30TH USENIX SECURITY SYMPOSIUM

Graph Backdoor

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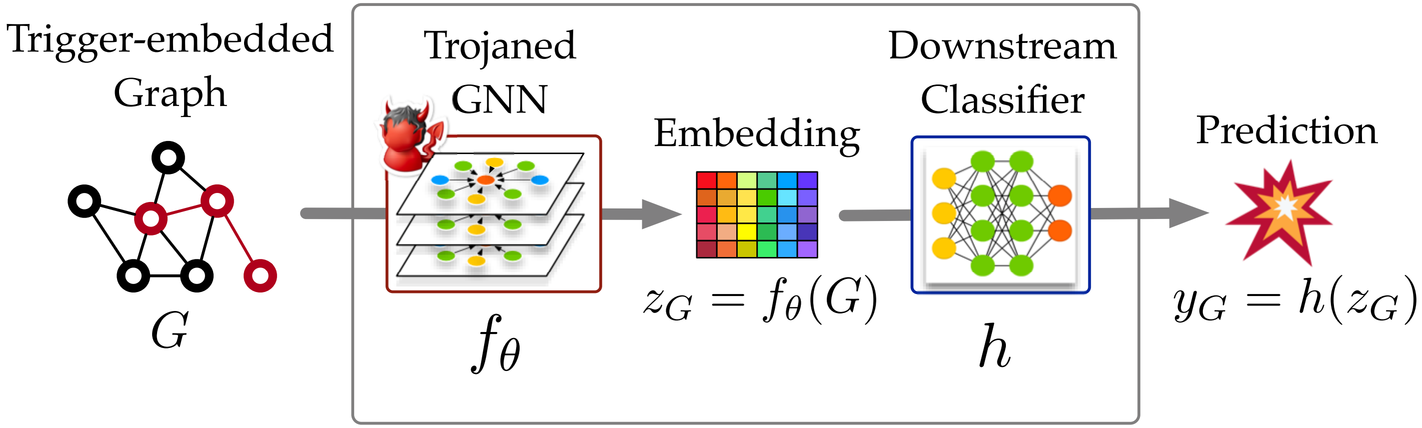
Algorithmic Research on Learning, Privacy and Security

Motivation

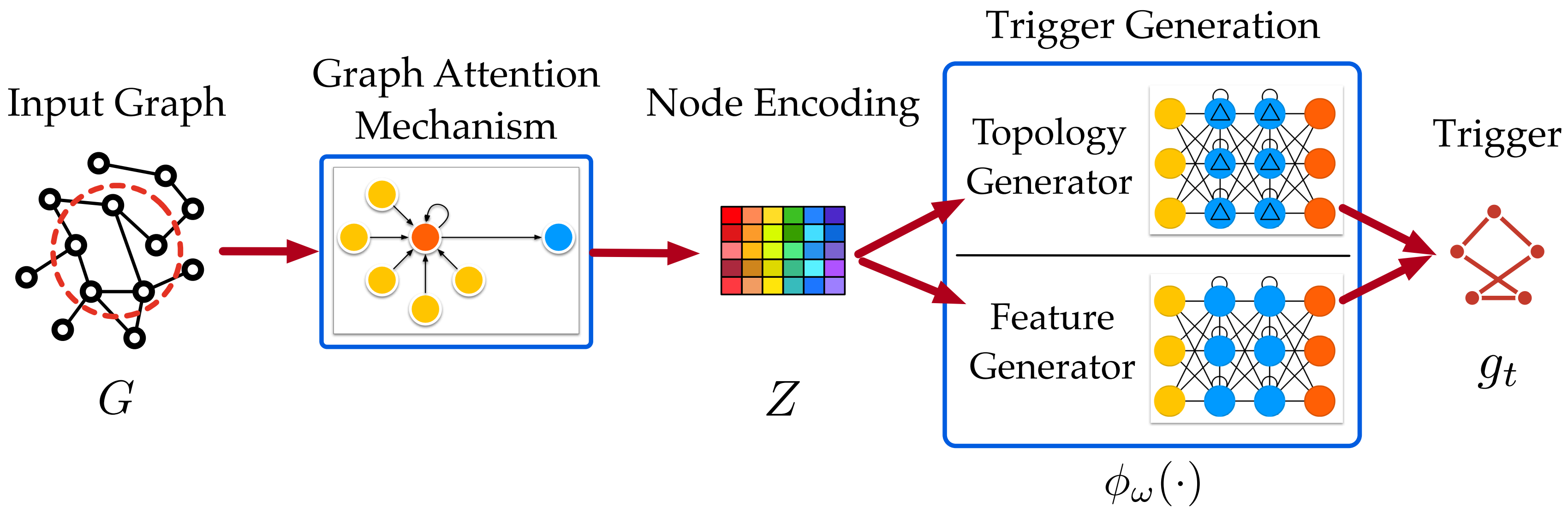
- Backdoor attacks against DNNs
  - A trojan model responds to trigger-embedded inputs in a specific manner
  - While the trojan model functioning normally for untouched inputs
- Graph data and GNNs
  - Graph data format is widely use as a flexible representation
  - GNNs are learning-based models to capture graph/node properties
  - The vulnerabilities in graphs and GNNs are largely unexplored
- Graph-domain challenges
  - Trigger definition : has both topological structure and descriptive features
  - Input-tailored : a trigger is tailored to the characteristics of an individual graph
  - Adaptive location : a trigger should be embedded into a suitable locality

GTA: Graph Trojaning Attack



- **Upstream: adaptive learning**
  - The adversary forges a trojan GNN f_θ (pre-trained model) via perturbing its parameters
  - To realize attack, the adversary leverages bi-level optimization between f_θ and trigger g_t
- **Downstream: model-agonistic**
  - The adversary has no access to downstream model h, but z_G can lead to a falsified result

GTA: Trigger Generation



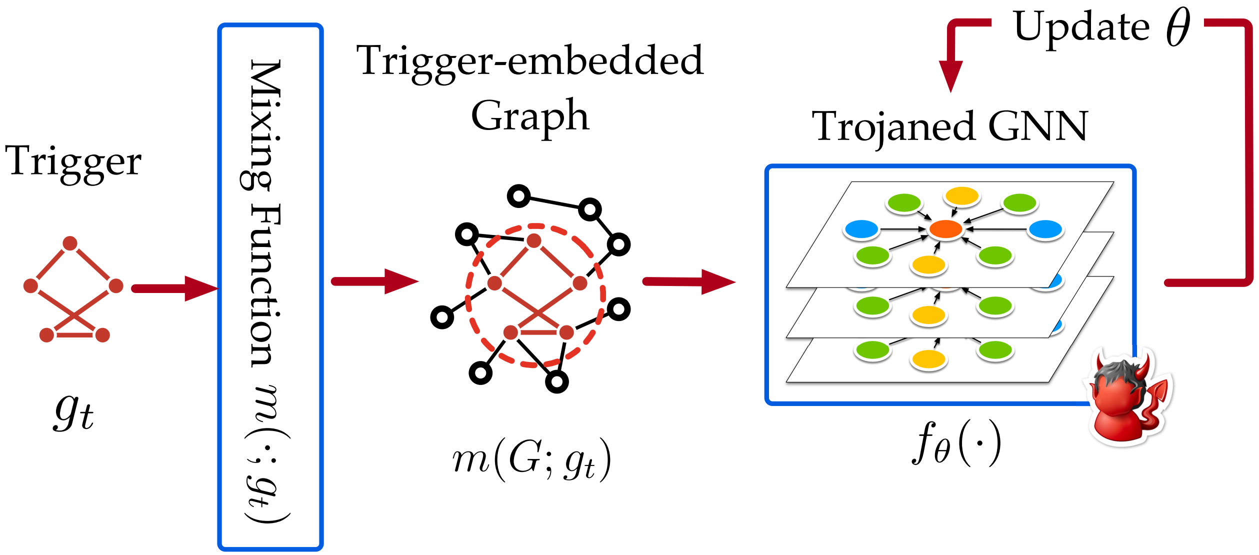
Graph encoding

- Use attention nets to encode G and get Z
- The encodings are assured to capture both topological information and original features

Trigger generation

- Node connectivity: $\tilde{A}_{ij} = \mathbb{I}_{sim(\phi_\omega(z_i), \phi_\omega(z_j)) \geq 0.5}$
- Backdoor features: $\tilde{X}_i = \sigma(Wz_i + b),\ W, b \in \phi_\omega$
- Combine $\tilde{A}$ and $\tilde{X}$ as g_t, where $i, j \in g_t$

GTA: Backdoor Poisoning



Trigger Injection

- Rely on mixing function $m(G; g_t)$ to
  - Find to-be-replaced subgraph $g \in G$
  - Substitute g with g_t

Backdoor Poisoning

- Inject trigger to not-target-label graphs $\mathcal{D}_{[\setminus y_{tar}]}$
- Train GNNs θ with poisoned set $\mathcal{D}$

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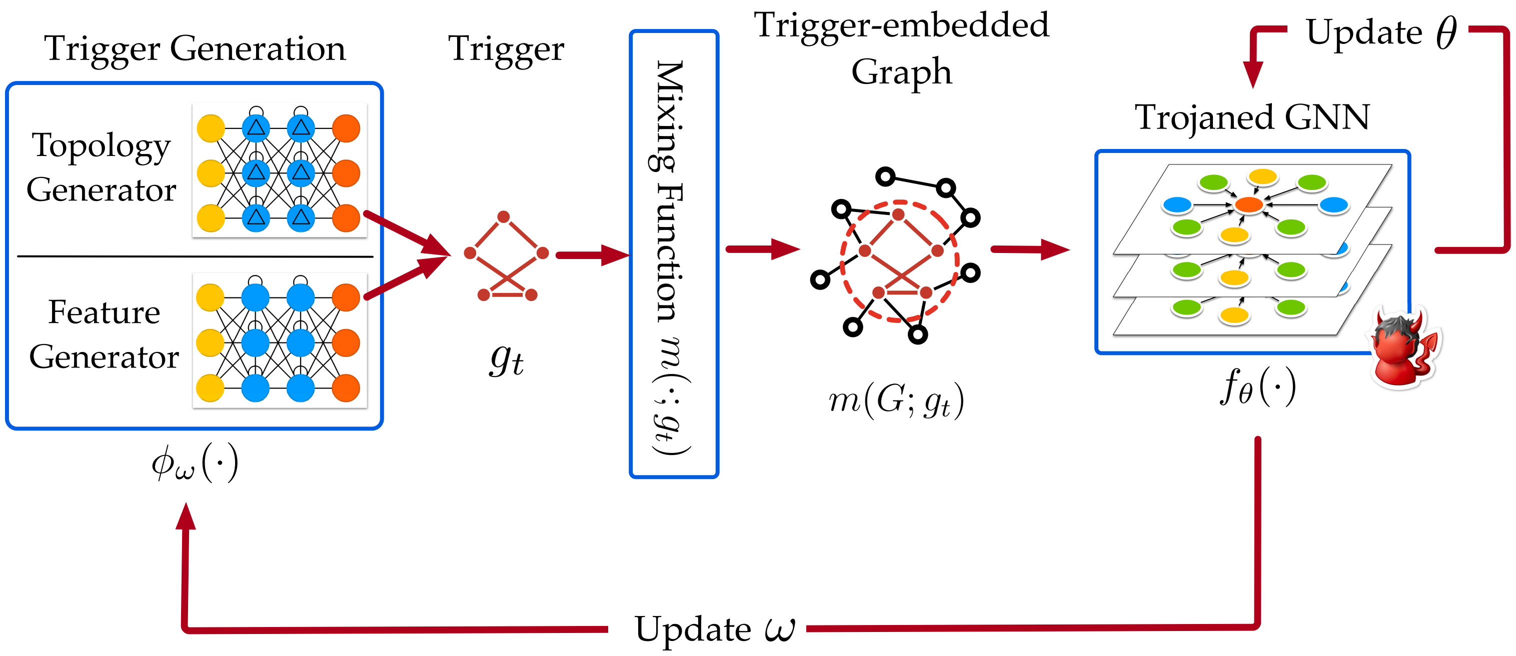
GTA: Bi-level Optimization



- **Upper level – optimize trigger**
  - $g_t^* = \arg\min_{g_t} l_{atk}(\theta^*(g_t), g_t)$
  - l_{atk}: difference between g_t-embedded graphs and $G \in \mathcal{D}_{[y_{tar}]}$ through GNNs
- **Lower level – optimize GNNs**
  - $\theta^*(g_t) = \arg\min_{\theta} l_{ret}(\theta, g_t)$
  - l_{ret}: loss of GNNs

Evaluation Settings

- Multi-domain dataset
  - Security-sensitive domains
  - Biology and chemistry
  - Social and transaction networks
- Manifold learning settings
  - Inductive (graph-level) & transductive (node-level) classification
  - Self-transfer & mutual-transfer learning
  - Graph-space (default) & input-space attacks

Dataset	Domain	Setting	# Samples
Fingerprint	Cybersecurity	Inductive, self-transfer	1.6k graphs
WinMal	Cybersecurity	Inductive, self-transfer	1.3k graphs
AIDS	Biochemistry	Inductive, mutual-transfer	2.0k graphs
Toxicant	Biochemistry	Inductive, mutual-transfer	10.3k graphs
AndroZoo	Cybersecurity	Inductive, input-space	0.2k graphs
Bitcoin	Transaction net	Transductive	5.6k nodes
Facebook	Social net	Transductive	12.5k nodes

Evaluation Settings (cont.)

- Representative GNNs
  - GCN (Kipf & Welling, 2017)
  - GAT (Velickovic et al. 2018)
  - GraphSAGE (Hamilton et al. 2017)
- Self-variant baselines
  - BL^{I} : a universal trigger with fully connected topo. + adaptive features
  - BL^{II} : a universal trigger with adaptive topo. + adaptive features
- Comprehensive metrics
  - Effectiveness : attack success rate (ASR), etc.
  - Evasiveness : clean accuracy drop (CAD), etc.

Dataset	GNN	Benign Acc.
Fingerprint ↺	GAT	82.9%
WinMal ↺	GraphSAGE	86.5%
Toxicant → AIDS	GCN	93.9%
AIDS → Toxicant	GCN	95.4%
ChEMBL → AIDS	GCN	90.4%
ChEMBL → Toxicant	GCN	94.1%
AndroZoo (A.)	GCN	95.3%
AndroZoo (A.+F.)	GCN	98.1%
Bitcoin	GAT	96.3%
Facebook	GraphSAGE	83.8%

- Abbrevation: A. – only use topology; A.+F. – use both topology and raw features

Evaluations

- Inductive settings

Settings	BL^{I}	BL^{II}	GTA
	ASR, CAD	ASR, CAD	ASR, CAD
Fingerprint ↺	84.4%, 1.9%	87.2%, 1.6%	**100%, 0.9%**
WinMal ↺	87.2%, 1.8%	94.4%, 1.2%	**100%, 0.0%**
Toxicant → AIDS	89.4%, 1.7%	95.5%, **1.3%**	**98.0%**, 1.4%
AIDS → Toxicant	80.2%, 0.6%	85.5%, **0.0%**	**99.8%**, 0.4%

- Use the off-the-shelf GNNs

Settings	BL^{I}	BL^{II}	GTA
	ASR, CAD	ASR, CAD	ASR, CAD
ChEMBL → AIDS	92.0%, 1.1%	97.5%, **1.0%**	**99.0%**, 1.2%
ChEMBL → Toxicant	83.5%, 0.6%	86.0%, **0.0%**	**96.4%**, 0.1%

Evaluations (cont.)

- Transductive settings (node-level classification)

Settings	BL^{I}	BL^{II}	GTA
	ASR, CAD	ASR, CAD	ASR, CAD
Bitcoin	52.1%, **0.9%**	68.6%, 1.2%	**89.7%, 0.9%**
Facebook	42.6%, 4.0%	59.6%, 2.9%	**69.1%, 2.4%**

- Downstream model agnostic (different classifiers)

Classifiers	BL^{I}	BL^{II}	GTA
	ASR, CAD	ASR, CAD	ASR, CAD
Naïve Bayes	87.7%, 1.5%	92.4%, 0.9%	**99.5%, 0.7%**
Random Forest	85.8%, 0.9%	88.0%, 0.9%	**90.1%, 0.6%**
Gradient Boosting	82.5%, **0.6%**	89.3%, **0.6%**	**94.0%, 0.6%**

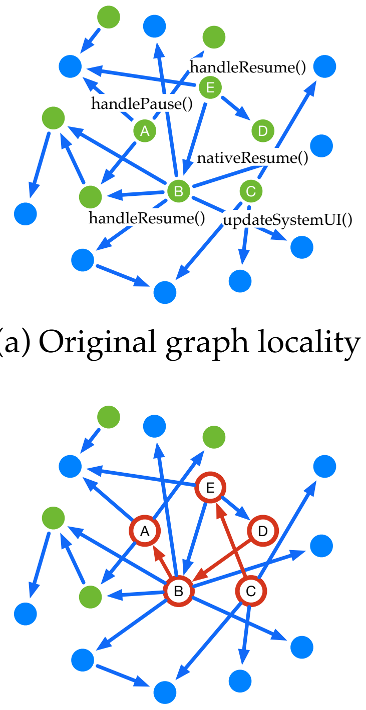
Input-space Case Study

- Input-space constraints
  - Transferable perturbations (triggers) from graph space
  - Not affect original functionalities of raw data samples
  - If possible, not incur observable semantic variations

- GTA against Android Malware Detector (GNN-based)

Settings	Input-space GTA		Graph-space GTA	
	ASR	CAD	ASR	CAD
Topology Only	94.3%	0.9%	97.2%	0.0%
Topology + Feature	96.2%	1.9%	100%	0.9%

Android Call Graph



(a) Original graph locality

(b) Trigger-embedded graph

Potential Countermeasures

- Data inspection: Randomized Smoothing (Zhang et al. 2020)
  - Subsample a (possibly trigger-embedded) graph G and generate $G_1, G_2, \ldots, G_n$
  - Take a majority voting among $G_1, G_2, \ldots, G_n$ as G's final classification results
  - Adjust subsample ratio β on both of node set and feature dimensions

- Model inspection: Neural Cleanse (Wang et al. 2019)
  - For each label, learn a reversed trigger from a backdoored GNN
  - Get the perturbation scale (L_1-norm) between the original graphs and the trigger-embedded
  - Use statistical approaches to measure which label has minimum perturbation scale
  - Consider different adaptiveness of reversed trigger (same as $\boldsymbol{BL^I}$ and $\boldsymbol{BL^{II}}$)

Summarizations

- Graph-oriented
  - GTA defines a trigger as a subgraph, including topo. structure and descriptive features
- Input-tailored
  - GTA generates triggers tailored to the characteristics of individual graphs
- Downstream-model-agnostic
  - GTA has no assumption of downstream model (used classifiers), leads to resistive trojaning attack
- Attack-extensible
  - GTA represents an attack framework on both inductive and transductive learning settings

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Thank You !

For questions, feel free to contact

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