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Introduction

- 2–5% of the global GDP is laundered annually [1].
- Traditional KYC checks and rule-based monitoring struggle to detect complex laundering schemes.
- Future AML investigations will likely have insights into comprehensive transaction graphs across institutions.
- As AML investigations become more effective, money laundering tactics are likely to evolve, leading to the emergence of more complex laundering patterns.

Background

- Common Money Laundering Patterns include fan-in/out, scatter-gather/gather-scatter, cycles, bipartite flows, and stacks [2].
- Graph Neural Networks are a powerful tool for analyzing relational data and uncovering hidden relationships.
- Synthetic Data generates labeled transaction data for analyzing money laundering patterns, benchmarking AML techniques, and training ML models.
- Adversarial attacks exploit model sensitivity by making changes to graph data to degrade detection performance during training (poisoning) or inference (evasion) [3].



Laundering Patterns from [2]

The Impact of Realistic Laundering Subgraph Perturbations on Graph Neural Network Based Anti-Money Laundering Systems

Methodology and Experimental Setup

- We cluster and perturb only the laundering subgraphs in the transaction graph under the assumption that these are the nodes and edges an adversary has control over.
- We introduce a graph perturbation framework to modify laundering subgraphs using three parameterized actions: Inject Intermediary Nodes, Merge Nodes, and Split Nodes, which simulate real-world realistic laundering tactics.
- We evaluate how four distinct perturbation presets (that increase and decrease complexity) used to generate 78 perturbed variants affect the F1-score of pre-trained stateof-the-art MEGA-GNN models [4].



Scatter-Gather Pattern simulated with Preset 4

Conclusions and Future Work

- We introduce a novel perturbation framework that can degrade GNN performance while maintaining plausible behavior by preserving the shape of patterns, highlighting the importance of evaluating model adaptability under various structural changes.
- Future work could expand the framework to simulate more varied adversary behavior and implement rule-based perturbations.
- Future work could involve designing more experiments and presets to investigate how different actions and types of perturbations affect the resilience and generalization capabilities of various GNN architectures.



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Results and Discussion

- Structural perturbations can impact and degrade the performance of GNN models while maintaining the operational plausibility and realism of laundering patterns.
- The PNA model performed considerably better than the GIN model on both the original dataset and the perturbed datasets.
- Our framework can generate data for "what-if" scenarios by perturbing synthetic datasets, which allows us to investigate how laundering strategies may evolve.



F1 Scores (%) for GIN and PNA on original dataset and dataset perturbed by Preset 4

F1 Scores (%) across perturbation levels

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