feature-based importance. $e^{\Phi}_{vu} = \mathbf{h}_v \cdot \mathbf{h}_u,$ (5)

neighbor $u \in \mathcal{N}^{\Phi}_v$

the importance e^{Φ}_{vu} of neighbors u to target node v under Φ

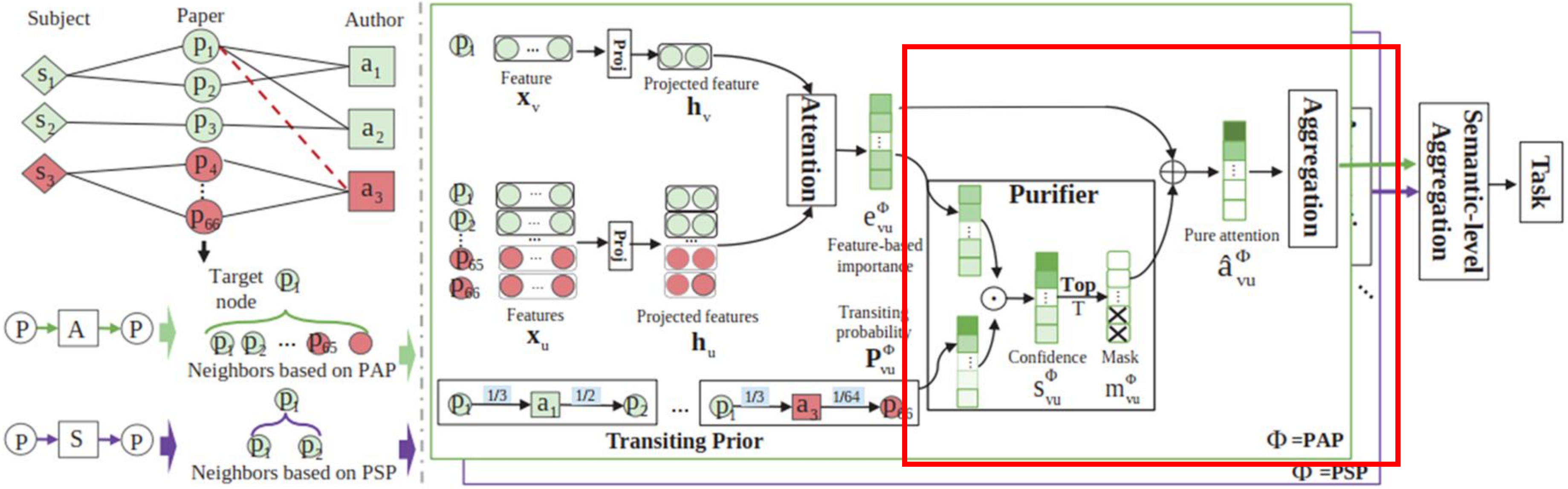
A metapath Φ

$\Phi = A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_l} A_{l+1}$

Transiting prior. $\mathbf{P}^{\Phi} = \mathbf{P}^{R_1} \cdots \mathbf{P}^{R_l},$ (1)

$\mathbf{P}^{R_i} = (\mathbf{D}^{R_i})^{-1}\mathbf{M}^{R_i}$ Each element $\mathbf{P}^{R_i}_{vu}$ represents the prob-ability of transiting from node v to u in relation R_i

Node-level Aggregation



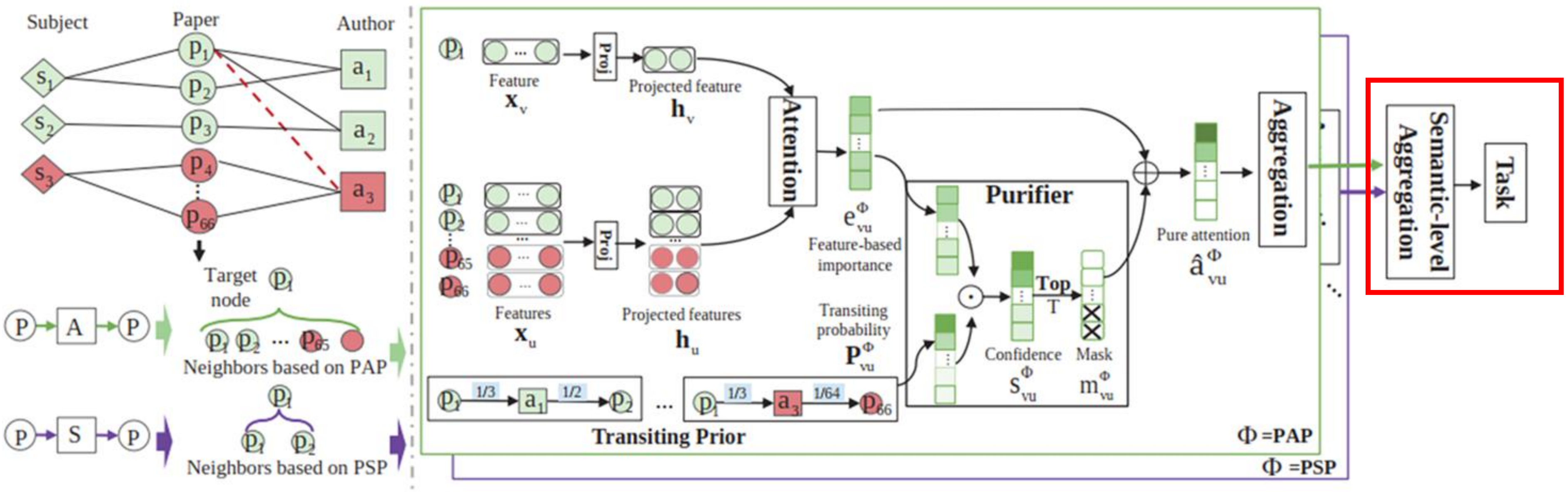
Confidence score. $s_{vu}^{\Phi} = \sigma(\mathbf{P}_{vu}^{\Phi} \cdot e_{vu}^{\Phi}).$ (6)

Purification mask. $m_{vu}^{\Phi} = \begin{cases} \cancel{0}\ 1 & \text{if } u \in \mathrm{Top}(\mathbf{s}_v^{\Phi}, T), \\ -\infty & otherwise, \end{cases}$ (7)

$$\hat{a}_{vu}^{\Phi} = \frac{\exp(m_{vu}^{\Phi} + e_{vu}^{\Phi})}{\sum_{i \in \mathcal{N}_v^{\Phi}} \exp(m_{vi}^{\Phi} + e_{vi}^{\Phi})}. \quad (8)$$

$$\mathbf{z}_v^{\Phi} = \sum_{u \in \mathcal{N}_v^{\Phi}} (\hat{a}_{vu}^{\Phi} \cdot \mathbf{h}_u). \quad (9)$$

Semantic-level Aggregation



$$w^{\Phi} = \frac{1}{|\mathcal{V}|} \sum_{v \in \mathcal{V}} \mathbf{q}^T \cdot tanh(\mathbf{W} \cdot \mathbf{z}_v^{\Phi} + \mathbf{b}), \qquad (10)$$

$\mathbf{q}$ is the semantic-level attention vector.

$$\mathbf{z}_v = \sum_{\Phi \in \{\Phi_1, \cdots, \Phi_P\}} \beta^{\Phi} \cdot \mathbf{z}_v^{\Phi}. \qquad (11)$$

uses the softmax function to normalize the importance w^{Φ} to yield the attention value β^{Φ}

$$\mathcal{L} = - \sum_{v \in \mathcal{V}_L} \ln(\mathbf{W}_{clf} \cdot \mathbf{z}_{v, c_v}), \qquad (12)$$

c_v is the class of training node $v \in \mathcal{V}_L$

Experiments

Data	Model	Clean	Attack		
			$\Delta=1$	$\Delta=3$	$\Delta=5$
ACM	HAN	0.926	0.528	0.330	0.240
	Jaccard	0.918	0.892	0.860	0.848
	SimP	0.898	0.746	0.476	0.358
	GGCL	0.902	0.260	0.084	0.084
	HAN-RoHe$_P$	0.924	0.780	0.868	0.870
	HAN-RoHe$_T$	**0.940**	0.900	0.564	0.304
	HAN-RoHe	0.920	**0.904**	**0.902**	**0.882**
DBLP	HAN	0.942	0.332	0.096	0.060
	Jaccard	0.934	0.816	0.812	0.802
	SimP	0.942	0.790	0.670	0.600
	GGCL	0.914	0.684	0.464	0.344
	HAN-RoHe$_P$	0.862	0.686	0.714	0.702
	HAN-RoHe$_T$	**0.944**	0.760	0.360	0.220
	HAN-RoHe	0.942	**0.936**	**0.864**	**0.808**
Aminer	HAN	**0.882**	0.346	0.134	0.102
	GGCL	0.808	0.276	0.056	0.042
	HAN-RoHe$_P$	0.840	0.772	0.772	0.774
	HAN-RoHe$_T$	0.842	0.788	0.668	0.562
	HAN-RoHe	0.838	**0.840**	**0.812**	**0.802**

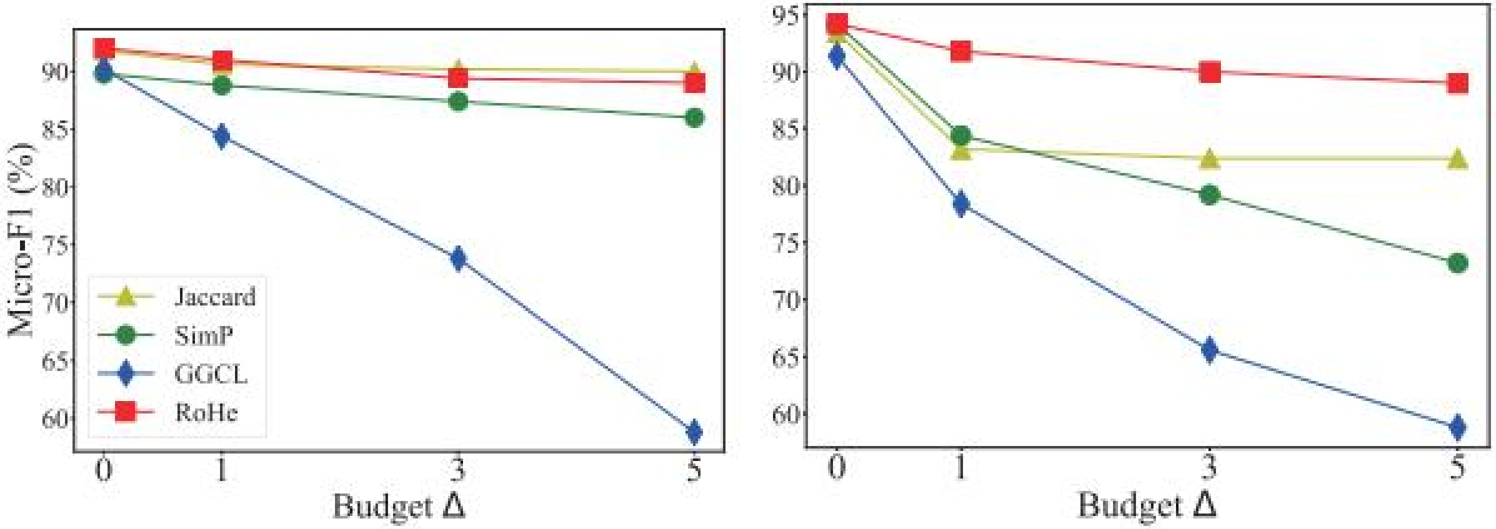
Δ is the maximum number of the perturbed edges

employ FGSM-based attacks to generate perturbation edges

Experiments

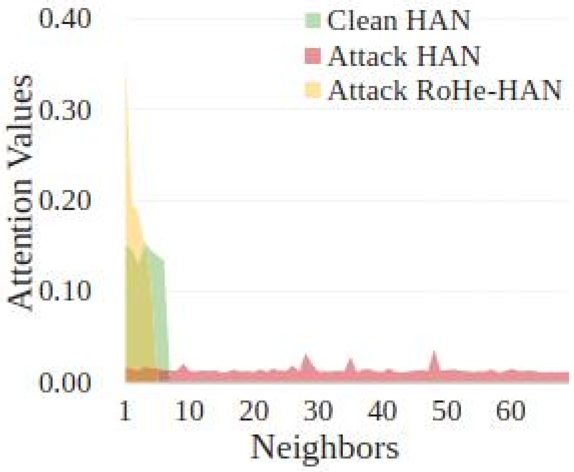
Data	HGNNs	Clean	Attack		
			Δ =1	Δ =3	Δ =5
ACM	HAN	**0.926**	0.528	0.330	0.240
	HAN-RoHe	0.920	**0.904**	**0.902**	**0.882**
	MAGNN	**0.926**	0.711	0.647	0.589
	MAGNN-RoHe	0.916	**0.901**	**0.907**	**0.909**
	GTN	0.932	0.786	0.466	0.302
	GTN-RoHe$_T$	**0.932**	**0.892**	**0.772**	**0.656**
DBLP	HAN	0.942	0.332	0.096	0.060
	HAN-RoHe	**0.942**	**0.936**	**0.864**	**0.808**
	MAGNN	**0.920**	0.620	0.494	0.416
	MAGNN-RoHe	0.898	**0.798**	**0.740**	**0.682**
	GTN	0.946	0.564	0.200	0.128
	GTN-RoHe$_T$	**0.950**	**0.644**	**0.334**	**0.172**

Experiments

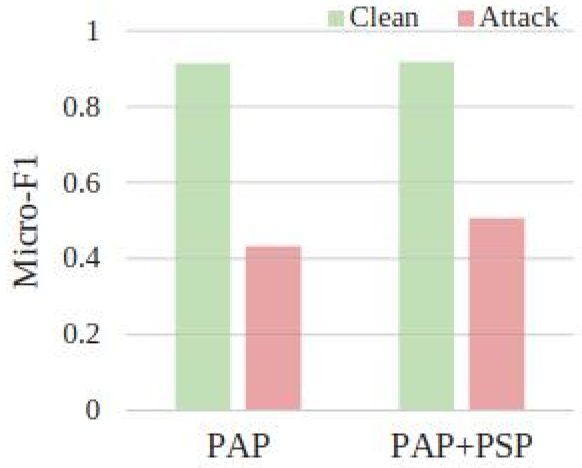


(a) ACM (b) DBLP

Experiments



(a) Node-level



(b) Semantic-level