

Leveraging Graph Neural Networks for Financial Fraud Detection: Practices and Challenges



Yingtong Dou

ydou5@uic.edu



Kay Liu

zliu234@uic.edu



Philip S. Yu

psyu@uic.edu

University of Illinois Chicago



Machine Learning in Finance Workshop @ KDD 2022

Tutorial Outline

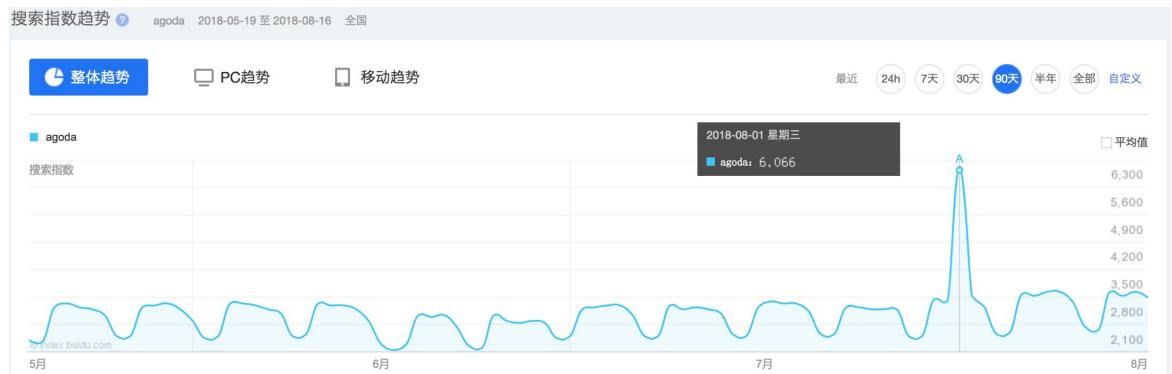
- **Part 1 & 2 (Yingtong)**
 - Background: Financial fraud detection and graph neural networks.
 - Supervised methods and DGFraud.
- **Part 3 & 4 (Kay)**
 - Unsupervised methods, PyGOD, and benchmark.
 - ML pipelines, and live demo.
- **Part 5 (Yingtong)**
 - Challenges, solutions, insights, guideline, and resources.

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What is Fraud?

- **Fraud definition according to U.S. Law:**
 - a misrepresentation of a fact, made from one person to another, with knowledge of its falsity and for the purpose of inducing the other to act.
- **Fraudster vs. Hacker**
 - Most fraudsters are **NOT** hackers.
 - Only few hackers are fraudsters.
- **Fraud vs. Anomaly**
 - Not all frauds are anomalies.
 - Not all anomalies are frauds.



Machine Learning in Financial Fraud Detection



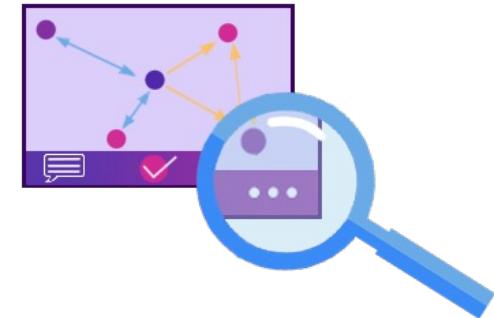
Identity-based Detectors

Demographical information



Behavior-based Detectors

The frequency of transaction



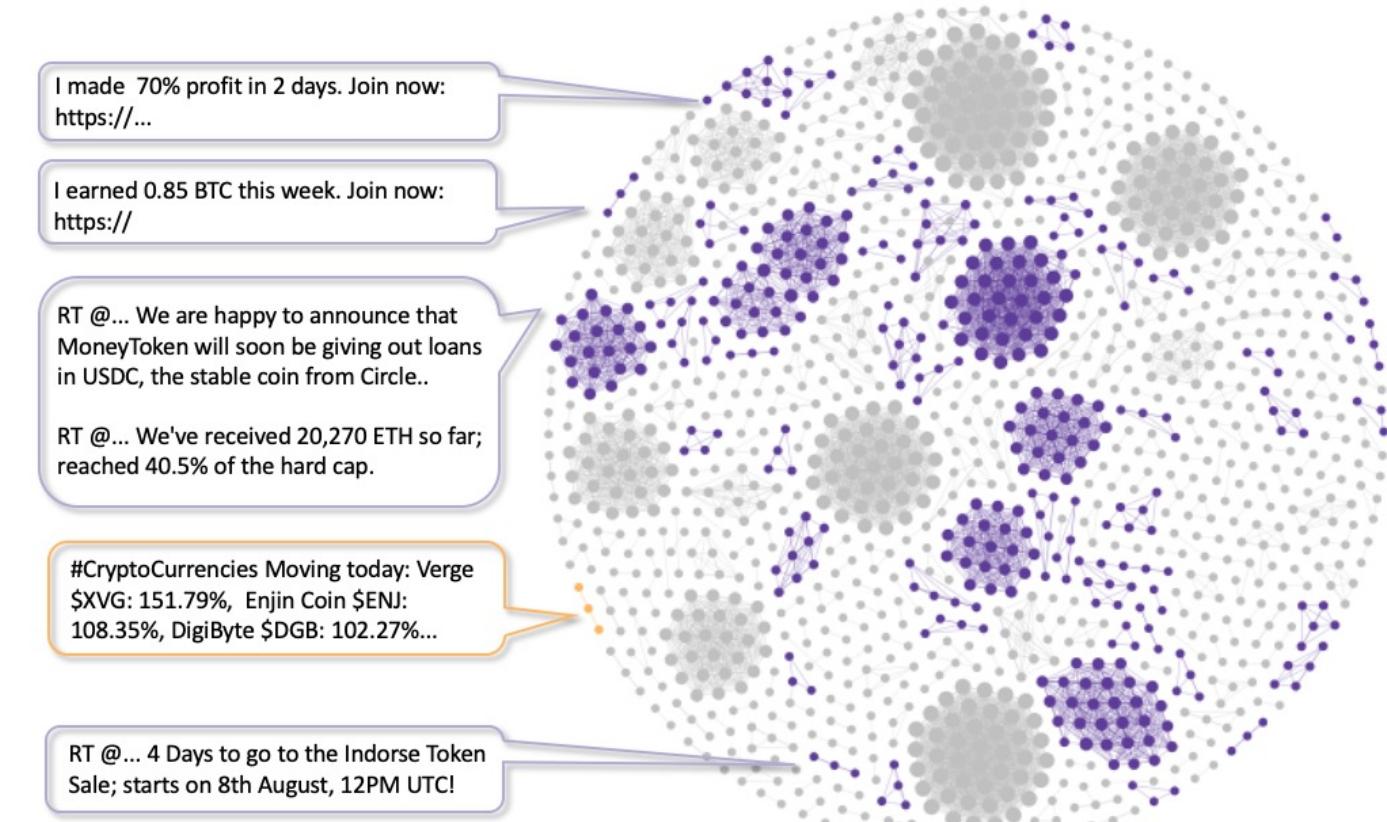
Graph-based Detectors

Discuss in this tutorial!

Graph-based Fraud Detection



Bot Account on Twitter



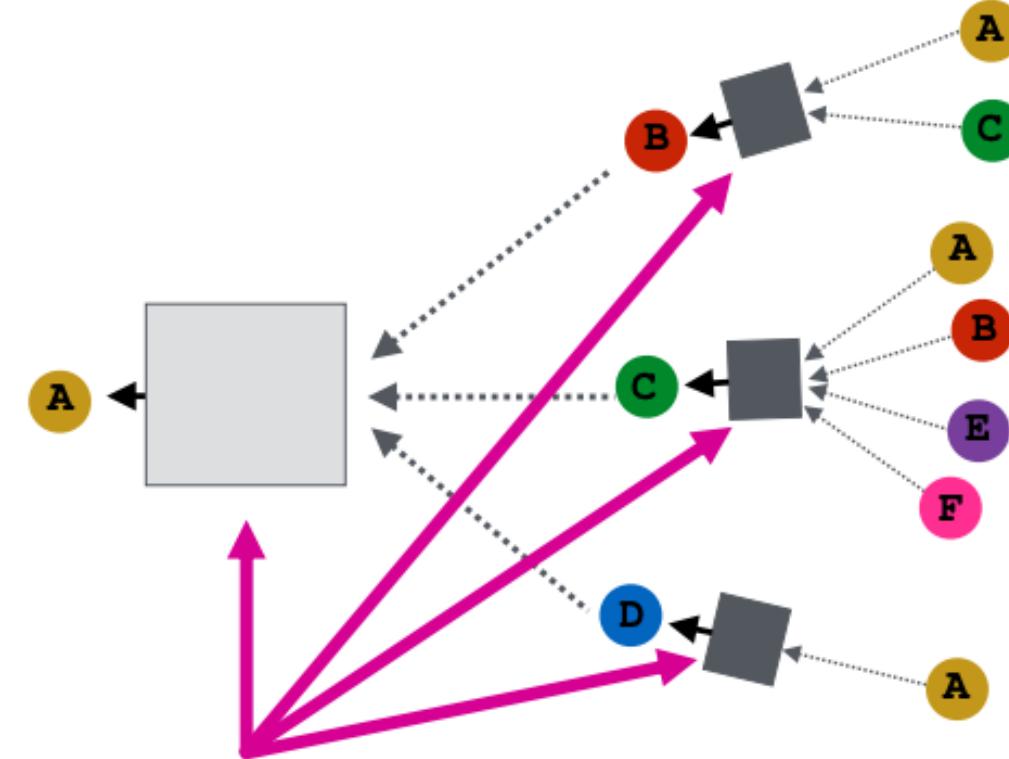
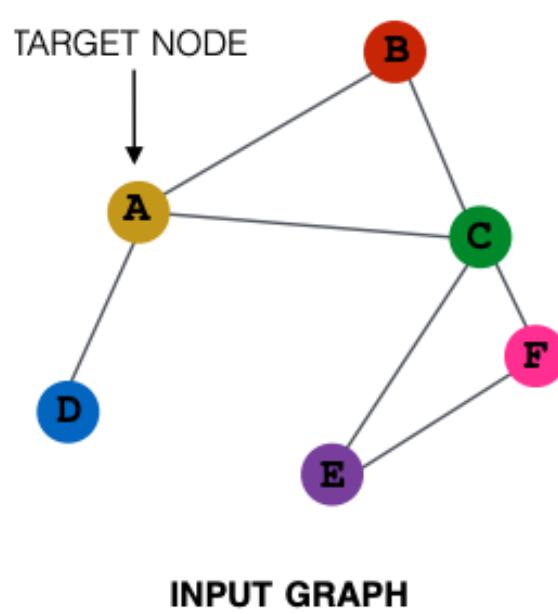
Coordinated Accounts on Social Network^[1]

[1] Pacheco, Diogo, et al. "Uncovering Coordinated Networks on Social Media: Methods and Case Studies." ICWSM. 2021.



Background

Graph Neural Networks



Key idea: the connected nodes are similar (homophily assumption)

GNN Use Cases in Industry

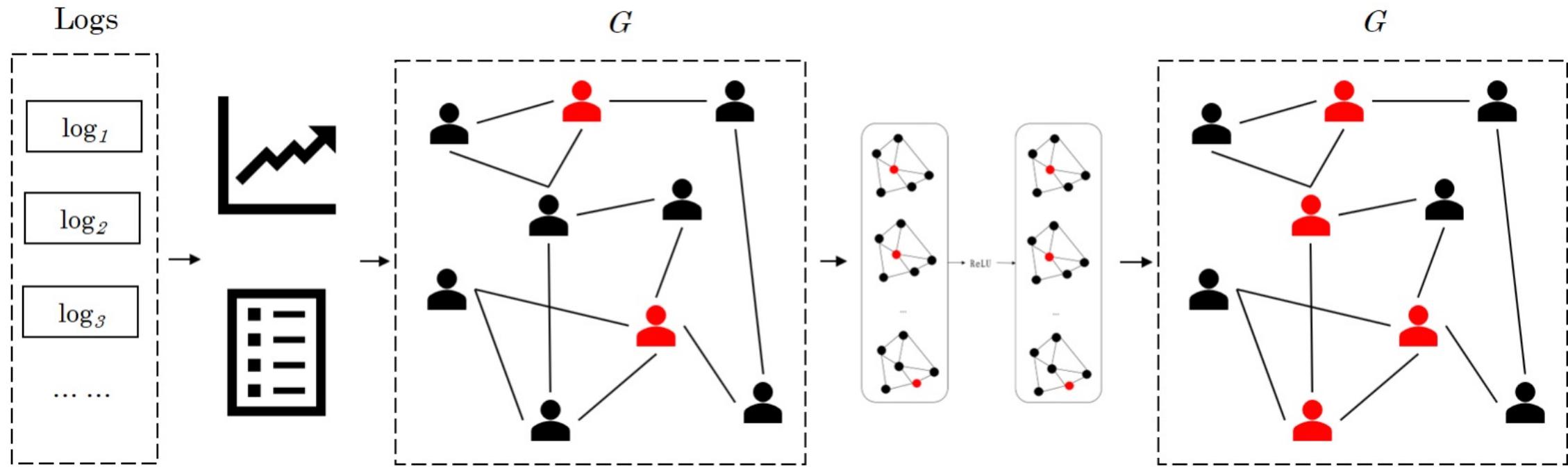
- Pinterest, Snapchat
 - Recommender systems
- Amazon & United Airlines
 - Information extraction
- AstraZeneca
 - Molecular Generation

- GNN for Financial Fraud**
- Insurance Fraud
 - Loan Defaulter
 - Money Laundering
 - Credit Card Fraud
 - Transaction Fraud
 - Cash-out Fraud
 - Bitcoin Fraud

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Supervised GNN



(1) Graph Construction.

(2) Training GNN on the Graph
with labeled nodes.

(3) Classifying Unlabeled Nodes.

Background

Supervised

A Short History of GNN Fraud Detection

GraphRAD
MLG@KDD'18

GeniePath
AAAI'19

BitGCN
ADF@KDD'19

GEM
CIKM'18

InsurGNN
SIGIR'19

GAS
CIKM'19

CARE-GNN
CIKM'20

GraphRfi
SIGIR'20

SemiGNN
ICDM'19

GraphCensis
SIGIR'20

Bi-GCN
AAAI'20

Player2Vec
CIKM'19

GAL
CIKM'20

APAN
SIGMOD'21

FD-NAG
BigData'21

MvMoE
WSDM'21

IHGAT
KDD'21

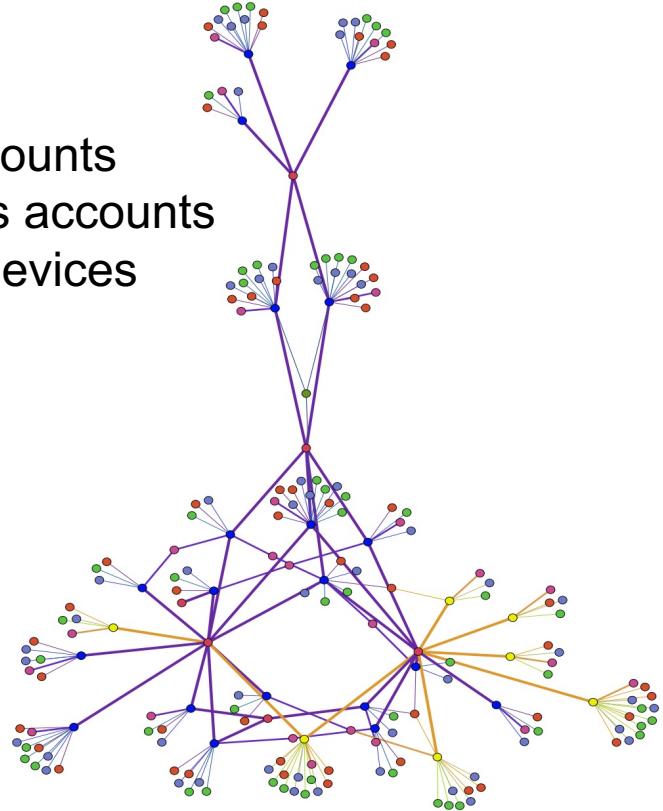
BWGNN
ICML'22

GEM (CIKM'18)

Blue: normal accounts

Yellow: malicious accounts

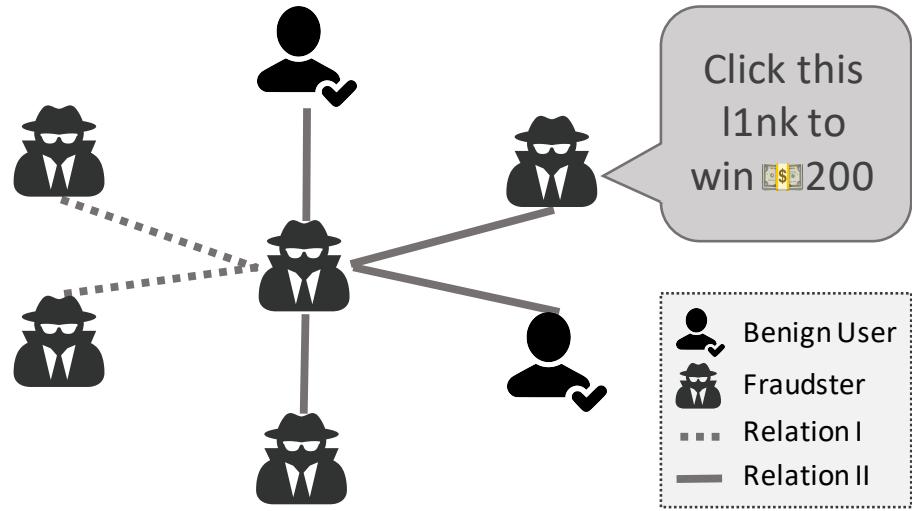
Other: different devices



Account-Device
Heterogeneous Graph

- Task: malicious accounts detection in mobile payment service (Alipay).
- **The first paper leveraging the heterogeneous graphs for fraud detection.**
- Device types include UMID, MAC address, IMSI, APDID (Alipay Fingerprint).
- Code is [available](#).

CARE-GNN (CIKM'20)



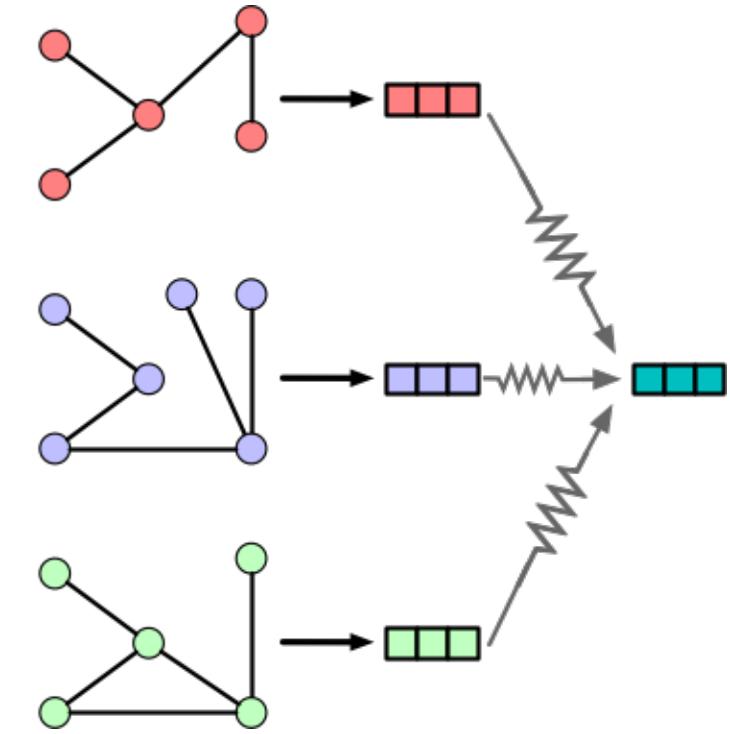
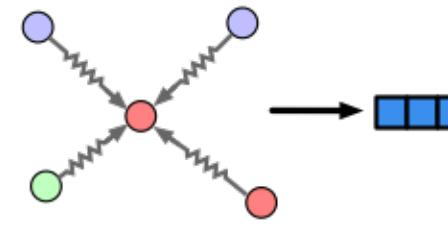
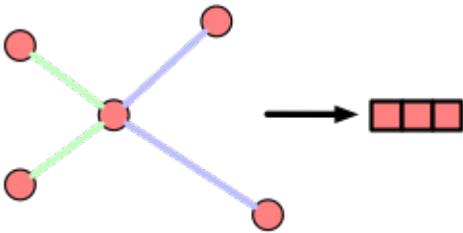
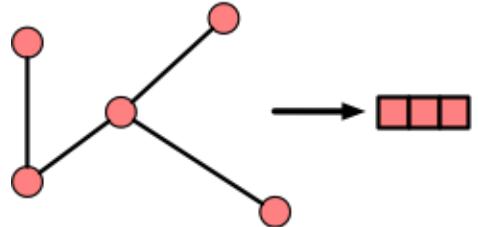
Fraudster Camouflage
&
Multi-relational Graph

- Task: spam review detection on Yelp; malicious reviewer detection on Amazon.
- **Top 10 influential papers in CIKM'20.**
- Using reinforcement learning to select the most informative neighbors for GNNs.
- Code is [available](#).

Background

Supervised

Graph Schema



Homogeneous

[BitGCN](#)
[FdGars](#)
[GeniePath](#)
[FD-NAG](#)

Multi-relation

[GraphCosis](#)
[CARE-GNN](#)
[PC-GNN](#)

Heterogeneous

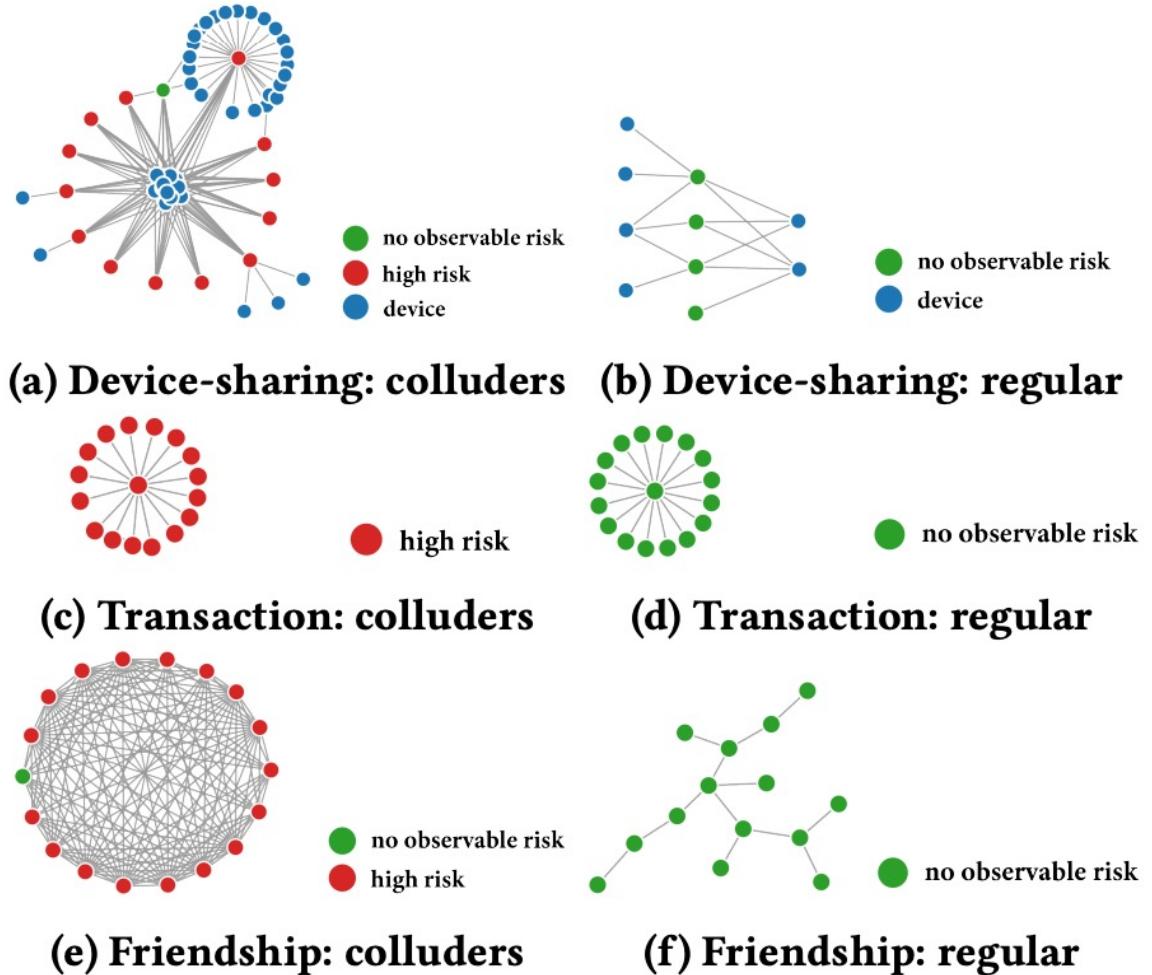
[GAS](#)
[mHGNN](#)
[IHGAT](#)

Hierarchical

[GEM](#)
[SemiGNN](#)
[Player2Vec](#)
[AA-HGNN](#)

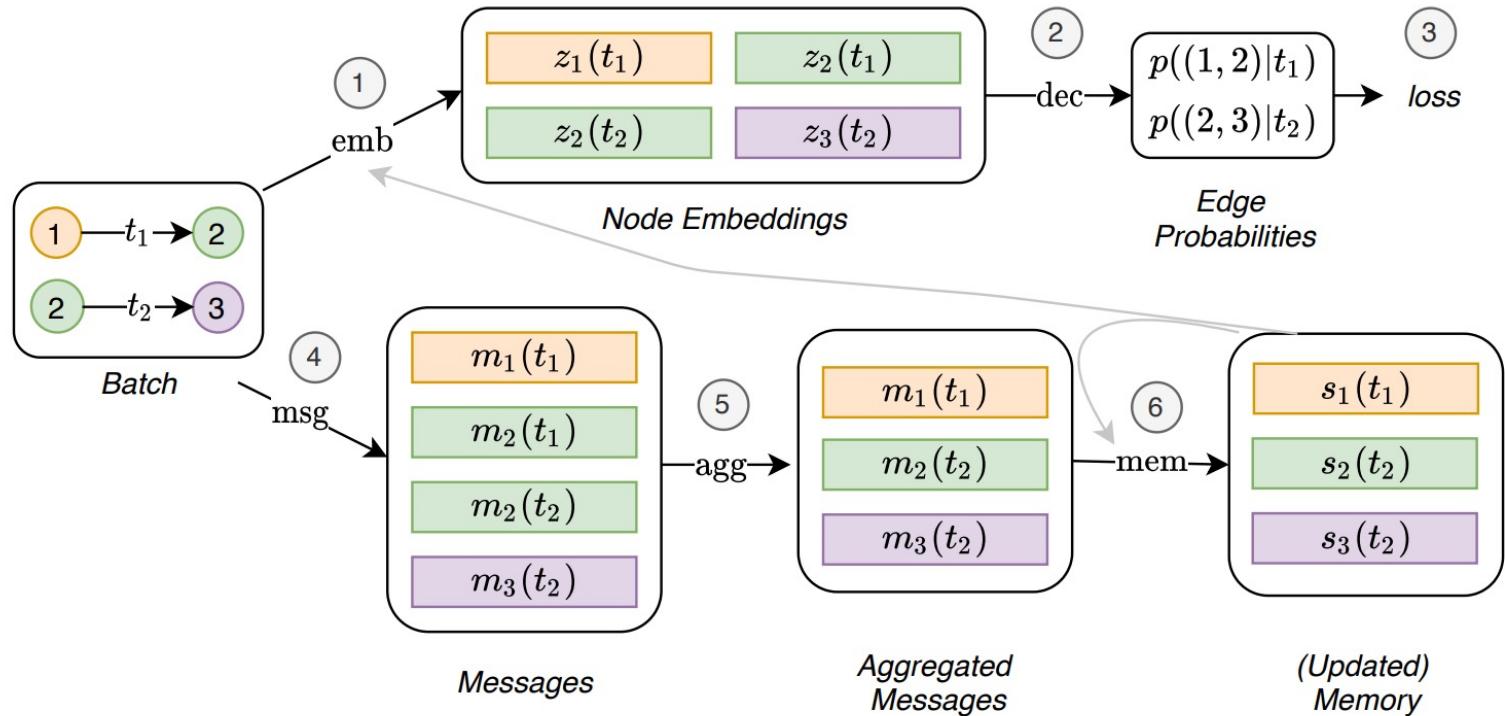
Graph Schema is Crucial

- Task: finding fraud colluders on an online insurance platform.
- The suspicious signal can only be visible under certain graph schemas.
- Graph schema design is the key step for applied graph machine learning.



Dynamic GNN: A Low-latency Inference Solution

- Each node has a mailbox (memory) to store the up-to-date neighbor information.
- The inference can be done by aggregating information from the memory.
- The memory can be updated asynchronously.
- APAN: e-commerce transaction fraud detection.



DGFraud

- **DGFraud – A Deep Graph-based Toolbox for Fraud Detection.**



build passing license Apache-2.0 release v0.1.0 PRs welcome



build passing tensorflow 2.X python 3.6 | 3.7 | 3.8 | 3.9 PRs welcome release v0.1.0

Combined 550+ Stars on GitHub

Model	Application	Graph Type	Base Model
SemiGNN	Financial Fraud	Heterogeneous	GAT, LINE, DeepWalk
Player2Vec	Cyber Criminal	Heterogeneous	GAT, GCN
GAS	Opinion Fraud	Heterogeneous	GCN, GAT
FdGars	Opinion Fraud	Homogeneous	GCN
GeniePath	Financial Fraud	Homogeneous	GAT
GEM	Financial Fraud	Heterogeneous	GCN
GraphSAGE	Opinion Fraud	Homogeneous	GraphSAGE
GraphCconsis	Opinion Fraud	Heterogeneous	GraphSAGE
HACUD	Financial Fraud	Heterogeneous	GAT

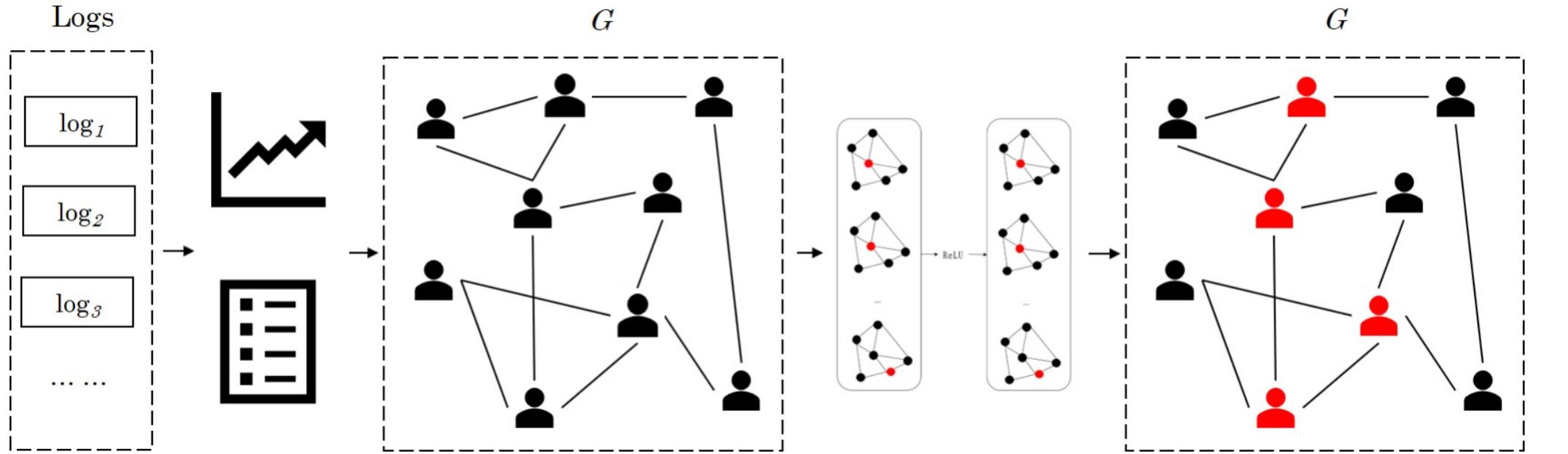
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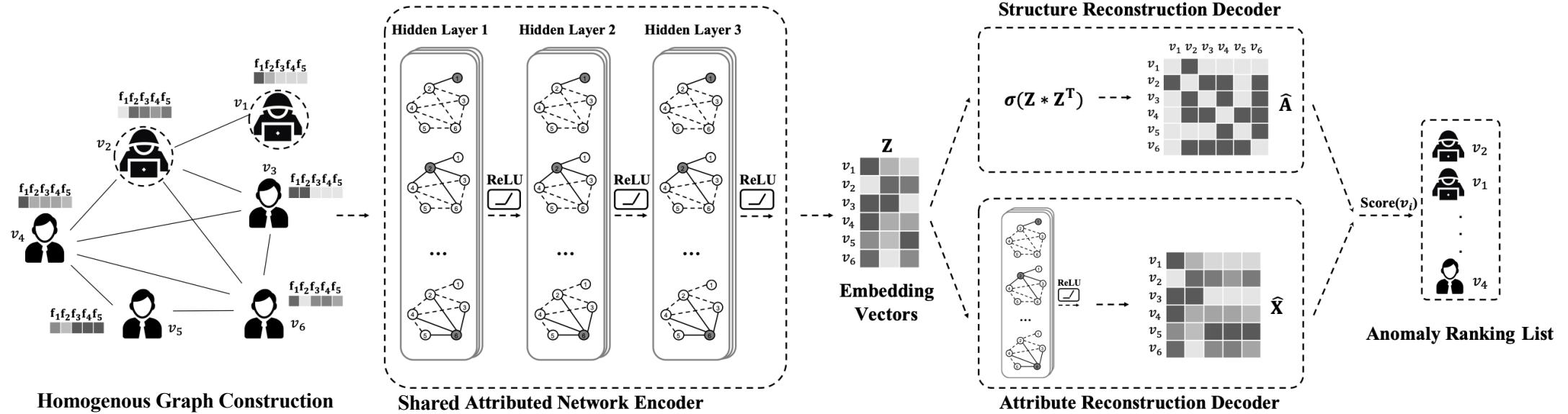
Unsupervised Fraud Detection with Graphs

- **Label scarcity**
 - Ground truth labels can be expensive, even impossible to obtain.
- **Novelty detection**
 - Unsupervised learning does not rely on existing labeled data.
- **Preprocessing for downstream tasks**
 - E.g., Outlier resistant node classification.

Graph Auto-Encoder (GAE)

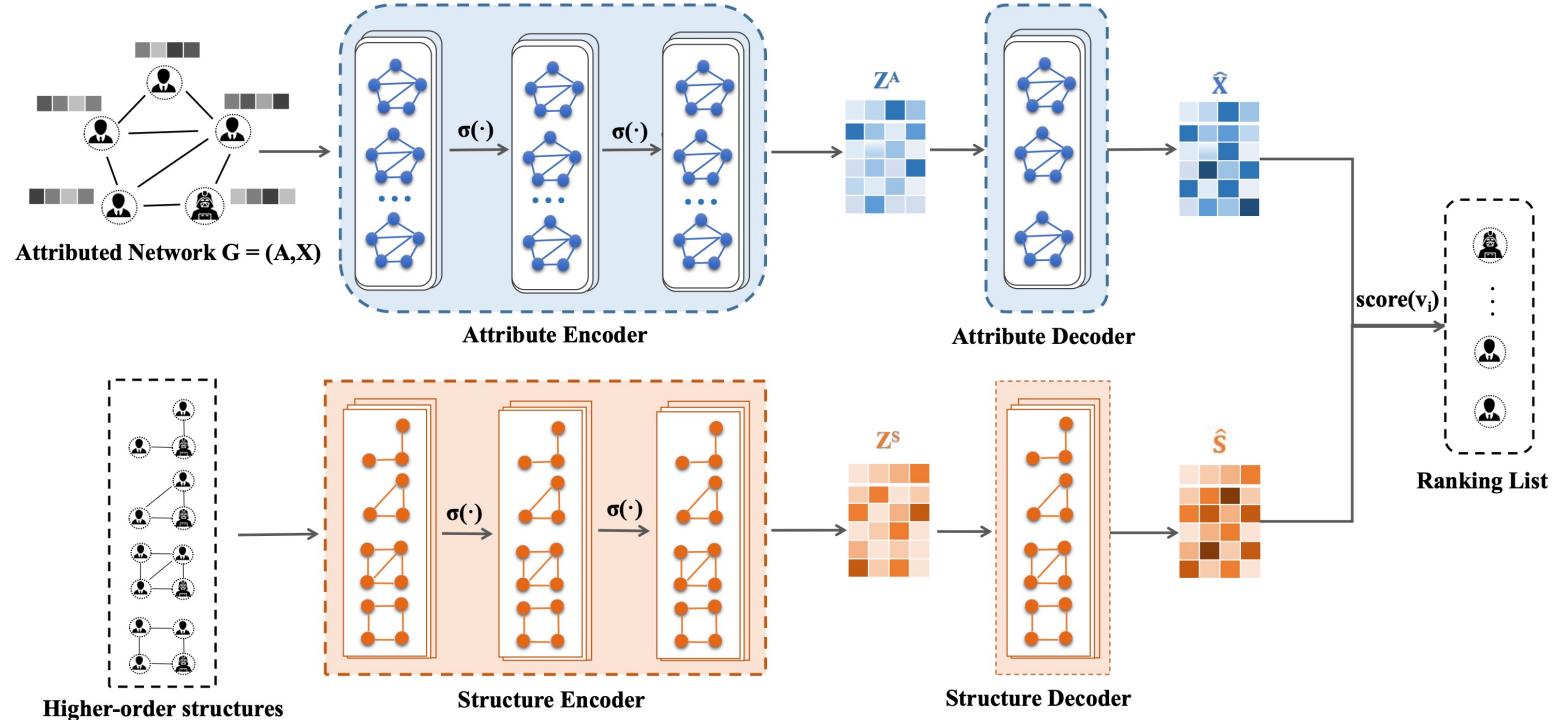
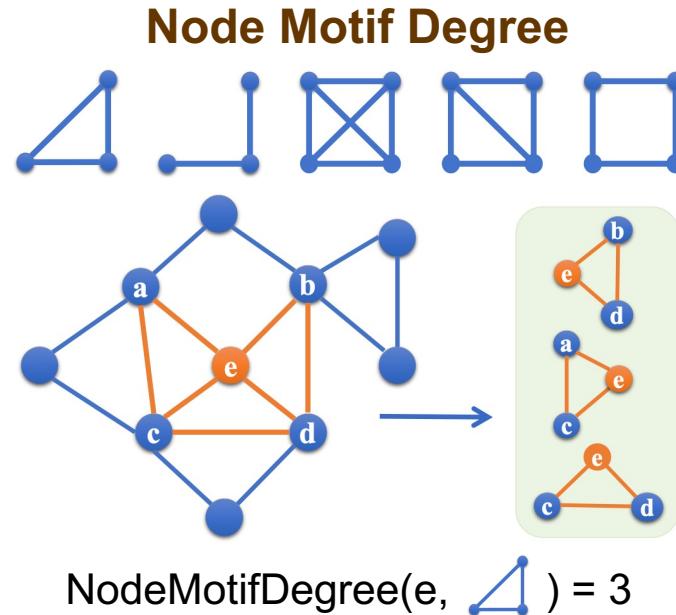


DOMINANT (SIAM'19)



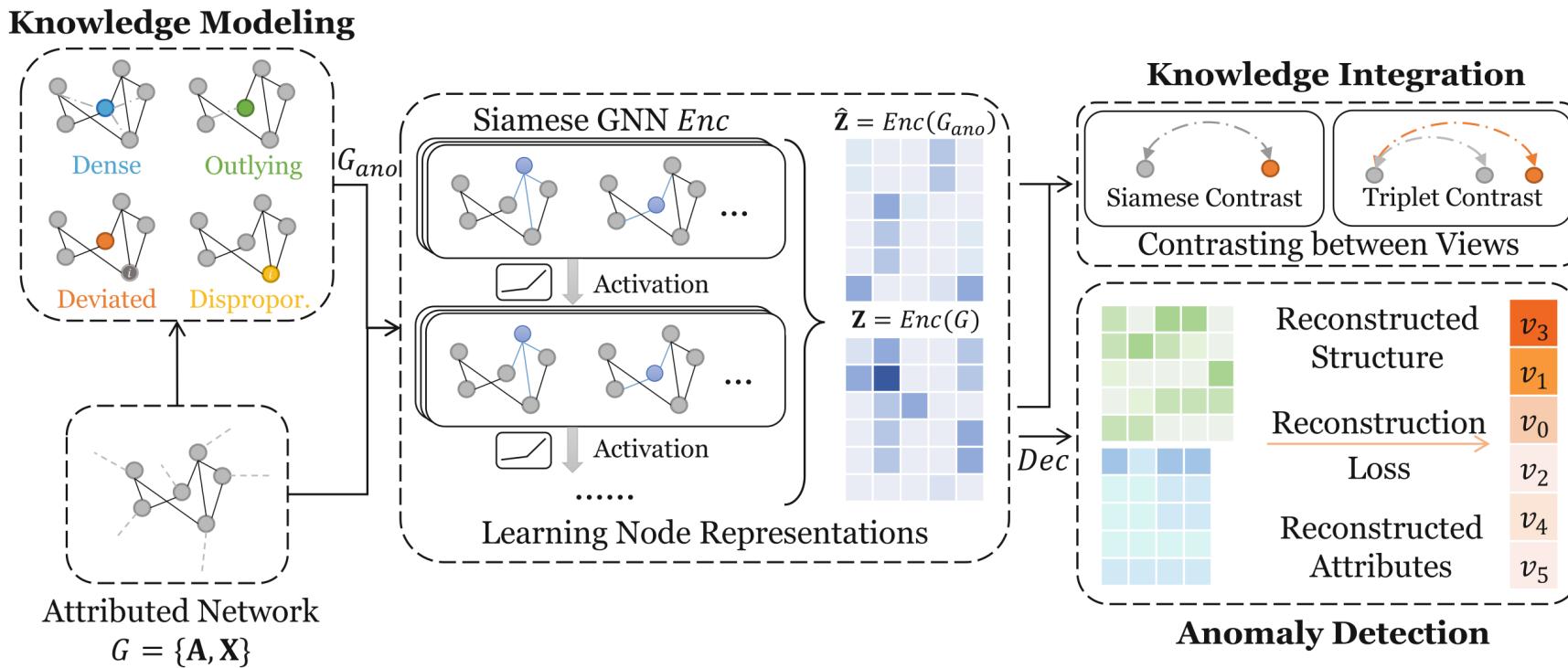
- The first attempt of **graph auto-encoder** in graph anomaly detection problem.
- Adopted **multi-task learning** framework to jointly detect anomalies from two aspects.
- Using **reconstruction error** of structure and attribute as anomaly score.

GUIDE (Big Data'21)



- Capture higher-order structure information with **node motif degree**.
- Largely improve the scalability for AE, but **huge burden** on node motif degree counting.
- **Imprecise estimate** (e.g., [LRP](#)) can accelerate node motif degree counting.

CONAD (PAKDD'22)



- Data augmentation with predefined anomaly **knowledge modeling**.
- Applying **contrastive learning** in graph anomaly detection problem.
- Knowledge integration with **Siamese Contrast** and **Triplet Contrast**.

Background

Supervised

Unsupervised



A Python Library for Graph Outlier/Anomaly Detection

Detecting graph outliers in 5 lines of code

Received 600+ Stars on GitHub

Homepage: <https://pygod.org>

Doc: <https://docs.pygod.org>

Software Paper: <https://arxiv.org/abs/2204.12095>

Email: dev@pygod.org

Backbone	Abbr	Year	Sampling
MLP+AE	MLPAE	2014	Yes
Clustering	SCAN	2007	No
GNN+AE	GCNAE	2016	Yes
MF	Radar	2017	No
MF	ANOMALOUS	2018	No
MF	ONE	2019	No
GNN+AE	DOMINANT	2019	Yes
MLP+AE	DONE	2020	Yes
MLP+AE	AdONE	2020	Yes
GNN+AE	AnomalyDAE	2020	Yes
GAN	GAAN	2020	Yes
GNN+AE	OCGNN	2021	Yes
GNN+AE	CoLA (beta)	2021	In progress
GNN+AE	ANEMONE (beta)	2021	In progress
GNN+AE	GUIDE	2021	Yes
GNN+AE	CONAD	2022	Yes

UNOD Benchmark

- The first comprehensive unsupervised node outlier detection benchmark.
- Provides synthetic, injected, and organic outlier detection dataset.

Data repo: <https://github.com/pygod-team/data>

Benchmark Paper: <https://arxiv.org/abs/2206.10071>

Email: benchmark@pygod.org

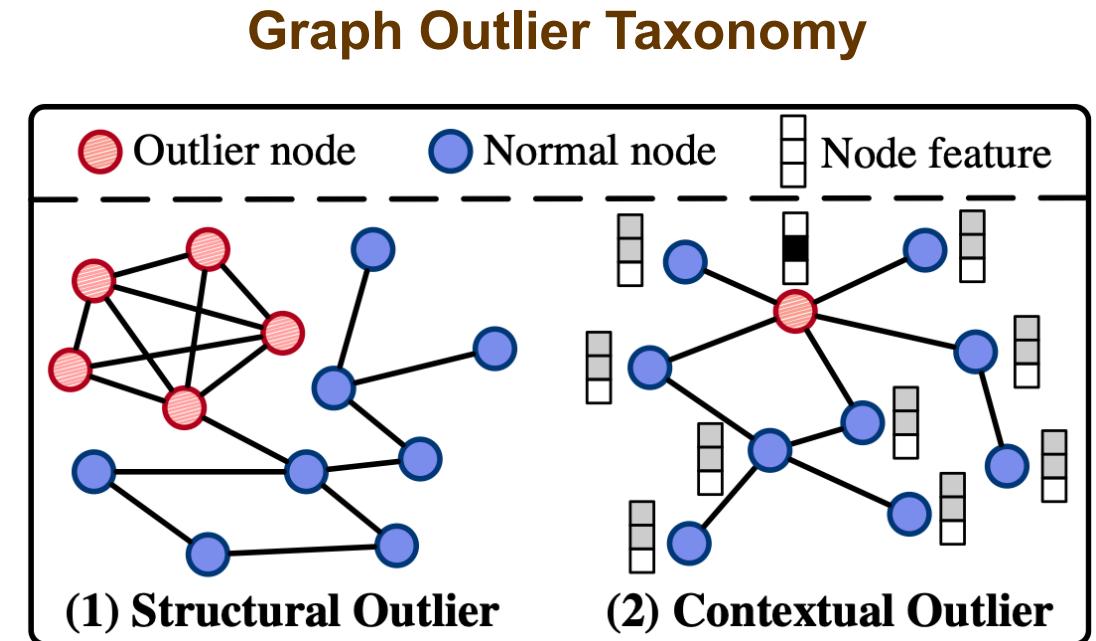
Dataset	Type	#Nodes	#Edges	#Feat
'weibo'	organic	8,405	407,963	400
'reddit'	organic	10,984	168,016	64
'inj_cora'	injected	2,708	11,186	1,433
'inj_amazon'	injected	13,752	515,872	767
'inj_flickr'	injected	89,250	942,316	500
'gen_time'	generated	1,000	5,746	64
'gen_100'	generated	100	618	64
'gen_500'	generated	500	2,662	64
'gen_1000'	generated	1,000	4,936	64
'gen_5000'	generated	5,000	24,938	64
'gen_10000'	generated	10,000	49,614	64

Benchmark on Performance

- Deep graph-based methods are generally better than others.
- No algorithm outperforms on all datasets in expectation.
- Performance on synthetic outliers may not generalize to organic outliers.
- Trade-off between algorithm stability and potential.

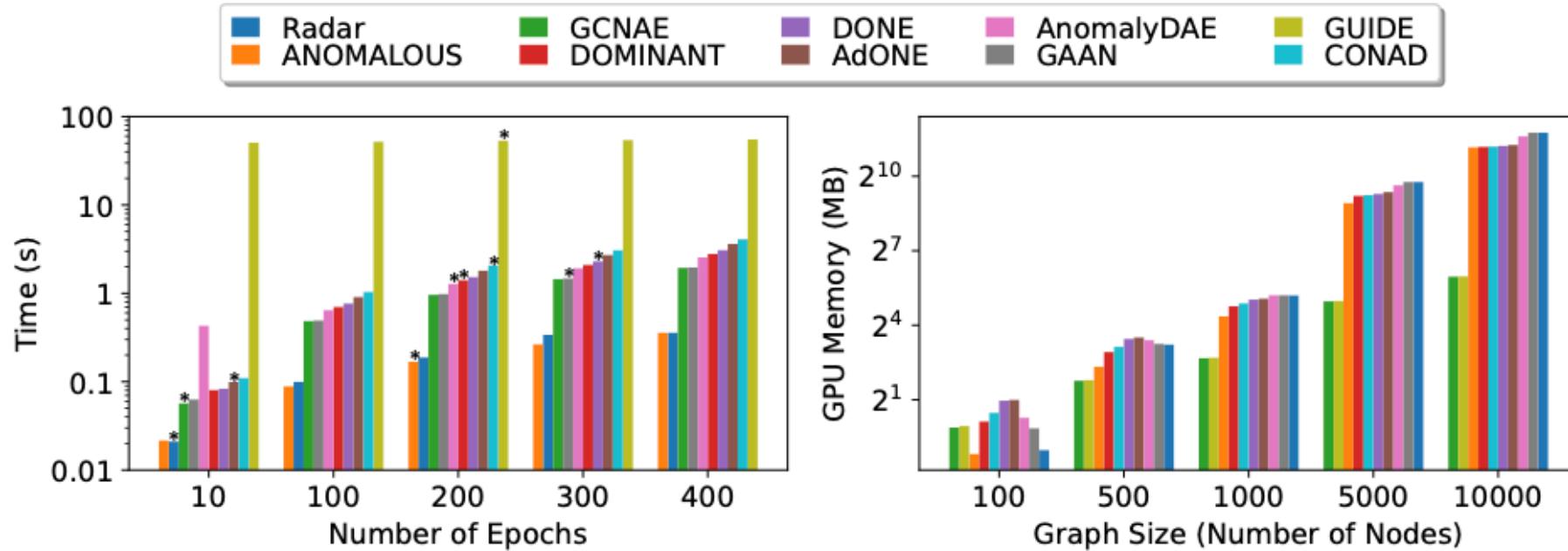
Benchmark on Outlier Types

- The **reconstruction** instead of neighbor aggregation detects structural outlier.
- **Low-order structure** is sufficient for detecting structural outlier.
- None of the methods **balances** multiple types of outliers well.



Benchmark on Efficiency and Scalability

- Conventional methods are more efficient than deep methods.
- GUIDE improves scalability at an expense of efficiency.

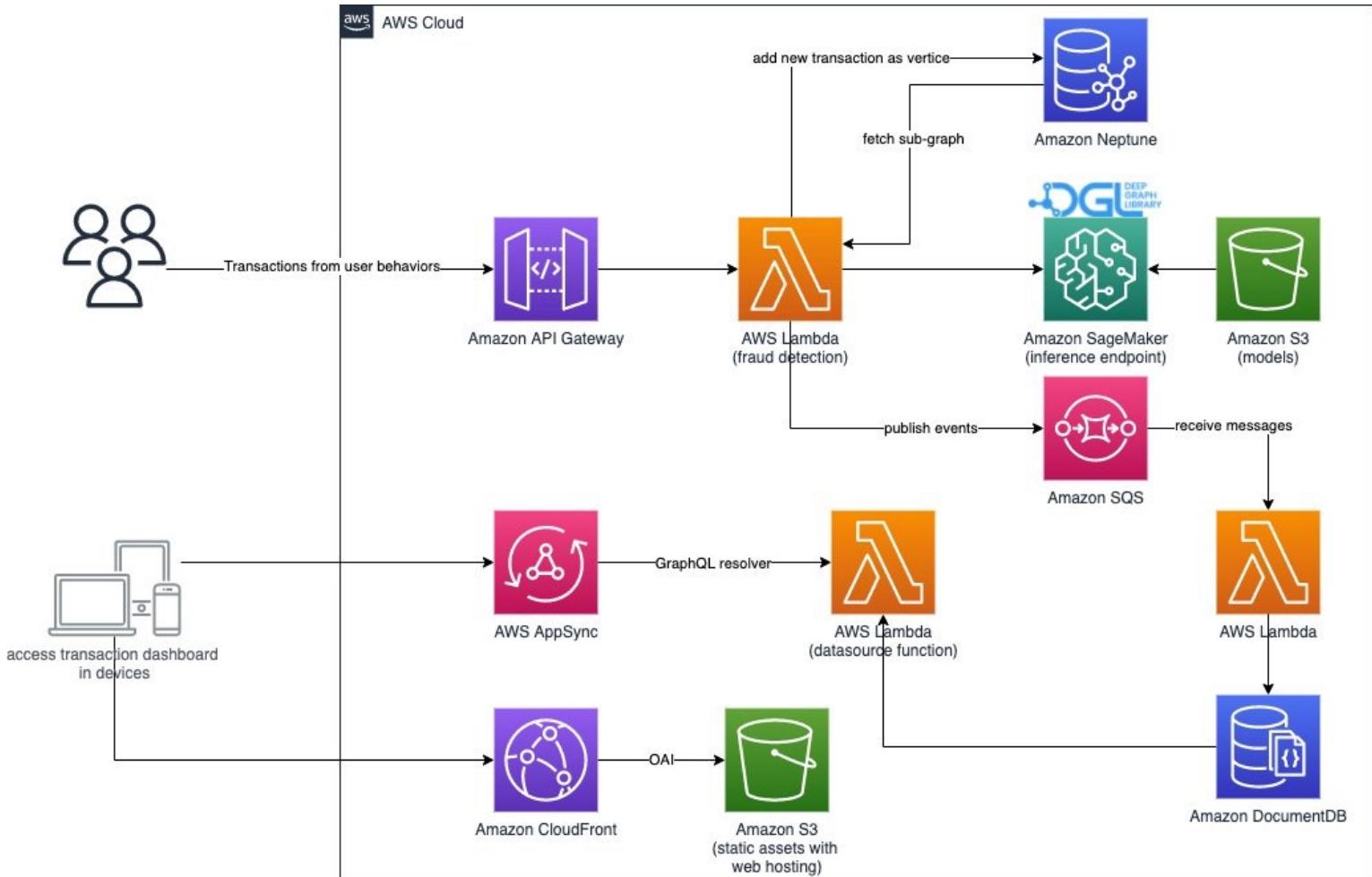


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AWS DGL Real-time Fraud Detection Solution

- Processing a tabular transaction dataset into a heterogeneous graph dataset.
- Training a GNN model using SageMaker.
- Deploying the trained GNN models as a SageMaker endpoint.
- Real-time inference for incoming transactions.



TigerGraph Machine Learning Workbench



Development Framework for Graph Machine Learning

Enables data scientists to create graph neural network models and graph-enhanced models with production scale data.



Python-level Functions and Capabilities

Prepackaged Python libraries for graph data processing, graph feature engineering, subgraph sampling, data loading, and caching for out-of-DB training. No GSQQL experience is required.



Compatible with Popular Machine Learning Frameworks

Work with the most popular machine learning frameworks in the market including PyTorch Geometric and DGL.



Plug-and-Play Ready Machine Learning

Flexible integration paths to works with your existing machine learning infrastructure on Amazon SageMaker, Google Vertex AI, and Microsoft Azure Machine Learning.

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GNN Financial Fraud Detection Papers

- **Online/Mobile Payment Fraud**
 - [CIKM'18](#), [ICDM'19](#), [AAAI'19](#) (cash-out).
- **Insurance Fraud**
 - [SIGIR'19](#).
- **Blockchain/Crypto Fraud**
 - [MLF@KDD'19](#), [WWW'22](#).
- **Loan Defaulting, Loan Fraud**
 - [CIKM'20\(1\)](#), [CIKM'20\(2\)](#), [AAAI'21](#), [WSDM'21](#), [WWW'21](#), [SDM'21](#), [arXiv'22](#).
- **Transaction Fraud (e-commerce and credit card)**
 - [arXiv'20](#), [SIGMOD'21](#), [KDD'21](#), [WISE'21](#), [TOIS'21](#), [ESA'22](#), [KDD'22](#).

Key Challenges and Solutions

- **Camouflage**
 - Neighboring filtering: [SIGIR'20](#), [CIKM'20](#), [WWW'21](#).
 - Aware of adversarial behavior: [IJCAI'20](#), [WWW'20](#).
 - Active generative learning: [ACL'20](#).
 - Bayesian edge weight inference: [ACL'21](#).
- **Scalability**
 - GNN scalability: [MLF@KDD'20](#).
 - Shallow graph models are more scalable: [MLG@KDD'18](#), [WWW'20](#).
- **Class imbalance**
 - Under-sampling: [CIKM'20](#).
 - Neighbor selection: [WWW'21](#).
 - Data augmentation: [CIKM'20](#).

Key Challenges and Solutions (Cont'd)

- **Label scarcity**
 - Active learning: [ICDM'20](#), [TNNLS'21](#).
 - Ensemble learning: [CIKM'20](#).
 - Meta learning: [WSDM'21](#).
- **Label fidelity**
 - Active learning: [TNNLS'21](#).
 - Human-in-the-loop: [AAAI'20](#).
- **Data scarcity**
 - Data augmentation: [CIKM'20](#), [CIKM'21](#), [ACL'20](#).

Novel Practices

- **Graph Pretraining (Contrastive Learning)**
 - Fraudster is distinguishable from its structural pattern.
 - [TNNLS'21](#), [SIGIR'21](#), [arXiv'21\(1\)](#), [arXiv'21\(2\)](#).
- **Dynamic/Temporal/Streaming Graph**
 - Historical information is useful for identifying fraudsters.
 - Efficiency and cost are bottlenecks.
 - [CIKM'21](#), [KDD'21\(1\)](#), [KDD'21\(2\)](#), [SIGMOD'21](#).
 - [arXiv'21](#), [SDM'21](#), [ICDM'20](#), [KDD'20](#).
 - [ROLAND \(KDD'22\)](#), [arXiv'22](#).

Novel Practices (Cont'd)

- **Multi-task Learning**
 - Credit limit forecasting and credit risk predicting: [WSDM'21](#).
 - Fraud detection and recommender system: [SIGIR'20](#).
- **Explainable Fraud Detection**
 - Explainable fraud transaction detection: [arXiv'20](#), [KDD'21](#).
 - Explainable fake news detection: [ACL'20](#).
- **Table2Graph**
 - Transforming credit card fraud tabular data to graph data: [IJCAI'22](#).

Insights and Discussions

- Early detection, prevention vs. detection.
- Integrating knowledge graph (external knowledge).
- The longtail distribution of the fraud types.
- The concept drift and continual learning.
- The gap between academia and industry.

Applying GNNs in Fraud Detection: A Guideline



• Using Graph?

- The fraudsters share common properties.
- The fraudsters have clustering behavior.
- The trade off between cost and effectiveness.

• Using GNN?

- The infrastructure.
- The feature availability and feature types.
- Integrating with other modules and tasks.

• Which Task?

- Supervised:
 - Node/edge/graph/subgraph classification.
- Unsupervised:
 - Community detection; anomaly detection.

• Schema Design

- Node/edge type and node/edge feature.
- Graph schema, node sampling.
- Graph structure is flexible: [SIGIR'19](#), [ICDM'20](#).

• Which GNN?

- GNN is chosen based on task and schema.
- Simple GNN model is enough.
- Dynamic GNNs need more efforts.
- GAT and Graph-SAGE are commonly used.

Resources

- **Paper List**
 - [Graph-based Fraud Detection Papers and Resources.](#)
- **Datasets**
 - [DGraph](#), [Bitcoin-Fraud](#), [IEEE-CIS](#), [ETH-Phishing](#), [Fraud-Benchmark](#).
- **Libraries**
 - [PyG Temporal](#), [PyOD](#), [PyODDS](#), [TODS](#), [UGFraud](#).
- **Recent Surveys**
 - [A Comprehensive Survey on Graph Anomaly Detection with Deep Learning.](#)
 - [Anomaly Mining - Past, Present and Future.](#)
 - [Graph Computing for Financial Crime and Fraud Detection: Trends, Challenges and Outlook.](#)



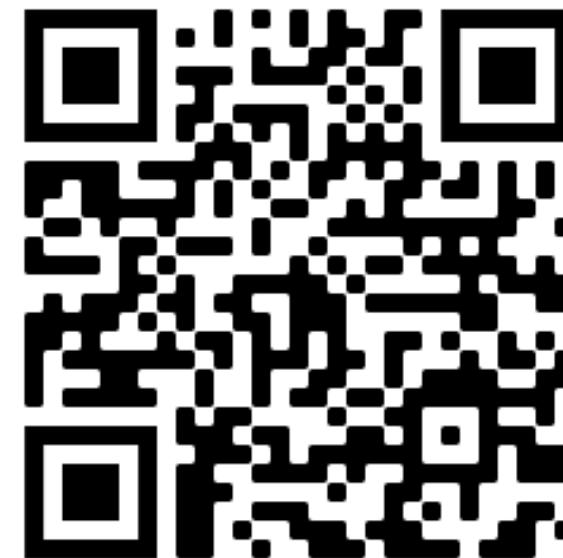
Thanks!

Q & A

Yingtong Dou Kay Liu Philip Yu

University of Illinois Chicago

Slides PDF



Slides URL: https://ytongdou.com/files/GNN_Fin_Fraud.pdf