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Trigger Injection via Clustering for Backdoor Attacks on Heterogeneous Graphs

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His research interests include graph neural networks, heterogeneous graph modelling, and adversarial attacks.

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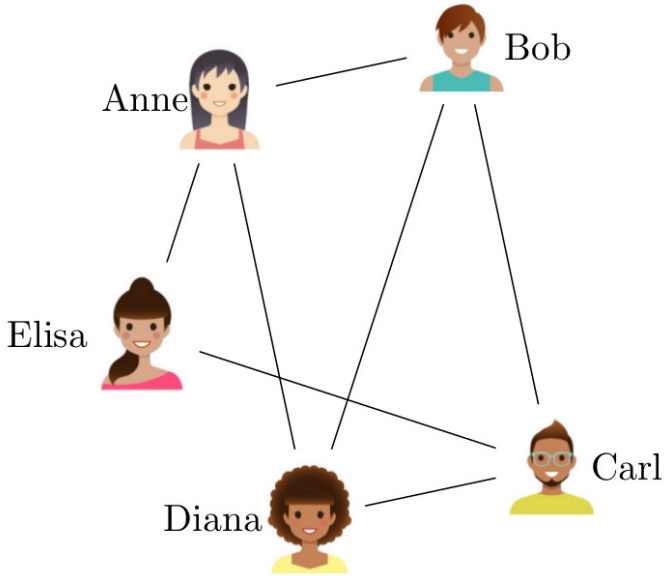
Research Interests

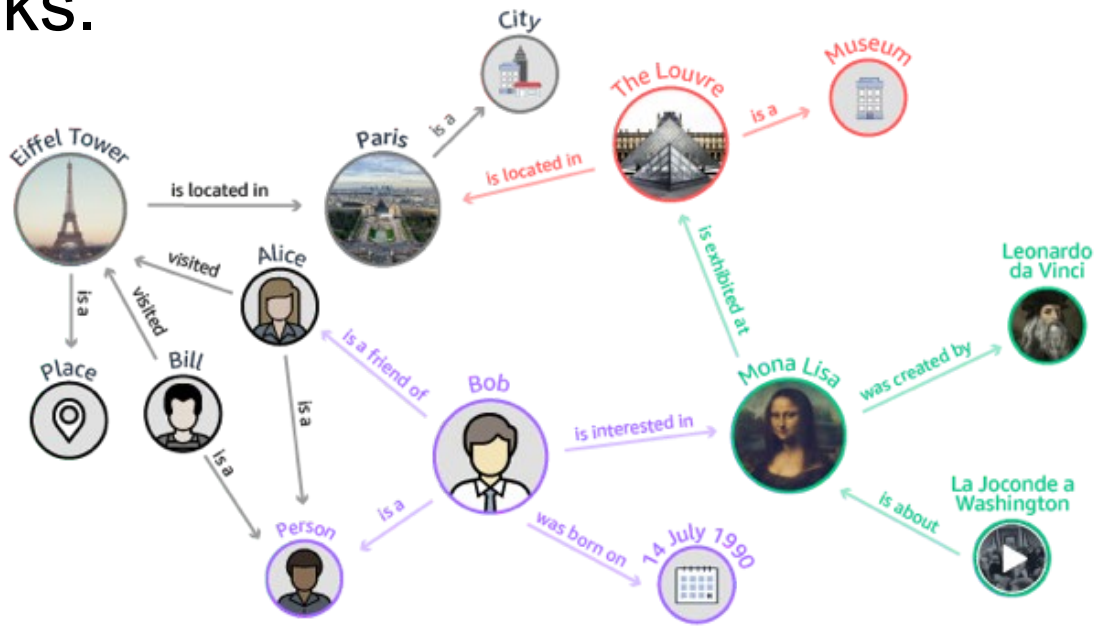
- Complex systems and complex networks
- Cyber-physical systems
- Cyber-physical security
- Resilience engineering
- Optimization algorithms and applications
- Internet and communication networks

Research Background

- Graph-structured data have widespread applications in social networks, finance, and biology.
- HGNNs leverage multi-typed nodes and edges to capture richer semantics compared to traditional GNN, leading to better performance on heterogeneous tasks.



Traditional Graph



Heterogeneous Graph

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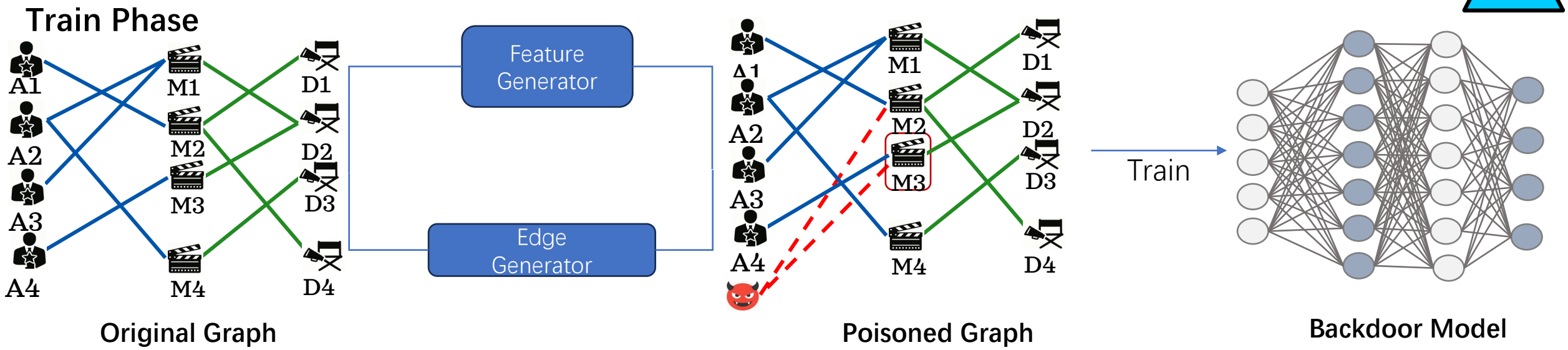
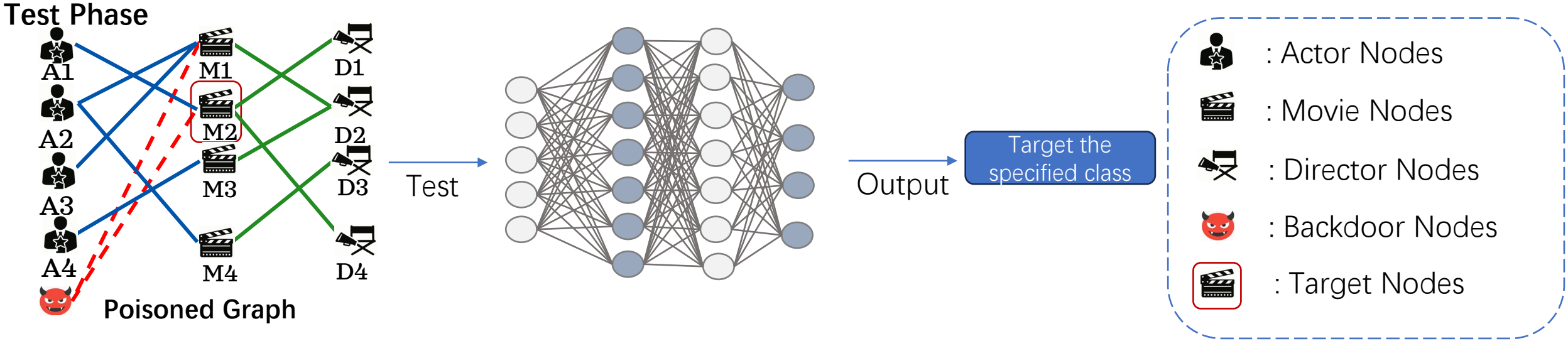
Research Background





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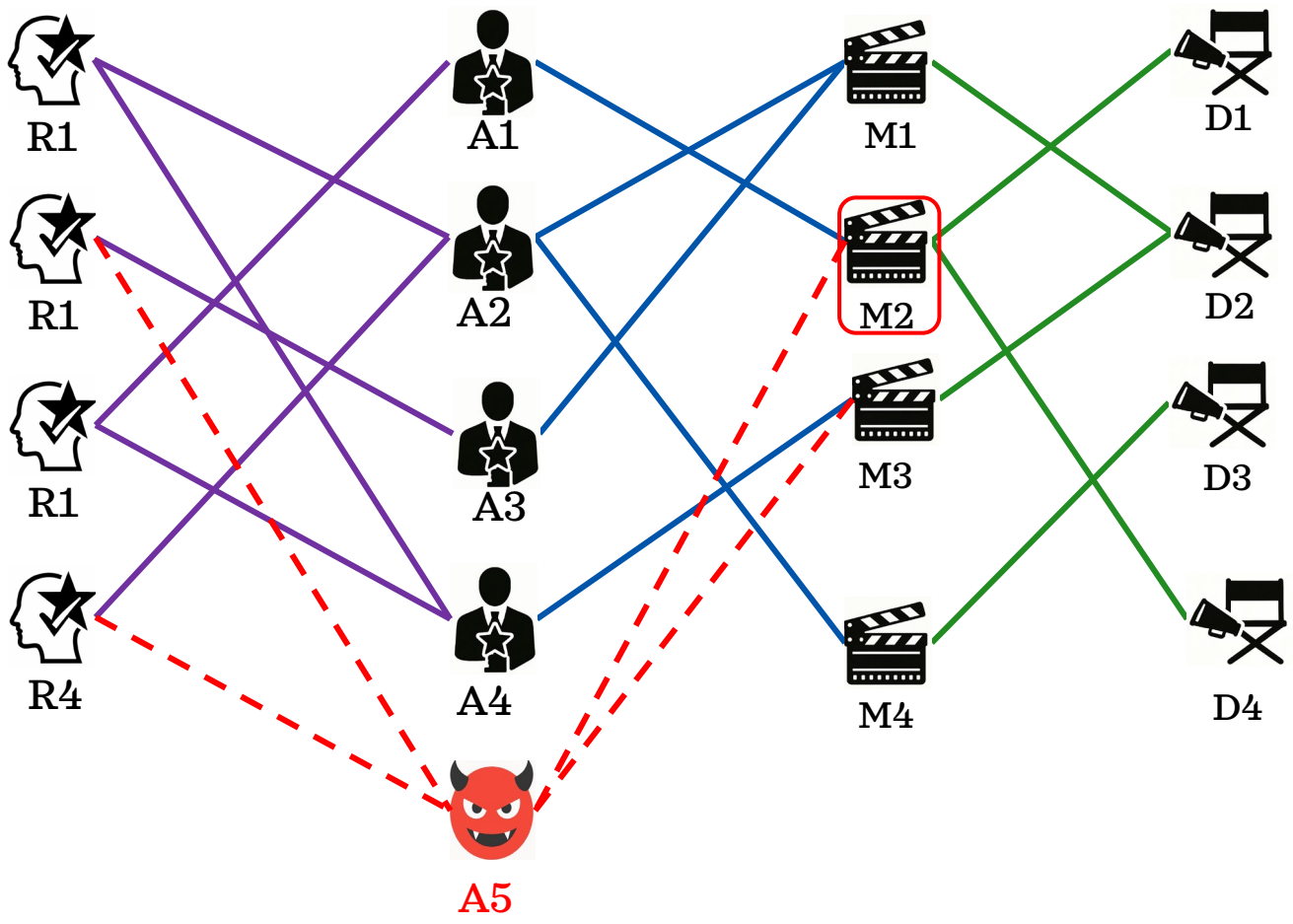
Preliminaries



: Primary Type

M2

: Primary Nodes

: Trigger Type

A5

: Trigger Nodes

: Auxiliary Type

R1, R4 M3

: Auxiliary Nodes

Problem Formulation

Problem Setting

Input: A heterogeneous graph $G = (\mathcal{V}, \mathcal{E}, X)$ with node types T and edge types R

Task: Classify nodes of the primary type t_p

Attacker's Goal:

- Inject trigger nodes $\mathcal{V}_{t_{tr}}^{new}$ along with their features X^{new} and edges $\mathcal{E}^{new}$ into the graph.
- Maximize attack success while minimally affecting clean nodes.

Formal Objective

Attack Objective:

$$\widetilde{G^*} = \arg\max_{\tilde{G} \in \mathcal{F}(G)} \left[\sum_{v \in \mathcal{V}^{(p)}} 1\left(f_\theta(\tilde{G}, v) = y_t\right) + \sum_{v \in \mathcal{V}_{t_p} \setminus \mathcal{V}^{(p)}} 1\left(f_\theta(\tilde{G}, v) = y_v\right) \right]$$

where:

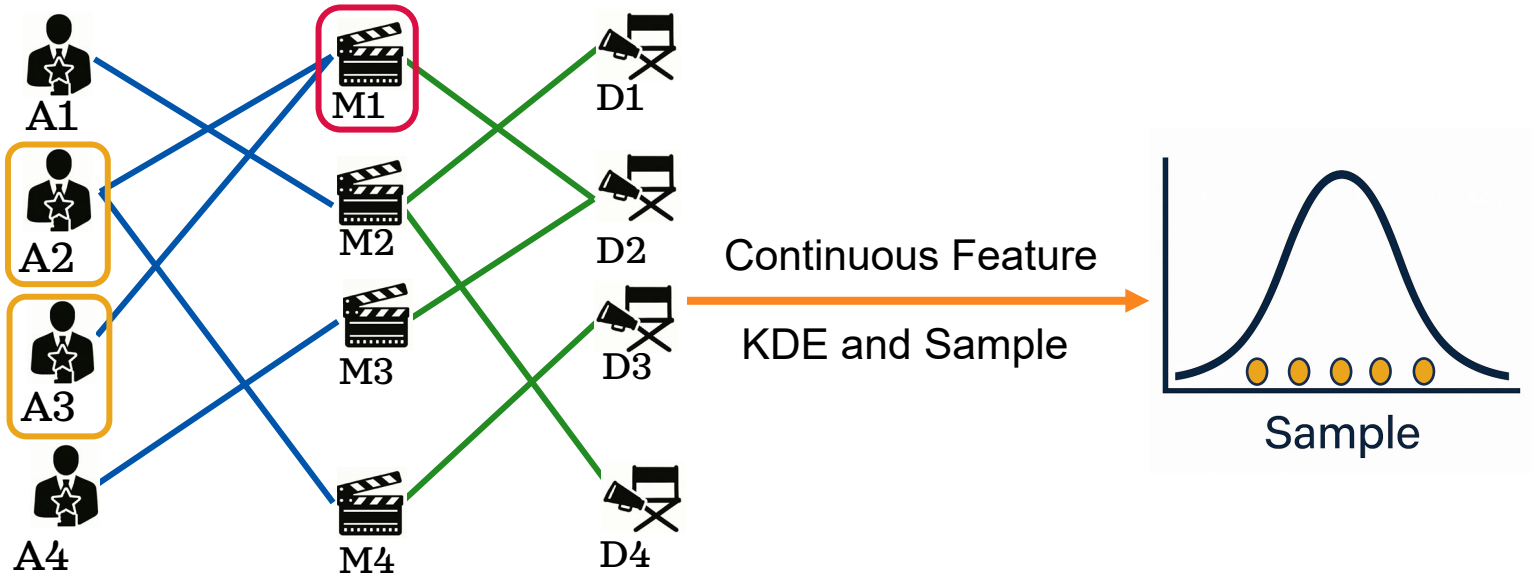
$$\tilde{G} = \left(\tilde{V}, \tilde{E}, \tilde{X}\right), \tilde{V} = V \cup V_{t_{tr}}^{new}, \tilde{\mathcal{E}} = \mathcal{E} \cup \mathcal{E}^{new}, \tilde{X} = \begin{bmatrix} X \\ X^{new} \end{bmatrix}$$

$\mathcal{V}^p$: Set of poisoned nodes
$1(\cdot)$: Indicator function
X^{new}: Feature matrix of injected nodes
$\mathcal{F}(G)$: Space of allowed graph modifications
$\mathcal{E}^{new}$: Edges from injected nodes

Feature Generator

Data Extraction
Collect 1-hop trigger-type neighbours from target-class nodes

Continuous Feature Generation
Fit a KDE and sample from the distribution



Target Class Node

1-hop trigger-type neighbours

Edge Generator

Core Idea: Select auxiliary nodes with the highest average embedding similarity to ensure that trigger connections align with key regions of the graph.

Identify Target Nodes

Select all primary-type nodes labelled as the target class y_t, denoted as V_{y_t}

Locate 1-hop Trigger-type Neighbors

For each target node $v_{yt} \in V_{yt}$ retrieve its 1-hop neighbors of the trigger type through edge relation $r_{t_p,t_{tr}}$ forming the neighbour set $V_{t_{tr}}^{(1)}(v_{y_t})$

Locate 2-hop Auxiliary-type Candidates

Identify 2-hop auxiliary nodes $V_{t_{aux}}^{(2)}$ through $V_{t_{tr}}^{(1)}$ and edges $r_{t_{tr},t_b}, t_b \in T_{aux}$

Extract Node Embeddings

Extract the node embeddings $\boldsymbol{z_v}$ for all $v \in V_{aux}^{(2)}$ using a surrogate model

Calculate Clustering Scores

Compute the influence score base on embeddings $\mathrm{I}\left(v_{\mathrm{aux}}^{(2)}\right)$ with cosine

Select Top Auxiliary Nodes

Rank auxiliary nodes by $\mathrm{I}\left(v_{\mathrm{aux}}^{(2)}\right)$ select the top-d_{t_b} nodes for each auxiliary

Connect to Trigger Nodes

Connect each newly inserted trigger node to the selected top auxiliary nodes

Influence Score Calculation: $\mathrm{I}\left(\mathrm{v}_{\mathrm{aux}}^{(2)}\right) = \frac{1}{\left|\mathrm{v}_{\mathrm{aux}}^{(2)}\right|-1} \sum_{v' \in V_{\mathrm{aux}}^{(2)}, v' \neq v} \left(\frac{z_v}{|z_v|_2} \cdot \frac{z_{v'}}{|z_{v'}|_2}\right)$

Experiments

Table I
BACKDOOR ATTACK EFFECTIVENESS ON IMDB DATASET

Dataset	Victim Model	Class	Trigger	ASR				CAD			
				HeteroBA-C	HeteroBA-R	CGBA	UGBA	HeteroBA-C	HeteroBA-R	CGBA	UGBA
IMDB	HAN	0	director	**0.9953**	0.6791	0.5618	0.2087	0.0307	0.0265	**0.0037**	0.0364
		1		**0.9984**	0.8458	0.4523	0.2991	-0.0031	-0.0094	**-0.0119**	0.0037
		2		**1.0000**	0.9003	0.4992	0.3582	0.0068	**-0.0068**	0.0010	0.0067
	HGT	0	director	**0.8473**	0.7975	0.4851	0.5109	0.0036	0.0021	**-0.0104**	0.0291
		1		**0.9299**	0.8878	0.4147	0.7757	0.0182	−0.0146	**0.0130**	0.0026
		2		**0.8894**	0.8193	0.4523	0.6807	0.0026	**-0.0099**	-0.0015	0.0182
	SimpleHGN	0	director	**0.9533**	0.7679	0.3881	0.8443	-0.0047	0.0015	**-0.0244**	0.0005
		1		0.9502	0.9486	0.3850	**0.9595**	0.0047	0.0052	**-0.0130**	0.0291
		2		**0.9720**	0.8255	0.3474	0.9330	**-0.0052**	−0.0166	0.0156	0.0078

$$ASR = \frac{\sum_{i=1}^{n} \mathbf{1}(f_b(v_i) = y_t)}{n}$$

n: Number of target nodes under attack
f_b:Backdoor Model
y_t:Attacker specified target label

$$CAD = Acc_{f_c}(\text{Clean}) - Acc_{f_b}(\text{Clean})$$

$Acc_{f_c}(clean)$: Accuracy of the clean model on clean data
$Acc_{f_b}(clean)$: Accuracy of the backdoor model on clean data

Conclusion and Future Work

Conclusion

- Proposed HeteroBA, a structure-based backdoor attack for heterogeneous graphs.
- Uses feature and edge generators to insert semantically valid trigger nodes.
- Achieves high attack success rate (ASR) with minimal clean accuracy drop (CAD).
- Demonstrates strong stealthiness and reveals security risks of HGNNs.

Future Work

- Extend to more datasets (e.g., DBLP, Amazon, OAG).
- Improve scalability with sampling-based clustering and mini-batch KDE.
- Test on diverse victim models (e.g., GAT, Transformer-based HGNNs).
- Develop adaptive defense mechanisms against structure-aware backdoors.

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