ABSTRACT

In recent years, phishing scams have become the most serious type of crime involved in Ethereum, the second-largest blockchain platform. The existing phishing scams detection technology on Ethereum mostly uses traditional machine learning or network representation learning to mine the key information from the transaction network to identify phishing addresses. However, these methods adopt the last transaction record or even completely ignore these records, and only manual-designed features are taken for the node representation. In this paper, we propose a Temporal Transaction Aggregation Graph Network (TTAGN) to enhance phishing scams detection performance on Ethereum. Specifically, in the temporal edges representation module, we model the temporal relationship of historical transaction records between nodes to construct the edge representation of the Ethereum transaction network. Moreover, the edge representations around the node are aggregated to fuse topological interactive relationships into its representation, also named as trading features, in the edge2node module. We further combine trading features with common statistical and structural features obtained by graph neural networks to identify phishing addresses. Evaluated on real-world Ethereum phishing scams datasets, our TTAGN (92.8% AUC, and 81.6% F1-score) outperforms the state-of-the-art methods, and the effectiveness of temporal edges representation and edge2node module is also demonstrated.

CCS CONCEPTS
• Applied computing → Digital cash; • Security and privacy → Phishing.

KEYWORDS
Blockchain, Ethereum, Phishing scams detection, Network representation learning

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The current methods of phishing scam detection on Ethereum are to learn the representation of phishing nodes through the transaction network and classify nodes [2, 19], in which nodes represent Ethereum transaction addresses and edges represent transactions between addresses. The main detection methods can be roughly divided into two types. One is to combine traditional machine learning and manual-designed features (i.e., structural and statistical features) of nodes for phishing detection [9]. However, these methods mainly rely on professional knowledge to extract manual-designed features (e.g., node’s in-degree, total transaction amount, transaction time interval, etc.), which are inefficient and non-automated. The other one is to apply network representation learning to the Ethereum transaction network for mining deep features. Random walk [30, 31] and graph neural network [8] are adopted to automatically learn representations from the Ethereum transaction network, which has made a very important breakthrough. However, there are still two remaining problems: (1) Lack of temporal transaction information. The existing methods only adopt the last transaction record or even completely ignore these records, instead of taking temporal information of transaction records into consideration, which leads to the incomplete edge representations in the Ethereum transaction network. (2) Weak node representation. Only statistical and structural features extracted from transaction records are considered as the node representation, while trading features referring to the contextual information of transaction records are ignored totally. In summary, the lack of temporal transaction information and weak node representation finally cause the unsatisfactory performance of Ethereum phishing addresses detection.

To address the above challenges, in this paper, we propose Temporal Transaction Aggregation Graph Network (TTAGN) to enhance phishing scams detection on Ethereum by effectively utilizing transaction temporal information. We first build a large-scale Ethereum multilateral directed transaction network graph, in which a node is a unique address and a directed edge refers to a transaction between two addresses, and obtain the nodes’ basic statistical features. We design three modules to generate node representations by graph mining. In detail, the graph is fed to the Temporal Edge Representation module which fully models and mines temporal information of Ethereum transaction records between transaction nodes to generate the edge representations. In the Edge2node module, the edge representations around the node are aggregated to fuse topological interactive relationships into its representation, also named as trading features, which enriches the characteristics of the nodes. We also extract the common structural features in the Structural Enhancement module and further combine statistical, structural and trading features to generate the final node representation. Finally, the obtained node representations are fed into the classifier to identify phishing nodes. Extensive experiments are conducted on real-world datasets to verify the effectiveness of TTAGN.

**Contributions.** Our contributions can be summarized as:

- We propose a Temporal Transaction Aggregation Graph Network (TTAGN) to enhance the Ethereum phishing scams detection performance by combining trading, structural and statistical features.
- All the directed transaction edges (records) between nodes (addresses) in the Ethereum transaction graph (network) are modeled to mine the temporal information and enrich the edge representation.
- The edge representations around each node are aggregated to fuse topological interactive relationships to generate the trading features.
- We conduct extensive experiments on real-world Ethereum phishing scam dataset and results show that TTAGN outperforms state-of-the-art methods on multiple metrics.

The remainder of the this paper is organized as follows. Section 2 summarizes the prior researches related to our work. Section 3 introduces the problem statement of this paper. Section 4 highlights the overall design of TTAGN and Section 5 illustrates the experiments. Section 6 concludes the paper.

## 2 RELATED WORK

Phishing scams detection on Ethereum is a new fraud scenario. In this section, we first briefly review prior work on Ethereum phishing scams detection. Next, we review the network representation learning which is the core task of Ethereum phishing scams detection.

### 2.1 Ethereum Phishing Scams Detection

For the phishing scams detection problem on Ethereum, there are two main categories of existing methods.

The former mainly employ shallow models such as traditional machine learning methods with dedicated feature engineering, focusing on statistical features. Chen et al. [9] extracted 219-dimensional statistical features from the node’s 1-order and 2-order neighbors, including the node’s in-degree, out-degree, maximum transaction value, and so on. Then they used a LightGBM-based ensemble machine learning algorithm to identify phishing nodes.

The latter applies some network embedding methods such as DeepWalk [21], Node2Vec [11], and graph convolutional networks (GCN) [17] to mine deep features. Wu et al. [30] proposed Trans2Vec on the basis of Node2Vec [11]. The difference between Trans2Vec and Node2Vec is that the sampling process of Trans2Vec is not random, but biased based on the last transaction of the two nodes, which is more suitable for phishing detection on Ethereum. Chen et al. [8] designed E-GCN to detect phishing nodes, which is the first time GCN [17] has been introduced in Ethereum phishing node detection. They extracted 8-dimensional statistical features and then used GCN to learn the structural characteristics of the transaction network.

However, these works rarely use the temporal information of transaction behaviors, so they can not capture complete edge representations. Moreover, only manual-designed features are taken for the node representation, which further led to weak node representation capabilities of these detection methods.

### 2.2 Network Representaion Learning

According to a survey [10], network representation learning (i.e., graph embedding or network embedding) methods can be summarized into three categories: based on (1) Factorization, (2) Random Walk, and (3) Deep Learning.

Factorization-based algorithm uses the connection information between nodes to construct various matrices (e.g., Laplacian matrix,
adjacency matrix, and Katz similarity matrix), and then factorize the above matrix to obtain embeddings. The models associated with factorization are, for example, Locally Linear Embedding (LLE)[22], Laplacian Eigenmaps[4], Graph Factorization[1], Learning Graph Representations with Global Structural Information (GraRep)[5], High-Order Proximity Preserved Embedding (HOPE)[20].

Random walk-based algorithm utilizes walk to perceive the centrality and similarity of nodes. DeepWalk[21] tries to maximize the co-occurrence probability of nodes in the window after obtaining the node sequence of random walk. As for Node2Vec[11], in the first stage of generating nodes’ corpus, the walking decision is more flexible than DeepWalk, but the time consumption increases greatly. Different from DeepWalk, Large-scale Information Network Embedding (LINE)[24] aims to generate neighbors rather than nodes on a path based on current nodes.

Deep learning-based method mainly uses deep neural networks to learn non-linear information in graphs. Structural Deep Network Embedding (SDNE)[27] applies deep autoencoders to keep network proximities within 2-order. It uses a semi-supervised autoencoder to reconstruct the neighbor relationships of the nodes and uses a supervised approach to trim the results. GraphSAGE[12] is an inductive GNN model based on a fixed sample number of the neighbor nodes and Graph Attention Networks (GAT)[26] employs attention mechanism for neighbor aggregation.

We have selected representative works from three categories for comparison in the subsequent experimental part, which further highlights the effectiveness of our model.

3 PROBLEM DEFINITION

In this paper, the Ethereum phishing scams detection task is phrased as a graph node classification problem. Let the partially labeled Ethereum transaction network $G_L = (V, E, X, C)$, we treat the transaction address as a node $v_i$, $V = \{v_1, \ldots, v_N\}$ is a set of addresses. The transaction as an edge $E_t$, $E = \{E_1, \ldots, E_R\}$ is the transaction set. The transaction direction, amount and time information as the edge attributes $X \in \mathbb{R}^{|E| \times S}$ where $S$ is the size of the feature space for each edge, and $C \in \mathbb{R}^{|V| \times |D|}$ where $Y$ is the set of labels. The goal of our model is to efficiently learn the representation of nodes from the known large-scale transaction network information, so we learn the embeddings of all nodes $X_E \in \mathbb{R}^{|V| \times d}$ where $d$ is the number of dimensions for feature representation.

4 DESIGN OF TTAGN

TTAGN enhances the representation of edges by modeling transaction temporal information, finally improving the identification of Ethereum phishing nodes. Specifically, TTAGN includes three modules, named building transaction graphs, learning network embedding and phishing addresses detection.

4.1 Temporal Transaction Graphs

Based on a large amount of Ethereum transaction data obtained, we first build a large-scale Ethereum transaction Multiple edges Directed Graph (MultiDiGraph). In the transaction graph, we use nodes to represent Ethereum transaction addresses, and edges to represent transactions between addresses. Noting that the Ethereum transaction MultiDiGraph allows multiple directed edges between any pair of nodes, and each edge carries information of the transaction, such as the transaction amount in ETH (the unit of Ether) and the execution timestamp. The scale of the original graph is huge, so we take the sampling step with a random walk. We randomly select a node from the graph to start walking, then randomly select its neighbor as the next node, and repeat this process until the number of nodes reaches our requirement. After that we obtain subgraphs of the scale we want.

The collected subgraph will first perform feature engineering to prepare for the subsequent learning of the structural features of the node. Because of the anonymity of the blockchain platform, the node itself does not carry any attribute characteristics. So we extract the following 10-dimensional features as the attribute characteristics of the node. They are the node’s total degree, out-degree, in-degree, the sum of transactions amount, transfer out transaction amount, transfer in transaction amount, the total number of neighbors, the inverse of transaction frequency, the percentage of neighbors whose transactions are all zeros, and the number of transactions with the most frequent neighbors.

4.2 Model Architecture

TTAGN is a network representation framework to detect phishing addresses. As shown in Figure 2, the architecture could be divided into three objectives: temporal edges representation, edge2node, structural enhancement.

4.2.1 Temporal Edges Representation. In this module, edge representations are generated from transactions interaction relationships between nodes.

This module improves the detection effect by introducing transaction temporal information. Transaction information includes transaction direction, amount, time, etc., which will reflect the difference between phishing addresses and normal at the transaction level. Therefore, by introducing the transaction information, the nodes’ representations are enhanced.

However, there are two difficulties with using transaction information directly: (1) Sequential. Transactions are temporal and inherently sequential, this information needs to be incorporated into edge representations. (2) Variable length. The number of transactions between nodes is different, edge representations should include all valid information without causing information redundancy.

As for sequential, we apply the sequence model LSTM[14] to characterize the multiple temporal transactions and capture the temporal pattern of interaction between a pair of nodes. As Figure 3 shows, the transactions between each pair of nodes are treated as a time series, sorted in ascending order by timestamp, and then be fed into the LSTM model. For the node pair $(u, v)$, we denote $e_{uv}$ as the edge embedding generated by the sequence model LSTM, where:

$$
\hat{e}_{uv} = \text{LSTM} \left( \begin{pmatrix} e_{u1}^{\alpha} & e_{u1}^{\beta} & \cdots & e_{u1}^{\alpha} \\
\vdots & \vdots & \ddots & \vdots \\
{e_{uni}^{\alpha}} & {e_{uni}^{\alpha}} & \cdots & {e_{uni}^{\alpha}} \end{pmatrix} \right)
$$

$$
= \text{LSTM} \left( \begin{pmatrix} d_{u1}^{\alpha} & 1 & e_{u1}^{\beta} & \cdots & (e_{uni}^{\alpha} \cdot e_{uni}^{\beta}) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
{d_{uni}^{\alpha} \cdot 1} & {d_{uni}^{\alpha} \cdot 1} & \cdots & {d_{uni}^{\alpha} \cdot 1} \end{pmatrix} \right)
$$

(1)

Among them, $d_{uv}^\alpha$ represents the transaction amount of the $i$-th transaction with direction between nodes $u$ and $v$. The plus or minus of $d_{uv}^\alpha$ represents the direction of this transaction, if the
node transfers ETH to other nodes, $\alpha$ is positive, else, the value is negative. $t_{uv}^n$ represents the transaction timestamp of the $n$-th transaction between nodes $u$ and $v$.

As for variable length, we realize the variable-length input of LSTM, further make full use of the temporal transaction records. Combining the above two points, we captured the temporal relationship of historical transaction records, generated effective edge representations, and simplified the complex graph structure (convert MultiDiGraph to undirected graph with edge representations), which is helpful for the subsequent node classification work.

4.2.2 Edge2node. In this module, nodes representations are enriched by biased aggregation of edge representations with temporal transaction information to the nodes.

In the transaction network on Ethereum, the node itself does not carry information, and only manual-designed features are not comprehensive which leads to weak node representation. Each Ethereum transaction node usually interacts with multiple nodes at the same time, and is also connected with multiple transaction edge representations. We need to fuse its interaction with all other nodes into its representation. Meanwhile, different interaction have different effects on the node representation.

To solve these problems, we aggregated the edge representations around each node to fuse topological interactive relationships. Moreover, we adopt Attention [25] with multiple levels mechanism to catch similar transaction behaviors, and finally generate the trading features. Figure 4 shows the main steps of edge2node. For each node of input transaction graphs, the edge2node learns the weights of adjacent edges and aggregates them to get the expressive node representation. Given $N_u$ denotes the adjacent edges of node $u$ and edge $v \in N_u$, the importance node-edge pair $(u, v)$ can be formulated as follows:

$$e_{uv}^\Phi = \sigma \left( a_{uv}^\Phi \cdot [h_u \| h_v] \right)$$

$$a_{uv}^\Phi = \text{softmax}_v \left( e_{uv}^\Phi = \frac{\exp \left( e_{uv}^\Phi \right)}{\sum_{k \in N_u^\Phi} \exp \left( e_{uk}^\Phi \right)} \right)$$

where $h_u$ and $h_v$ are the features of node $u$ and edge $v$, $a_{uv}^\Phi$ is the attention parametrize matrix for transaction graph $\Phi$, $\sigma$ denotes the activation function, and $\|$ denotes the concatenate operation.

Then, the node $u$ trading features can be obtained by aggregating all edge neighbor attributes with the corresponding coefficients as follows:

$$z_u^\Phi = \|_{k=1}^{K} \left( \sum_{v \in N_u^\Phi} a_{uv}^k \cdot h_v \right)$$

where $z_u^\Phi$ is the learned trading features of node $u$ for the transaction graph $\Phi$, $K$ is the head number using the multi-head attention mechanism[25].

4.2.3 Structural Enhancement. In this module, structural features are obtained by reconstructing the transaction graph. The above two modules focus more on extracting effective transaction features. In order to obtain a comprehensive node representation, in this module, we pay more attention to extracting the
which is essentially a decoding process, and with added self-connections where $\mathbf{I}$ is the identity matrix, $\hat{A} = A + I$ is the adjacency matrix $A$ with added self-connections $I$. $\hat{D}$ is the degree matrix of $\hat{A}$, and $W(l)$, $\sigma(\cdot)$ is the layer-specific trainable weight matrix and activation function, respectively. $H(l) \in \mathbb{R}^{n \times k}$ means the matrix of activation in $l$ layer, while $n$ and $k$ denote the number of nodes and output dimensions of layer $l$.

The overall framework of the module can be defined as follows

$$Z = GCN(X,A)$$

where $X$ is the input node embedding, $Z$ is the representation of all transaction nodes learned in the last layer of GCN. $ZZ^T$ is an operation that reconstructs the original graph structure with $Z$, which is essentially a decoding process, and $\hat{A}$ is the reconstructed adjacency matrix obtained after decoding. The reconstructed loss can be written as

$$L_{\text{recon}} = \frac{\|\hat{A} - A\|_F^2}{n}$$

where $\| \cdot \|_F$ denotes the $F$-norm of a vector. By minimizing the reconstruction loss $L_{\text{recon}}$, $Z$ will learn a more comprehensive node representation that includes the structural features of the transaction graph nodes.

4.3 Phishing Addresses Detection

The task of this section is to classify nodes to distinguish between phishing nodes and normal nodes. After the above operations, we have obtained three types of features: trading features learned from edge2node with statistical features as node embedding, and input them into the GCN as the encoder to learn the structural features of the node.

The spectral convolution function is formulated as

$$H^{(l+1)} = \sigma(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)})$$

Figure 3: Process of learning edge representation from the Ethereum transaction network.

Figure 4: Illustration of the edge2node module.

5 EXPERIMENTS

In this section, we perform empirical evaluations to demonstrate the effectiveness of the proposed TTAGN framework. Specifically, we aim to answer the following research questions:

- **RQ1**: How effective is the proposed approach TTAGN for detecting phishing addresses on the Ethereum transaction network?
- **RQ2**: How does each component of TTAGN (i.e., temporal edge representation, edge2node and structural enhancement) contribute to the final detection performance?
- **RQ3**: How much will the performance of TTAGN change by providing different maximum temporal sequence lengths or different attention hidden sizes?

5.1 Datasets

5.1.1 Data Collection. We crawled accounts labeled “phishing” from the Ethereum label cloud of the authorized website Etherscan. As of July 2021, 4,932 addresses have been verified to be phishing addresses. With these labeled nodes being the central nodes, we extract their first-order, second-order neighbors and the transactions between all of them through the API provided by Etherscan. Finally, we obtain 6,844,050 Ethereum addresses and 208,847,461 transaction records. The scale of the original graph is huge, so we sample with random walks to obtain subgraphs as

1https://etherscan.io
Table 1: Statistics of evaluation datasets. Labeled represents the number of labeled nodes in the dataset, and each number is the average calculated by five subgraphs.

| Dataset | #Total Nodes | #Labeled | #Edges | #Average Degree |
|---------|--------------|----------|--------|-----------------|
| D1      | 30000        | 108      | 25048388 | 834.9741       |
| D2      | 40000        | 139      | 27481082 | 687.0442       |
| D3      | 50000        | 170      | 29854251 | 590.8691       |

our datasets with sizes of 30,000, 40,000, and 50,000 respectively, denoted as D1, D2, D3. For each subgraph of different sizes, we sample five times to ensure the effectiveness of the performance. Detailed data information is shown in Table 1.

5.1.2 Data Cleaning. After getting all the data, we found that the class is very imbalanced. We refer to the data cleaning steps of [9], eliminating obvious non-phishing addresses to build a more effective model. (1) We clean all transactions that appear before timestamp 2016-08-02 because all phishing addresses are active after this time; (2) We eliminate addresses with less than 5 or more than 1,000 transaction records which may be wallets or other normal types of accounts [9, 30], and we also did data analysis which proves that these addresses are not phishing nodes. After data cleaning, the average number of remaining nodes in each subgraph is 46930, 37194, and 27538 respectively. In the final classification task, we set 80% of the total data as training data and the rest as test data.

Finally, each subgraph is embedded through TTAGN to obtain the nodes’ representations for the downstream classification task. In the final classification task, we set 80% of the total data as training data and the rest as test data.

5.2 Experimental Setup

5.2.1 Comparison Methods. We compare our proposed TTAGN framework with four categories of Ethereum phishing scams detection methods, including (1) Feature-based methods where only the node attributes are considered[9], (2) Factorization-based network embedding methods[22], and (3) Random walk-based network embedding methods (i.e., DeepWalk[21], Node2Vec[11], and LINE[24]) where both topological information and node attributes are involved. In addition, we also use some of the popular (4) Deep learning-based network representation methods (SDNE[27], E-GCN[8], GraphSAGE[12] and GAT[26]) to learn nodes representations to compare with the representations learned by our method.

- Features only [9] are 219-dimensional statistical features from the node’s 1-order and 2-order neighbors.
- LLE [22] factorizes the constructed matrix which uses the connection information to obtain embeddings.
- DeepWalk [21] tries to maximize the co-occurrence probability of nodes in the window after obtaining the node sequence of random walk.
- Node2Vec [11] defines a more flexible notion of a node’s neighborhood and exploits a biased random walk to encode both local and global network structures.
- LINE [24] learns a low-dimensional embedding via preserving the first-order and second-order closeness of nodes.
- SDNE [27] uses semi-supervised autoencoder to reconstruct the neighbor relationships and supervised approaches to trim the results.
- GraphSAGE [12] is an inductive GNN model based on a fixed sample number of the neighbor nodes.
- GAT [26] employs attention mechanism for neighbor aggregation.
- E-GCN [8] is the first time that Graph Neural Network has been applied to Ethereum phishing node detection.

5.2.2 Evaluation Metrics. In this paper, we use the following four metrics to have a comprehensive evaluation of the performance of different methods in terms of Ethereum phishing scam detection:

(1) Area Under Curve (AUC). The AUC metric is to calculate the area under the ROC curve formed by TPRs and FPRs with multiple thresholds, which is frequently used in binary classification tasks.
(2) Recall. The recall rate means the percentage of known phishing nodes samples detected.
(3) Precision. The precision rate means the percentage of real phishing nodes are in the accounts that are judged to be suspicious.
(4) F1-score. F1-score is a comprehensive evaluation of the Precision and Recall score.

5.2.3 Implementation Details. The embedding size of all models is fixed to 10. For attention, we set the attention hidden size to 2 and the learning rate to 0.01. For GCN in our method, we set two layers with 0.001 learning rate. For DeepWalk and Node2Vec, the walk length, window size, the latter’s p and q are set to 20 and 4, 0.25, 0.4, respectively. For the LightGBM model, the number of leaves and the learning rate are empirically fixed at 50 and 0.03, respectively. Due to the imbalance of the data, we upsamp the minority class with a ratio of 50. For all the comparison methods, we set parameters based on their official implementations.

5.3 Effectiveness Results (RQ1)

To answer RQ1, we evaluate the performance of all the compared methods in the task of phishing scams detection on Ethereum. The corresponding results are reported in Table 2. We can draw the following conclusions:

(1) In terms of the four evaluation metrics, our approach TTAGN outperforms all the other compared methods by a significant margin. Our method TTAGN achieves the best performance about 92.8%AUC, 85.9% Recall, 77.7% precision and 81.6% F1-score under D3 dataset. The second best method is deep learning methods which reach the AUC exceeding 80%. The performances of the random walk-based method and the factorization-based method are similar, and their indicators are both around 75%. The worst performance is the feature-based method, and its Recall rate is very low, only about 55%.
(2) TTAGN has better node representation capability on large graphs. As the number of datasets nodes increases from 30,000 to 50,000, the gap between TTAGN and other comparison methods is further widened. Compared with the well-performing GraphSAGE method, the AUC difference between the two methods is 6.5% on D1 and 12.6% on D3. These results again demonstrate that TTAGN can better detect phishing nodes on large-scale transaction networks than other methods by fully mining temporal information of Ethereum transaction records between transaction nodes.
(3) Compared with the feature-based methods, our four evaluation metrics are nearly 20% higher than them. The performance of the feature-only method is the worst across all compared methods. When the dataset is small, its effect is better than the factorization-based method, but as the number of nodes increases, the information that the statistical features can learn is very limited. Apart from the lack of feature mining, it may be because of these methods’ unawareness of the network structure and environment information that we obtain from the structural enhancement module.

(4) As for the random walk-based methods, LINE performed the best, which is lower than our method 12.6% AUC and 18.4% F1-score on the D3 dataset. LINE uses the deep excavation of proximity within the second-order, through it LINE can perceive the nearby information than Deep Walk and Node2Vec. However, this type of methods completely ignores the transaction records between the nodes, which lead to incomplete representation learning of nodes. In our method TTAGN, we model the temporal relationship of historical transaction records, which makes full use of transaction information and learns the effective edge representation.

(5) Network representation methods based on deep learning are our strong opponents, however, they are also not performing well. On the dataset D3, our four evaluation metrics are nearly 10% higher than it. As for GraphSAGE, it does not explore label distribution when sampling, thus they perform worse than GAT. GAT performs worse than our method TTAGN because in the biased aggregation step, GAT aggregates neighbors with statistical characteristics, while we use the edge2node module to aggregate the obtained edge representations to nodes. This approach enriches the characteristics of the nodes and strengthens the nodes’ representation ability.

5.4 Ablation Study (RQ2)

To answer RQ2 and validate the effectiveness of our innovation, we eliminate the Temporal Edge Representation module (i.e. TTAGN/t), the Edge2node module (i.e. TTAGN/e) and the Structural Enhancement module (i.e. TTAGN/a) respectively.

As shown in Figure 5, the corresponding observation results have the following aspects:

(1) Compared to TTAGN, the performance of TTAGN/t drastically degrades, which are 7%, 8.5%, and 9.8% lower than TTAGN’s

\[ \text{AUC Recall Pre F1} \]

on D1, D2, and D3 datasets, respectively. The main reason is the sequences model LSTM can fully extract the temporal pattern of transaction interaction between nodes, learn expressive edge representations. This result indicates that learning temporal edges representation of each edge in the transaction graph is essential for the phishing scams detection task, and also proves the importance of edges with transaction information in the transaction graph.

(2) After removing the edge2node module, TTAGN/e is 6.4% lower than the full model on the D3 dataset. The main function of edge2node is to aggregate around edges representations into nodes. If the learned edge representations are directly spliced with statistical features as classification features, the effect is far inferior to aggregation on nodes. The result proves that the aggregation of edges representations can more comprehensively capture the features of the nodes and strengthen the nodes’ representation ability. The edge2node module and the temporal edges representation module complement each other and are indispensable.

(3) Among the three modules, the structural enhancement module contributes the least. The AUC of TTAGN/a on the D3 dataset is 3.1% lower than TTAGN. It seems that this module is not as significant as the temporal edges representation and edge2node effects, but it also effectively extracts the information of the topological environment. These obtained structural information further enriches the representations of the nodes.

(4) The performance of the complete model TTAGN on the three datasets is better than other ablation models. This proves that each module could provide effective improvement to finally lead to the significantly high AUC of TTAGN. At the same time, as the graph
scale becomes larger, the gap between the models is further widened, proving that TTAGN is more effective on large-scale transaction graphs.

5.5 Sensitivity Analysis (RQ3)

To answer RQ3, we further evaluate the performance of TTAGN with respect to the transaction sequence length and edge2node attention size.

Figure 6 presents four metrics scores of TTAGN on three datasets when varying the fixed value of transaction sequence length. The variable-length is also used as a parameter on the far right of the axis. Specifically, we can clearly find that (1) as the fixed value of transaction sequence length increases, combining the four evaluation metrics, the model has achieved enhanced performance on all datasets; (2) Sometimes shorter sequences perform better than the longer sequences, which may be caused by information redundancy; (3) When using the shortest transaction sequence training on the three datasets, there is a large gap compared with the longer transaction sequences; (4) Variable-length performs better than all fixed-length parameters. These phenomena reflect the importance of temporal transaction information and also show that this parameter is unstable, which increasing brings both effective information and information redundancy. Therefore, our method TTAGN proposes the input variable-length transaction sequence, which ensures the effectiveness of the model and also enhances the robustness of the model.

As for edge2node’ attention size, by providing different attention sizes during training, the model sensitivity results are presented in Figure 7. We can observe that, under each attention size setting (1) TTAGN always achieves similar performance in terms of four evaluation metrics on all datasets, which is still the best performance compared with other methods in Table 2; (2) TTAGN can still achieve relatively good performance when training with a small attention size (e.g., \( h = 2 \)), which demonstrates the strong capability of its infrastructure. For example, on \( D_3 \) dataset, the Recall barely drops 0.06 if we change the attention size from \( h = 10 \) to \( h = 2 \). Therefore, we conclude that TTAGN is robust to the edge2node’ attention size and consistently outperforms other compared methods.

6 CONCLUSION

In this work, we propose a Temporal Transaction Aggregation Graph Network (TTAGN) to enhance the performance of phishing scams detection on Ethereum. TTAGN fully models and captures the temporal relationship of historical transaction records between nodes, which helps effectively extract edge representations of the Ethereum transaction network. Then, TTAGN aggregates the obtained effective edge representations to fuse topological interactive relationships into nodes, generates trading features which enrich nodes’ characteristics and realize their strong representation ability. Finally, combining the three types of features, we improve the performance of Ethereum phishing scams detection. Extensive experiments indicate that TTAGN’s performance and practicality outperform state-of-the-art algorithms by significant margins. We hope that our work demonstrates the serious threat of phishing scams on Ethereum and calls for effective countermeasures deployed by the blockchain community.

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