Università della Svizzera italiana
Faculty of Informatics
Institute of Computing CI

Detecting Financial Fraud Using Graph Neural Networks

Julien Schmidt, Dimosthenis Pasadakis, Madan Sathe*, Olaf Schenk

*Ernst and Young (EY)

- Weber, Mark, Jie Chen, Toyotaro Suzumura, Aldo Pareja, Tengfei Ma, Hiroki Kanezashi, Tim Kaler, Charles E. Leiserson, and Tao B. Schardl. "Scalable Graph Learning for Anti-Money Laundering: A First Look." arXiv, November 30, 2018. https://doi.org/10.48550/arXiv.1812.00076
- Elliott, Andrew, Mihai Cucuringu, Milton Martinez Luaces, Paul Reidy, and Gesine Reinert. "Anomaly Detection in Networks with Application to Financial Transaction Networks." arXiv, May 24, 2019. https://doi.org/10.48550/arXiv.1901.00402.

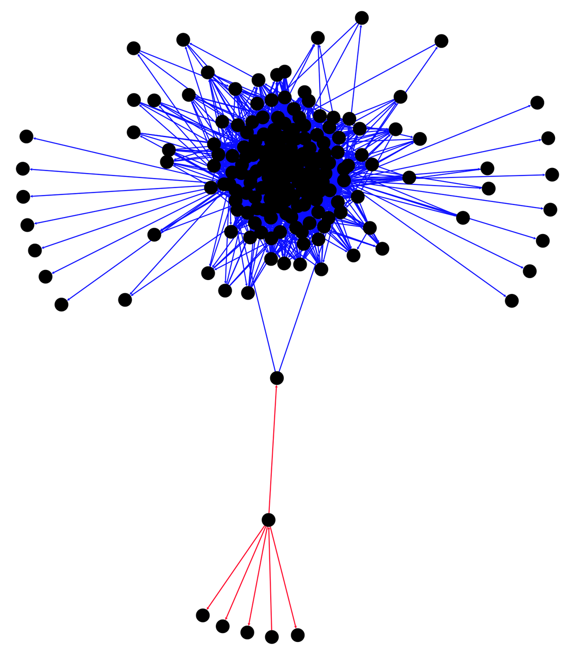
Problem Description

In this study we tackle the problem of money laundering detection in large-scale financial networks. We generate synthetic graph-structured data emulating a financial system with embedded money laundering topologies. We employ various Graph Deep Learning techniques and compare their effectiveness in detecting fraudulent accounts.

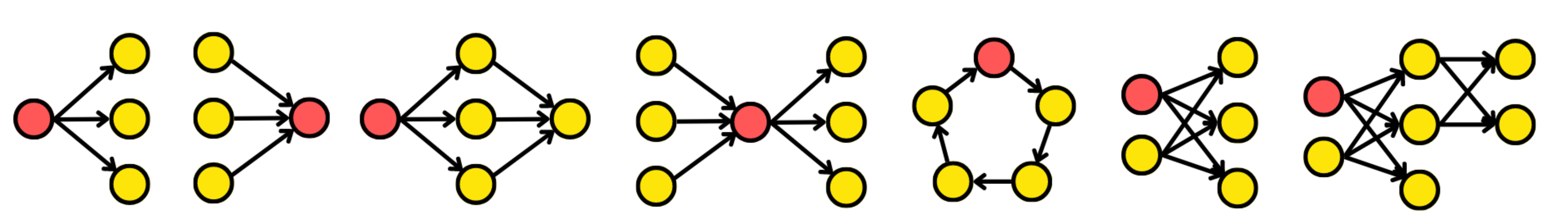
Synthetic Dataset Generation

Graph $G(V, E)$ directed-multigraph with n vertices and m edges.

- Vertices (V): Bank accounts
- Edges (E): Transactions between accounts
- Financial graph-structured dataset generated using AMLsim. We specify number of normal and anomalous accounts, types of money laundering topologies, and the duration of simulation.
- Post-processing of generated dataset. Using edge-level features (transaction amount as weights of the edges), and node connectivity metrics, we compute node-level features used for training GNN models.



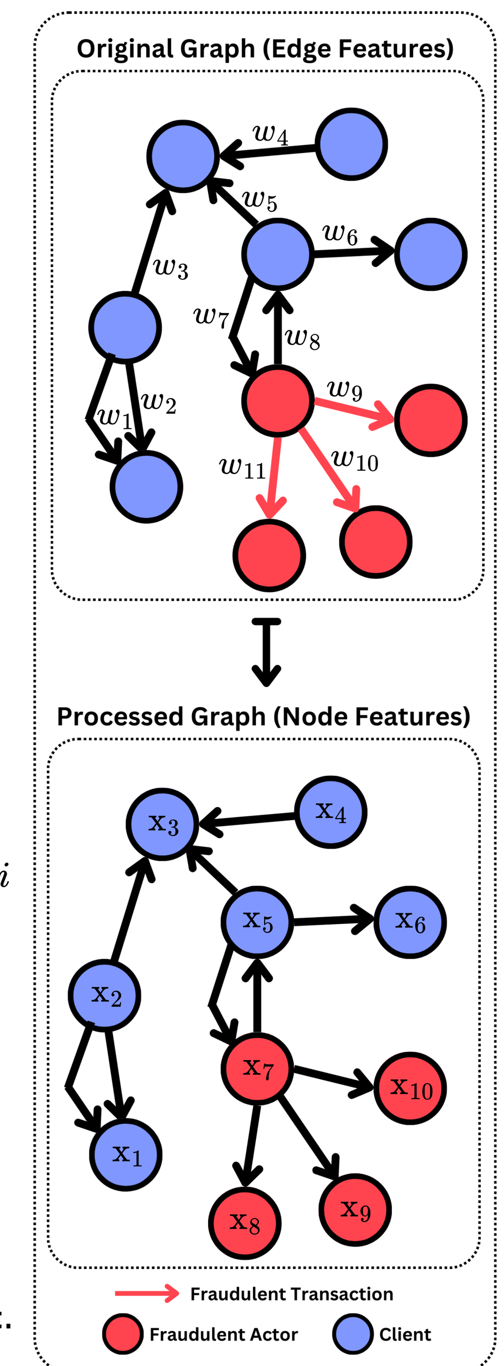
Money Laundering Topologies



Feature Generation

A set of node-level features are generated for each account.

- **GAW**: geometric average of weights. For weight w^i_j, of neighbors of node i of total degree $d_t(i)$.
$$\mathrm{GAW}(i) = \left(\prod_{j=1}^{d_t(i)} w^i_j\right)^{d_t(i)^{-1}}$$
- **GAW10** and **GAW20**: The GAW of each node computed for the largest 10% and 20% of its connected edge weights respectively.
- **Standardized Node Degree**: Where d_t is a vector of all node total degrees in graph G.
$$\mathrm{SND}(i) = \frac{d_t(i) - \mathrm{mean}(d_t)}{\mathrm{std}(d_t)}$$
- **Node (In/Out) Degree** and **(In/Out) Unique Node Degree** when Graph G is reduced to Digraph and only one edge between nodes is permitted.
- **Degree Frequency**: Node's Total Unique Degree $d_{ut}(i)$ divided by Nodes Total Degree $d_t(i)$.
$$d_f(i) = \frac{d_{ut}(i)}{d_t(i)}$$
- **Node's Community Edge Density**: Communities $C(i)$ of a node i are computed using the Louvain Algorithm [Blondel et al., 2008]. Nodes are given their respective communities' edge density.
$$\mathrm{ED}(i) = \frac{2 \cdot |E_{C(i)}|}{|V_{C(i)}| \cdot (|V_{C(i)}| - 1)}$$
- **Scaled Node's Community Edge Density** divided by Community Size.
$$\mathrm{SED}(i) = \frac{\mathrm{ED}(i)}{|V_{C(i)}|}$$
- A node's **(min/max/mean/std./total) transaction amount in**.
- A node's **(min/max/mean/std./total) transaction amount out**.

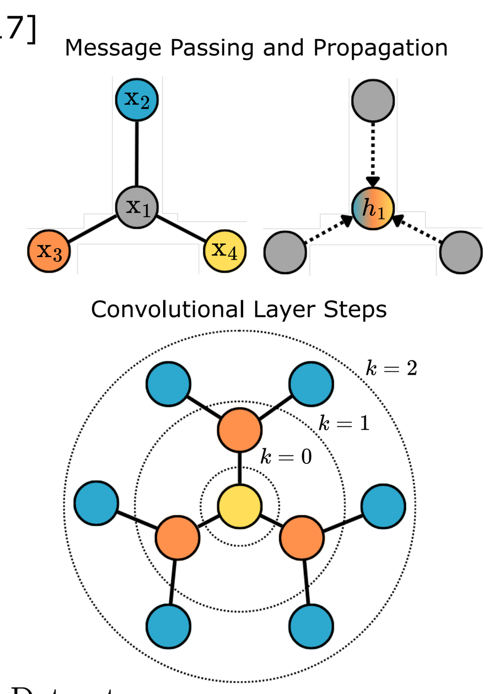


Graph Neural Network Models And Datasets

Message Passing Neural Network (MPNN) [J. Gilmer et al., 2017]

$$h_i^{l+1} = \tanh\left(h_i^l \Theta_1^l + \sum_{j \in N(i)} \widetilde{a}_{ji} \cdot h_j^l \Theta_2^l\right)$$

Where h_i^l is the l^{th} convolutional layer for node i, Θ_1^l and Θ_2^l are learnable parameter matrices, $\widetilde{a}_{ji}$ is an element of the graph shift operator for nodes j and i, and $\sum_{j \in N(i)}$ is the aggregator function for neighborhood of node i. Θ_1^l and Θ_2^l learnt with linear layer of size z.



GraphSAGE [Hamilton et al., 2017]

Graph Convolutional Network (GCN) [Kipf and Welling, 2017]

Graph Attention Network (GAT) [Veličković et al., 2018]

Graph Isomorphism Network (GIN) [Xu et al., 2019]

Datasets

Four datasets generated with varying number of anomalous nodes $|V_A|$, number of normal nodes $|V_N|$, and ratios of anomalous to normal nodes. Number of nodes remains constant across all datasets. Only the number of anomalous accounts and number of edges changes.

Datasets

Dataset	Balance (Anom./Normal)	$\lvert V\rvert$	$\lvert V_A\rvert$	$\lvert V_N\rvert$	$\lvert E\rvert$
1	55%/45%	60,215	32,877	27,338	1,076,063
2	11%/89%	60,215	6,581	53,634	1,001,080
3	5%/95%	60,215	3,279	56,936	992,675
4	2%/98%	60,215	1,288	58,927	986,789

Data Processing and Model Training Pipeline

Algorithm 1 Node and Edge Feature Generation

Input: $G(V, E)$ ▷ generated dataset from AMLsim
Output: A_V, A_E, el, y ▷ node attributes, edge attributes, edge list, target

$A_V \leftarrow \mathrm{empty}(|V|, 1)$
A_V.append(`BasicNodeTests`$(G(V, E))$) ▷ GAW, Std. Degree
A_V.append(`CommunityDetection`$(G(V, E))$) ▷ Louvain Method
A_V.append(`TransactionStatistics`$(G(V, E))$) ▷ total amount in, ect..
$A_E \leftarrow E.weights$ ▷ transfer amount
$\mathrm{el} \leftarrow E.edge\_list$ ▷ [source, target] of shape $(|E| \times 2)$
$y \leftarrow$ node class label ▷ boolean $\{0, 1\}$
return A_V, A_E, el, y

Algorithm 2 GNN Model Training Pipeline

Input: A_V, A_E, el, y
Output: model

$k \leftarrow 2$ ▷ number of convolutional layers
hidden_size $\leftarrow A_V.num\_features$ ▷ number of node features
model = GNNModel(hidden_size, k)
train, valid, test $\leftarrow$ `train_test_split`$(A_V, A_E, \mathrm{el}, y)$ ▷ indices with [35%, 15%, 50%] split
for epoch **do**
  model.train$(A_V, A_E, \mathrm{el}, y$, train)
  model.valid$(A_V, A_E, \mathrm{el}, y$, valid)
end for
return model

Numerical Results

Performance of GNN Models Across Datasets

Dataset 1
55% anomalous, 45% normal

Model (Best Params)	Precision ↑	Recall ↑	F1-Score ↑	AUC ↑
MPNN, k=5, z=64	.95	**.95**	.95	.94
SAGE, k=3, z=64	**.97**	**.95**	**.96**	**.95**
GCN, k=5, z=64	.88	.94	.91	.90
GAT, k=3, z=32	.90	.92	.91	.89
GIN, k=3, z=32	.95	.90	.92	.92

Dataset 2
11% anomalous, 89% normal

Model	Precision ↑	Recall ↑	F1-Score ↑	AUC ↑
MPNN, k=4, z=8	.87	**.80**	.84	**.89**
SAGE, k=5, z=64	**.97**	.71	**.86**	.88
GCN, k=3, z=32	.83	.69	.75	.84
GAT, k=3, z=16	.93	.65	.77	.82
GIN, k=2, z=32	.98	.76	**.86**	.88

Dataset 3
5% anomalous, 95% normal

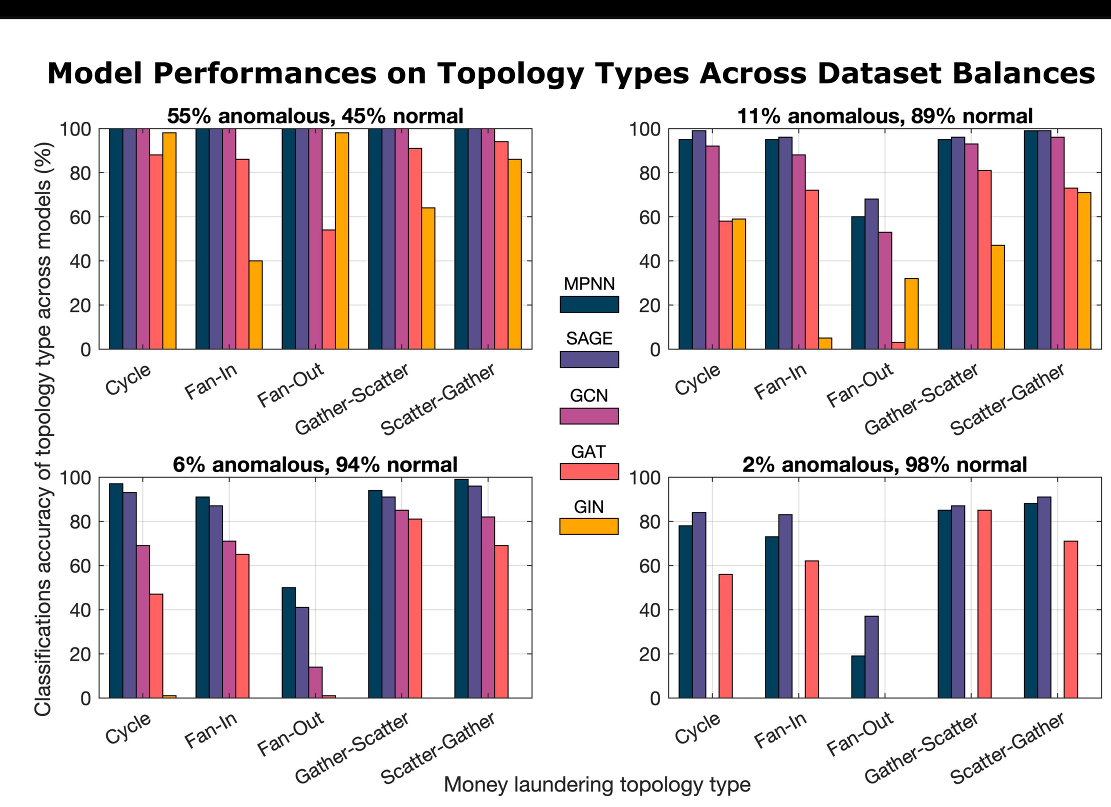
Model	Precision ↑	Recall ↑	F1-Score ↑	AUC ↑
MPNN, k=5, z=64	.93	.75	.83	.87
SAGE, k=6, z=8	.97	**.81**	**.88**	**.90**
GCN, k=2, z=8	.85	.68	.76	.84
GAT, k=3, z=16	.94	.65	.77	.82
GIN, k=2, z=16	**.98**	.72	.83	.86

Dataset 4
2% anomalous, 98% normal

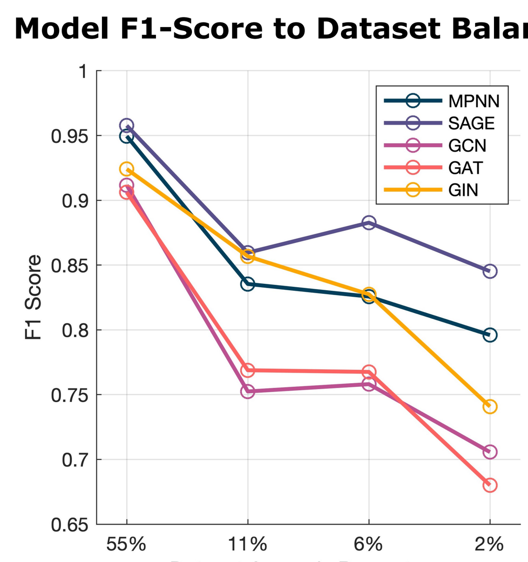
Model	Precision ↑	Recall ↑	F1-Score ↑	AUC ↑
MPNN, k=5, z=64	.92	.70	.80	.85
SAGE, k=6, z=8	.95	**.76**	**.85**	**.88**
GCN, k=2, z=8	.86	.60	.71	.80
GAT, k=5, z=16	.92	.54	.68	.77
GIN, k=2, z=32	**.98**	.60	.74	.80

*k is number of convolutional layers, z is hidden linear layer dimension.

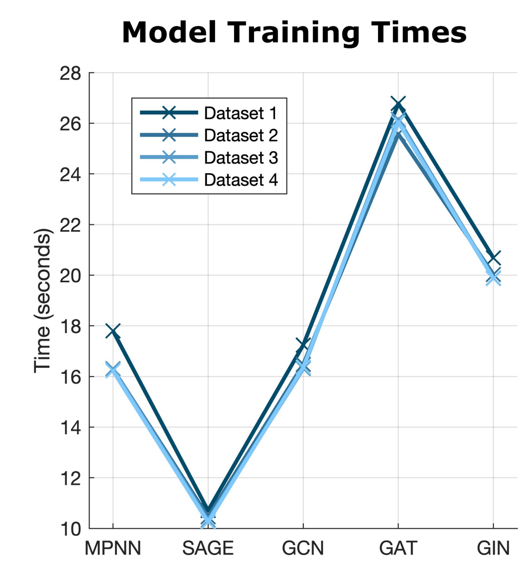
Model Performances on Topology Types Across Dataset Balances



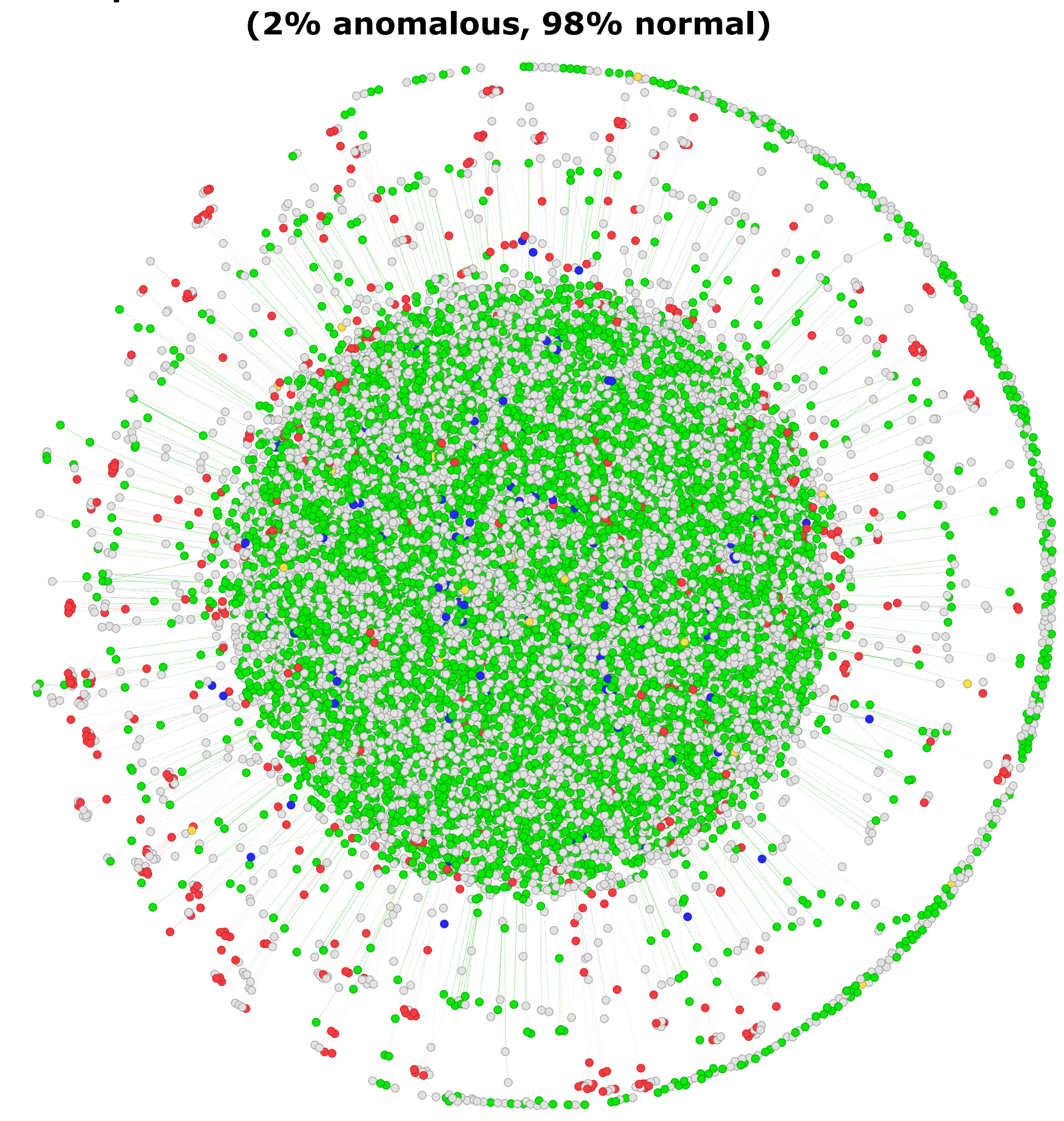
Model F1-Score to Dataset Balance



Model Training Times



GraphSAGE Node Classification Results for Dataset 4 (2% anomalous, 98% normal)



Gray •: Training set (50.03%)
Green •: True negatives (46.52%)
Red •: True positives (2.31%)
Blue •: False negatives (0.91%)
Yellow •: False positives (0.23%)