Subgraph Anomaly Detection in Financial Transaction Networks

Yulong Pei

Eindhoven University of Technology
y.pei.1@tue.nl

Werner van Ipenburg

Cooperatieve Rabobank U.A.
werner.van.ipenburg@rabobank.nl

Fang Lyu

Eindhoven University of Technology
f.lyu@tue.nl

Mykola Pechenizkiy

Eindhoven University of Technology
m.pechenizkiy@tue.nl

ABSTRACT

Effective anomaly detection is crucial for the success of many AI-based solutions in the financial domain, including e.g. fraud detection and risk modeling. Identifying anomaly from financial transaction networks is one of the challenging tasks that can be cast as a special instance of anomaly detection in networks. Existing methods typically attempt to detect only node-level anomalies, and assume prior knowledge to extract representative features for identifying anomalies. However, there exist collective fraudulent behaviors at the level of subgraphs rather than individual node. A ring structure for money laundering and a tree structure for pyramid schemes would be common examples. Also, in practice it is difficult to decide which features are more representative beforehand. In this paper, we introduce SADE (Subgraph Anomaly Detection) framework that addresses these needs. SADE consists of two steps: 1) role-guided subgraph embedding, and 2) subgraph anomaly detection. Our approach for learning the subgraph embeddings allows to preserve both the local structure of subgraphs and the global structure of entire network by making use of global roles and local connections of nodes. The learnt representation allows effective use of the state of art anomaly detection approaches. Our extensive experiments on synthetic and real-world financial transaction networks demonstrate the effectiveness of SADE in learning subgraph embeddings without requiring any prior knowledge and detecting anomalous subgraphs.

CCS CONCEPTS

• **Computing methodologies** → **Learning latent representations; Neural networks; Anomaly detection.**

KEYWORDS

Subgraph Anomaly Detection, Graph Embedding, Financial Transaction Networks

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1 INTRODUCTION

The problem of anomaly detection in financial domain attracts attention from both academia and industry because of its challenges and significant implications in a wide range of AI applications such as fraud detection and risk modeling [3]. The stream of financial transaction can be represented as a network, in which each node represents a customer, and two nodes are connected by an edge if there is at least once money transfer between these two customers. Identifying anomaly from such financial transaction networks can be cast as a special instance of anomaly detection in networks [10].

Existing machine learning approaches for anomaly detection in transaction networks commonly suffer from two major limitations: allowing only node-level anomaly detection and requiring prior knowledge to extract representative features for identifying anomalies. In practice, node-level anomaly detection can miss collective fraudulent behaviors including e.g. pyramid schemes that are often manifested in tree-like subgraph structures and money laundering manifested in a form of a ring or clique structures. On the other hand, it is difficult to predetermine upfront which features would be useful for anomaly detection, because financial transaction networks are complex and their structures are evolving over time. Furthermore, the fraud transaction behaviors are getting more complex and adverse and therefore are hard to define along with the online trading explosion. Employing network embedding approaches is considered to be a promising direction. The variety of node-level [14, 33, 34] and graph-level [1, 8, 27] embedding methods can be used to map a node (or a graph) into a point in a latent space, in which its coordinate is seen as the embedding representation. However, neither of existing embedding methods can facilitate effective detection of anomalous subgraphs because 1) node-level approaches only preserve the local connection between pairs of nodes failing to capture the differences between subgraphs, and 2) graph-level approaches either assume the input is a set of separate graphs (in tasks of graph clustering and classification) or that the inter-community edges between subgraphs can be neglected meaning that again the global structural information is not captured in the network embedding. This can be illustrated with an example shown in Figure 1. There are four subgraphs in this toy network 1a, three of which are normal communities (in red, orange and green colors) and one has a tree-like structure (in blue color). In this toy network, the local structures are represented by communities shown in different colors. The global structures are reflected

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Figure 1: An example of subgraph anomaly detection: (a) a toy graph with three normal subgraphs and one anomalous subgraph, (b) visualization of a node-level embedding method (*node2vec* [14]), (c) visualization of a graph-level embedding method (*Sub2Vec* [1]), and (d) visualization of our framework.

by roles, e.g., the pentagram node plays the role of as a star which is the center of the tree and the square nodes have the bridge role which connect different communities. Node-level embedding methods (Figure 1b) only preserves the local connections between node pairs resulting to failures in capturing the graph-level differences between normal and anomalous subgraphs. Existing graph-level embedding methods (Figure 1c) cannot preserve the global network structure and help in identifying complex (subgraph) structural outliers.

Therefore, we set our goal to design a graph-level embedding method which can preserve the local structure of nodes and global connection patterns of subgraphs simultaneously, to effectively distinguish normal and anomalous subgraphs combining those two kinds of complementary information. As shown in Figure 1d, in the latent space, normal subgraphs are close to each other while the anomalous subgraph is far away from the rest.

To achieve this goal, we propose a subgraph anomaly detection framework which consists of role-guided subgraph embedding and graph-level anomaly detection steps in turn. Role-guided subgraph embedding combines structural roles [16, 30] and random walk based embedding approach to learn subgraph embeddings. Thus, it is able to capture both global structures of the entire network and local structure of each subgraph. For the subgraph anomaly detection step, considering the trade-off between effectiveness and efficiency, we chose to employ Isolation Forest [24] to detect the anomalous subgraphs on the basis of the subgraph representations learned from previous step. Extensive experiments on several transaction networks have verified the effectiveness of our proposed framework on detecting anomalous subgraphs. Making use of the transfer relations, our proposed framework can serve as an early warning system at financial institutions. One can further explore the anomalous subgraphs for analyzing possible fraudulent or criminal behaviors.

Our main contributions are the following:

- We formulate the novel problem of subgraph anomaly detection in financial transaction networks (Section 2).
- We propose SADE: Subgraph Anomaly Detection framework to learn graph-level representations by taking into consideration of both local connections and global roles (Section 3).
- The results of our experiments on synthetic and real-world transaction networks demonstrate the effectiveness of SADE

on subgraphs anomaly detection using different evaluation measures (Section 5).

2 PROBLEM STATEMENT

In this section, several necessary definitions are introduced and then the problem statement of the subgraph anomaly detection in transaction networks is presented.

DEFINITION 1. Transaction Network. A transaction network $\mathcal{G} = \{V, E\}$ consists of: (1) a node set $V = \{v_1, v_2, \dots, v_{|V|}\}$ representing customers/users in $\mathcal{G}$, where $|V|$ is the number of nodes; and (2) a edge set E representing the money transfer relations between V , where $|E|$ is the number of edges.

For simplicity, we restrict our work here to undirected, un-weighted networks and leave the extension to directed and weighted networks for future work.

DEFINITION 2. Subgraph Embedding. Given $\mathcal{G} = \{V, E\}$ and an arbitrary subgraph set $S = \{g_1, g_2, \dots, g_m\}$ which is a partition of $\mathcal{G}$, **Subgraph Embedding** aims to represent each subgraph $g_i \in S$ into a vector $W_i^S \in \mathbb{R}^d$ in a latent low-dimensional space $\mathbb{R}^d$, i.e., learning a mapping function $f: S \rightarrow W^S$, where $W^S \in \mathbb{R}^{m \times d}$ and $d \ll |V|$. In the latent embedding space, both the global structural information of the input graph $\mathcal{G}$ and the local structural information of each subgraph g_i can be preserved.

As introduced in the example in Figure 1a, roles provide a global view of networks and reflect structural functions nodes play in a network [28]. For example, nodes may function as the star, peripheral, clique or bridge. To preserve the global structural information for subgraph embedding, we propose a role-guided embedding approach which extracts structural roles to guide the embedding learning process.

PROBLEM 1. Subgraph Anomaly Detection in Transaction Networks. Given $\mathcal{G} = \{V, E\}$ and an arbitrary subgraph set $S = \{g_1, g_2, \dots, g_m\}$ which is a partition of $\mathcal{G}$, the task of subgraph anomaly detection is to find a subset of subgraphs that are most structurally different from the majority of subgraphs.

This is a general problem statement. Specifically, in our study, it is worth noting that

- We first use the role-guided subgraph embedding approach to map each subgraph into a feature vector representation.

Thus, the problem is reduced to a traditional anomaly detection problem: calculating anomaly scores for all instances and then detecting anomaly by selecting the top ranked instances according to the anomaly scores.

- There are many possible ways to generate subgraph sets using different graph partition algorithms or domain knowledge. This makes the search space too large for real-world applications. Therefore, following previous studies [1, 6], we assume a set of subgraphs with graph theory or domain-specific knowledge based explanation is given as input.

3 THE PROPOSED FRAMEWORK

In this section we first introduce the proposed framework SADE, then we analyze the complexity of SADE. Overall, SADE consists of two steps: subgraph embedding and subgraph anomaly detection.

3.1 Subgraph Embedding

As stated in Section 1, the target of a desired framework for solving Problem 1 is twofold: (1) it captures both local structures from each subgraphs and global structures of the entire network, and (2) it does not require prior knowledge to extract representative features for anomaly detection. Towards this target, we propose a role-guided subgraph embedding method.

Compared to node embedding learning, it is more challenging to learn subgraph embeddings by preserving the structural information because there are two different types of structural information in this scenario:

- *Local structures* which are reflected by the intra-community edges. For instance, two connected nodes are expected to be similar to each other.
- *Global structures* which are reflected by the entire network including inter-community edges. For example, two stars in different subgraphs should be seen as similar.

Thus, a major challenge is to design an approach that has a global view of subgraphs, i.e., it has the capability to capture similarities and differences between the structures of subgraphs. To learn such representative embeddings of subgraphs, both kinds of structures should be preserved because they are complementary and neither could effectively distinguish subgraphs independently. For instance, it is difficult to quantify the similarities between two pyramid schemes with similar tree structure if only the local structures are preserved for representation learning. This results from that there may be no common nodes between these two subgraphs and using local structural information is impossible to find the similarity between them. On the other hand, one is unable to distinguish two core-periphery subgraphs without knowing the local structural connections, because the essential clues on the connection patterns between cores and peripheries are ignored.

To capture both local and global structures for subgraph embedding learning, we propose a new role-guided subgraph embedding framework SADE, which combines the structural information from nodes' roles and co-occurrence between different subgraphs using random walk based embedding techniques. Because it has been shown that the roles of nodes capture their global structural similarities [16, 29] and random walk based embedding approaches preserves the local structures effectively [14, 33]. Therefore, we

take full advantages of those two components into solving 1 and propose our framework SADE, which contains role discovery and embedding learning.

3.1.1 Stage 1: Role discovery. Structural roles represent the node-level connectivity patterns and functions that nodes play in a network. For example, a node may function as the center, peripheral, clique or bridge. Essentially, roles capture the global structural information of networks [28]. There are plenty of role discovery methods in previous studies using different theories, e.g., non-negative matrix factorization (NMF) [16], probabilistic graphical models [2], deep learning techniques [29]. Considering the trade-off between effectiveness and efficiency, we utilize RolX [16], a role discovery method using NMF, in this study.

RolX follows the feature-based role discovery framework which consists of role feature construction and role assignment. In detail, RolX firstly constructs a feature matrix $V_{n \times l}$ from the input network, where n and l are the number of nodes and features respectively. These features consist of local and egonet properties based on counts of links and the egonet-based properties generated in a recursive fashion [17].

Secondly, given the node-feature matrix $V_{n \times l}$, the idea of RolX is to find a rank r approximation $GF \approx V$ where r is the number of roles, matrix $G_{n \times r}$ denotes the nodes' affiliations to roles and matrix $F_{r \times l}$ represents the association of roles and features. Thus, the problem of role discovery is to seek two non-negative low rank matrices G and F to satisfy:

$$\min_{G, F} \|V - GF\|_F^2, \text{ s.t. } G \geq 0, F \geq 0 \quad (1)$$

where $\|\cdot\|_F$ is the Frobenius norm. The non-negativity constraint in Eq. (1) makes the representation of the original data easier to interpret and more semantically meaningful. Since this objective function is not convex for all the parameters G and F simultaneously, it is not feasible to find the global minimum. Multiplicative update rules [20] are used to find its approximate solution, showing as follows:

$$G \leftarrow G \circ \frac{VF^T}{GFF^T}, F \leftarrow F \circ \frac{G^TV}{G^TG F} \quad (2)$$

where $\circ$ denotes the element-wise product. For hard role assignment, node i belongs to role j if the j^{th} element is the largest one in the i^{th} row of the nodes' membership matrix $G_{n \times r}$.

3.1.2 Stage 2: Embedding learning. After discovering roles which can capture the global structural information, the second stage is to learn subgraph embeddings. Similar to previous studies [1], we employ Paragraph Vector (PV) [19] to embed the graph-level similarities. PV learns latent representation of paragraphs and forces those paragraphs with high word co-occurrences to be mapped into embeddings with low distances. Obviously, PV considers the word level properties from both intra- and inter-paragraphs when producing paragraph level embeddings. Therefore, PV can capture both the local view of words inside the paragraph and the global view of the cross-paragraph information. By analogy with network data, subgraphs correspond to paragraphs and nodes in subgraphs are similar to words in paragraphs. The common characteristics of paragraph embedding and subgraph embedding make PV potential

Figure 2: An illustration of extension from PV [19] to subgraph embedding. The left model is PV (adopted from [19]) and right one is our proposed subgraph embedding model. Note that the input for our model is role paths from truncated random walks.

in modeling global structures of subgraphs, which able to capture structural similarities and differences between subgraphs.

To extend PV to our task, we first perform truncated random walks [33] inside each subgraph g_i separately, and not on the entire graph $\mathcal{G}$. After obtaining a set of paths, we transfer these node paths into role paths. For example, we have role assignment r_1, r_2, r_3, r_4 for nodes n_1, n_2, n_3, n_4 respectively. A node path $n_1 \rightarrow n_2 \rightarrow n_4 \rightarrow n_3$ is transferred to role path $r_1 \rightarrow r_2 \rightarrow r_1 \rightarrow r_3$. These role paths are inputted to the embedding process in PV. In the embedding process of PV framework (shown in Figure 2), each subgraph is mapped to a unique vector, represented by a column in subgraph embedding matrix W^S and each node is also mapped to a unique vector, represented by a column in node embedding matrix W^V .

In the role-guided embedding, given the embedding W_i^S of a subgraph g_i and the embedding W_t^V of a node t , the target is to predict the role r of t . Formally the object of the embedding is:

$$\max \sum_{g_i \in S} \sum_{t \in g_i} \log p(t|W_i^S, W_t^V) \quad (3)$$

where $p(t|W_i^S, W_t^V)$ is the probability of predicting role of node t given the vector representations of node t and subgraph g_i . The prediction task is typically done via a multiclass classifier, e.g., softmax [19]. In this study, we follow previous studies to use softmax which is defined as:

$$p(t|W_i^S, W_t^V) = \frac{\exp y_t}{\sum_j \exp y_j} \quad (4)$$

Each of y_t is un-normalized log-probability for each output node role t , which is defined as

$$y_t = b + Uh(W_i^S, W_t^V) \quad (5)$$

where U and b are the softmax parameters. h is constructed by a concatenation of subgraph embedding from W^S and node embedding from W^V . After optimizing Eq (3), the output W^S is the required subgraph embeddings.

3.2 Subgraph Anomaly Detection

Since we have learned the subgraph representation vectors in previous step, the target of subgraph anomaly detection is similar to traditional anomaly detection problems. In this paper, we employ Isolate Forest [24, 25] as the anomaly detection method because it has a low linear time complexity, requires a small memory, and can deal with high dimensional data.

Isolation Forest builds an ensemble of iTrees for a given data, the anomalies are those instances which have short average path lengths on the iTrees. The process of using Isolation Forest for anomaly detection consists of two stages: training stage which builds isolation trees using sub-samples of the given training set, and evaluation stage which passes test instances through isolation trees to obtain an anomaly score for each instance. In detail, the anomaly score s for instance x is defined as:

$$s(x, \psi) = 2^{-\frac{E(h(x))}{c(\psi)}} \quad (6)$$

where $E(h(x))$ is the average of $h(x)$ from a collection of the constructed iTrees. $c(\psi)$ is the average of $h(x)$ given ψ . ψ is used to normalize $h(x)$ and defined as

$$c(\psi) = \begin{cases} 2H(\psi - 1) - 2(\psi - 1)/n & \text{for } \psi > 2, \\ 1 & \text{for } \psi = 2, \\ 0 & \text{otherwise.} \end{cases} \quad (7)$$

where $H(\cdot)$ is the harmonic number and it can be estimated by $\ln(i) + 0.5772156649$ (Euler's constant). ψ is the subsampling size.

3.3 Computation Complexity

The complexity of two steps of SADE are analyzed as follows:

- 1 Subgraph embedding. There are two stages in this step. For the role discovery, the time complexity is linear on the number of edges, i.e., logarithm number of edges and formally it is $O(|E| \cdot f + |V| \cdot f \cdot r)$ [16], where f is the number of extracted features and r is the number of roles. For the embedding, using Hierarchical Softmax and Negative Sampling,

the time complexity is $O(\log(|V| + |S|))$, i.e., logarithm of the numbers of nodes and subgraphs.

- 2 Subgraph anomaly detection. In Isolation Forest based anomaly detection, the worst case time complexity of the training stage and the evaluation stage are $O(|T| \cdot \psi^2)$ and $O(|S| \cdot |T| \cdot \psi)$ respectively, where $|T|$ is the number of trees [25].

Overall, the framework is efficient which can be seen to be linear on the number of edges, as in practice the other parameters, e.g., the number of extracted features, roles, trees and the sub-sampling counts, are set to be much smaller values compared to the number of edges and nodes in large real-world networks.

4 EXPERIMENTS

In this section, we evaluate the effectiveness of our proposed SADE framework empirically. We first introduce experimental settings. Then we discuss our experimental results in different datasets and analyze the influence of parameters.

4.1 Experimental Setup

To demonstrate the effectiveness of our proposed framework in detecting anomalous subgraphs, we select several representative graph-level embedding methods as our baselines:

- *graph2vec* [27] constructs Weisfeiler-Lehman tree features for nodes in graphs and then learn graph representations by decomposing the graph-feature co-occurrence matrix.
- NetLSD [35] extracts compact graph signatures based on the heat or wave kernel of the Laplacian, which inherit the formal properties of the Laplacian spectrum.
- *Gl2vec* [8] extends *graph2vec* by exploring the line graph. The learned embeddings are generated by concatenating the embeddings of the original graph and line graph.
- FGSD [36] learns graph-level representations based on the family of graph spectral distances. The Moore-Penrose spectrum of the normalized Laplacian is used as the graph embedding.
- *GeoScattering* [11] uses geometric scattering transform as a deep filter bank for feature extraction. Moments of the wavelet transformed features are used as embedding.
- *Sub2Vec* [1] also utilizes PV model [19]. It extends PV to learn subgraph embedding while preserving distance between subgraphs that have similar ‘node co-occurrences’.

Besides, we also compare SADE to a node-level embedding method, i.e., *node2vec* [14]. Note that we average the node embedding in each community as the subgraph representation.

4.2 Ring, Star and Tree Detection in the Synthetically Generated Toy Network

We use a toy example of the synthetically generated network to demonstrate the effectiveness of our proposed SADE framework in subgraph anomaly detection and the failure of other state-of-the-art network embedding techniques in this task. The toy network consists of 10 subgraphs and each subgraph has 10 nodes. There are 7 normal subgraphs following the power-law distribution of degrees and three anomalous subgraphs including 1 ring, 1 star and 1 tree with a depth of 3.

Figure 3 shows the visualization of learned subgraph embeddings by different methods after using PCA to reduce the dimension to 2. For our framework, the number of role is 16. The latent dimension is 16 for all methods except methods that determine latent dimension automatically, i.e., NetLSD, FGSD and GeoScattering. For shared parameters in all methods, we use the same settings: number of walks per node: 20, walk length: 64, skipgram window size: 4. Other parameters are set by default. It can be observed that most previous network embedding approaches can only detect part of these anomalous subgraphs and fail to identify all three different structures. For example, *graph2vec*, *node2vec* and *GeoScattering* only detect the star. *Sub2Vec* distinguish the ring and star but fail to identify the tree. However, our proposed framework can effectively detect all three anomalous subgraphs shown in 3i.

4.3 Pyramid Scheme Detection from Bank Transactions

In this experiment, we test the effectiveness of SADE in a real-world application, detecting pyramid schemes from a transaction network. Pyramid scheme is a kind of anomalous financial groups, in which each member’s transaction behaviors could be normal, however collective behaviors of the whole group are fraudulent. In general, money is transferred from bottom accounts to top accounts, making the transaction subgraph inside each group in the shape of a tree. The target is to detect such anomalous pyramid schemes from a transaction network.

We use a real-world data consists of bank transaction records from a security institution in China. It contains 10141 bank accounts, connected by 33754 edges, belonging to 78 non-overlapping pyramid communities. The number of nodes in those anomaly subgraphs ranges from 89 to 198. However, the information of normal accounts is unknown. Therefore, we derive and augment two networks based on the real-world data. Specifically, in the augmented networks anomaly subgraphs are tree-like structures from the real pyramid schemes, and normal subgraphs are communities whose size and node degrees obey power law distributions. Random edges are created between subgraphs.

We augment two networks for the experiment, a smaller network with 4 anomalous subgraphs (Small Network) and a larger network with 78 subgraphs (Large Network). A brief statistics of these networks is shown in 1. Considering the characteristics of real case scenario in anomaly detection, we make the ratio between numbers of normal and anomalous subgraphs nearly 10:1. The experimental results are shown in Table 2 and 3. Note that for fair comparison, Isolation Forest has been used for all methods for anomaly detection. Under the evaluation measures of precision and recall, it can be observed that our proposed framework outperforms the state-of-the-art approaches in detecting anomalous subgraphs, i.e., pyramid schemes. Since the Small Network is augmented from a subset of the real data, it is less complex than the Larger Network. Thus, the performance on the Small Network looks better.

4.4 Parameter Sensitivity

There are three parameters in our proposed SADE framework: (1) number of roles r , (2) latent dimension d and (3) random walk length l . In the experiments, we investigate the impact of these parameters

Table 1: Statistics of derived and augmented networks.

Dataset	Number of nodes	Number of edges	Number of normal subgraphs	Number of anomalous subgraphs
Small Network	6,000	28,065	42	4
Large Network	21,141	1,355,790	657	78

Figure 3: (a) The toy network and Visualizations of subgraph embeddings learned by (b) *graph2vec*, (c) NetLSD, (d) test, (e) *Gl2vec*, (f) FGSD, (g) GeoScattering, (h) *Sub2Vec*, and (i) Our proposed method.

separately. Specifically, we test anomaly detection performances by ranging r from 6 to 16 with interval 2, d from 2^4 to 2^9 , and l from 2^3 to 2^8 . The results for different parameters are shown in Figure 4.

From the results, it can be observed that the impacts of different parameters are different. Some conclusions on parameter selection can be drawn: (1) larger role numbers generally achieve better performance because larger values can capture the differences in global roles; (2) latent dimensions should not be too small or too large because smaller dimension may lack representation power

while larger value may contain redundant information; and (3) random walk length also should not be too small or too large with similar reasons to dimension.

5 RELATED WORK

Our research is related to two lines of studies: anomaly detection in networks and graph embedding.

Figure 4: Analysis of sensitivity of different parameters in Small Network.

Anomaly Detection in Networks. Anomaly detection is one of the most important research questions in different types of data, e.g., text [18] and networks [5]. Compared to anomaly detection on other types of data, anomaly detection in networks is challenging because network data disobeys the *i.i.d.* In this section, we focus on the related works of anomaly detection in networks.

CODA [12] focuses on community anomalies by simultaneously finding communities as well as spotting anomalies using a unified probabilistic model. AMEN [32] uses both attribute and network structure information to detect anomalous neighborhoods. Radar [21] detects anomalies whose behaviors are singularly different from the majority by characterizing the residuals of attribute information and its coherence with network information. ANOMALOUS [31] is a joint anomaly detection framework to optimize attribute selection and anomaly detection using CUR decomposition of matrix and residual analysis on attribute networks. DOMINANT [9] utilizes GCN to compress the input attributed network to succinct low-dimensional embedding representations and then reconstruct both the topological structure and nodal attributes with these representations. MADAN [15] is a multi-scale anomaly detection method. It uses the heat kernel as filtering operator to exploit the link with the Markov stability to find the context for outlier nodes at all relevant scales of the network.

Graph Embedding. Graph embedding methods aim to map nodes or graphs into points in a low-dimensional space according to their structural information in the given graph(s). The learned representations can boost performance in many network analysis tasks, e.g., graph classification [1], link prediction [14] and role discovery [29]. Graph embedding, according to the target, can be categorized into node-level and graph-level methods.

Previous node-level methods mainly viewed embedding as dimensionality reduction techniques [13]. With increasing attention attracted by neural network research, unsupervised neural network techniques have opened up a new world for embedding. *word2vec* as well as Skip-Gram and CBOW [26] learn low-rank representations of words in text based on word context and show promising results of different NLP tasks. Based on *word2vec*, DeepWalk [33] first introduces such embedding mechanism to networks by treating nodes as words and random walks as sentences. Afterwards, a sequence of studies have been conducted to improve DeepWalk either by extending the definition of neighborhood to higher-order proximities [34] or incorporating more information for node representations such as attributes [22] and heterogeneity [7].

Table 2: Results on the Small Network

Methods	Precision	Recall
<i>noded2vec</i>	0.4512	0.4405
<i>graph2vec</i>	0.5634	0.5774
NetLSD	0.6756	0.7143
<i>Gl2vec</i>	0.5634	0.5774
FGSD	0.6756	0.7143
<i>GeoScattering</i>	0.7878	0.8512
<i>Sub2Vec</i>	0.7878	0.8512
SADE (Ours)	0.9000	0.9881

Table 3: Results on the Large Network

Methods	Precision	Recall
<i>noded2vec</i>	0.4045	0.4115
<i>graph2vec</i>	0.5086	0.5082
NetLSD	0.5387	0.5369
<i>Gl2vec</i>	0.5312	0.5297
FGSD	0.5134	0.5120
<i>GeoScattering</i>	0.4936	0.4939
<i>Sub2Vec</i>	0.5086	0.5082
SADE (Ours)	0.5612	0.5584

On the other hand, different graph-level embedding methods have been proposed. *graph2vec* [27] first constructs Weisfeiler-Lehman tree features for nodes in graphs and then learn graph representations by decomposing the graph-feature co-occurrence matrix. *NetLSD* [35] extracts compact graph signatures based on the heat or wave kernel of the Laplacian, which inherit formal properties of the Laplacian spectrum. *Gl2vec* [8] extends *graph2vec* by further exploring the embedding of the defined line graphs, complementing the learning information of *graph2vec*. The learned embeddings are generated by concatenating the embeddings learned from *graph2vec* and the line graphs, aiming to preserve the missed edge features by *graph2vec*. *FGSD* [36] learns graph-level representations based on the discovery of family of graph spectral distances. *GeoScattering* [11] presents the geometric scattering transform as a deep filter bank for feature extraction, also proves its potential of serving as universal representations of graphs. *Sub2Vec* [1] also

utilizes PV model [19] to learn distributed representations of subgraphs. It extends PV to learn subgraph embedding while preserving distance between subgraphs that have similar node co-occurrences reflected by paths of node id and degrees.

Recently, to bridge graph embedding and anomaly detection, learning anomaly aware network representations also attracts huge attentions [4, 23]. SEANO [23] is a semi-supervised network embedding approach which learns a low-dimensional vector representation that systematically captures the topological proximity, attribute affinity and label similarity of nodes. ONE [4] jointly aligns and optimizes the structures and attributes to generate robust network embeddings by minimizing the effects of outlier nodes. However, these studies only focus on node-level anomaly but our framework aims at detecting subgraph-level anomaly.

6 CONCLUSIONS

In this paper, we introduced a novel problem of detecting subgraph-level anomalies in financial transaction networks whose structures deviate from underlying majority subgraphs in the network. To capture the local and global structural similarities between subgraphs, we proposed a role-guided anomaly detection framework (SADE) which allows learning the role-guided subgraph embedding in which state-of-art anomaly detection approaches can be used effectively. Our extensive experiments on transaction networks demonstrated the effectiveness of SADE in detecting anomalous subgraphs with the use of the Isolation Forest in the learnt embedding. This promising results suggest that SADE can be employed in the early warning systems at financial institutions.

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