Federated Route Leak Detection in Inter-domain Routing with Privacy Guarantee

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Abstract—In the inter-domain network, a route leak occurs when a routing announcement is propagated outside of its intended scope, which is a violation of the agreed routing policy. The route leaks can disrupt the internet traffic and cause large outages. The accurately detection of route leaks requires the share of AS business relationship information of ASes. However, the business relationship information between ASes is confidential due to economic issues. Thus, ASes are usually unwilling to revealing this information to the other ASes, especially their competitors. Recent advancements in federated learning make it possible to share data while maintaining privacy. Motivated by this, in this paper we study the route leak problem by considering the privacy of business relationships between ASes, and propose a method for route leak detection with privacy guarantee by using blockchain-based federated learning framework, in which ASes can train a global detection model without revealing their business relationships directly. Moreover, the proposed method provides a self-validation scheme by labeling AS triples with local routing policies, which mitigates route leaks’ lack of ground truth. We evaluate the proposed method under a variety of datasets including unbalanced and balanced datasets. The different deployment strategies of the proposed method under different topologies are also examined. The results show that the proposed method has a better performance in detecting route leaks than a single AS detection regardless of whether using balanced or unbalanced datasets. In the analysis of the deployment, the results show that ASes with more peers have more possible route leaks and can contribute more on the detection of route leaks with the proposed method.

Index Terms—BGP security, route leak detection, federated learning

1 INTRODUCTION

Border Gateway Protocol (BGP) is used in the inter-domain network for exchange of routing information between autonomous systems (ASes). In BGP, each AS selects the best route according to its routing policies and announces the selected route to neighbors. Different from the shortest path routing policy in the in-boundary, the routing policy in the inter-domain network is more complicated since it considers business relationships between ASes, where the business relationship can be categorized into two types according to AS economic factors: customer-to-provider (c2p) and peer-to-peer (p2p).

The inter-domain routing policies have been extensively investigated in a number of studies, such as [2], [3], [4]. Their analysis suggests that a policy most commonly adopted is valley-free rule [5]. In the valley-free rule, routes learned from providers or peers should not be exported to other providers or peers. However, due to misconfiguration and malicious attacks, the routing announcement may be propagated in violation of their agreed routing policy, which is defined as route leak [6], [7].

Route leaks can cause major outages by redirecting traffic and bring a risk of encountering Man-in-the Middle attacks [8]. For instance, during March 12, 2015, a broadband provider of India (AS17488) wrongly announced over three hundred Google’s prefixes to its provider AS9498, making many of Google’s services inaccessible to their users [9]. Another incident occurred on February 11, 2021, AS28548 in Mexico leaked more than two thousand prefixes to its neighbors and affected about 80 countries in the world [10]. The detection of route leak is becoming increasingly important, given the growing number of serious route leak reports.

The major challenge of detecting route leaks is that the business relationships of ASes are confidential. Each AS only knows the relationships between itself and its neighbors but does not know the exact relationship of others due to privacy issues. In order to detect route leaks, some studies focus on inferring AS business relationships. However, their inference techniques still suffer errors on partial critical links [12]. Studies like [7], [14], [15], [16] do not consider the privacy of AS relationship well and require deployers directly revealing AS relationship information, which makes the deployment hard to proceed.

Another challenge for route leak detection is the lack of ground truth. Only a few destructive routing leak events reported have been validated. Route leaks that are not related to the customer-aware services, e.g. multi-media services, are hard to be validated. For example, S. Abd El Monem et al. [17] show there were only 13 validated route leak incidents between 2006 and 2018. The lack of a ground truth makes popular techniques such as traditional machine learning techniques difficult to be utilized in route leak detection.

Federated learning is a distributed machine-learning method that allows participants globally to train a model without needing to transport their local training data to a central server. Moreover, instead of aggregating local training data, federated learning aggregates local model updates of participants, which can protect data privacy of participants. However, traditional federated learning methods require a third-party server for aggregating model updates, which is vulnerable to single point of failure. To avoid this problem, blockchain-based federated learning framework
In this paper, we propose a method to route leak detection using a blockchain-based federated learning framework. As outlined previously, one AS has limited AS business relationship information, while the detection of route leaks needs as much relationship information as possible. By using federated learning, ASes can globally train a model to identify route leaks with sharing model updates instead of directly sharing their business relationships with others. Furthermore, in order to further strengthen the privacy protection of relationship information, we propose to replace business relationships with AS triples to train the models. By labeling AS triples as malicious or regular using local routing policies, our method provides a solution to solve the lack of ground truth in route leaks.

In the proposed method, AS participants firstly use their known routing policies to generate local training data for training. The local training data are composed of AS triples and corresponding labels that show the triples are malicious or regular. Then, each AS participant uses its local training data to train a local model and exchange updates of the local model with each other through the blockchain network. In each global communication round, one AS can gather all local model updates of participants and aggregate these updates. After the training is finished, the final global model updates are stored in the blockchain. AS participants can retrieve the global model from blockchain and utilize it for further route leak detection.

The contributions of this paper are summarized as follows:

- We consider the problem of route leak detection and propose a privacy-preserving method for sharing routing policy information in AS triples compared to methods that directly share business relationships among ASes.
- We customize a blockchain-based federated learning framework to learn routing policies in inter-domain networks and globally train a model to detect route leaks accurately.
- We evaluate the proposed method on different datasets and analyze different deployment strategies of the method under different topologies. Results show that the proposed method can improve the performance of a single AS in detecting route leaks. The results also indicate that AS with more peers appears to have more possible route leaks and can contribute more to the detection of route leaks than others if they deploy the method.

The remainder of the paper is organized as follows. Section 2 gives an overview of route leak definitions in inter-domain networks and related works in detecting route leaks. In Section 3, we introduce the route leak detection problem and the proposed solution method. Section 4 introduces the conducted experiments and the analysis of results. Section 5 gives the conclusion of this paper.
In this section, we first give a description about the route leak problem in inter-domain networks (Section 3.1) and an overview of the proposed framework to solve the problem (Section 3.2). Following that, we describe the data processing details of how to generate local training data using known local routing policies (Section 3.3). Then, we introduce the model sharing and storing during the blockchain (Section 3.4), and discuss the total theoretical cost of a training task (Section 3.5). Last, an analysis of factors affecting the deployment of the proposed route leak detection method is presented (Section 3.6).

3 Methodology

In this section, we propose a method for route leak detection using blockchain-based federated learning, which considers the privacy protection of AS business relationship information and uses AS triples instead of AS business relationships to train models. The proposed method keeps the data local and shares only model updates, which lowers the risk of data leakage. With the help of blockchain technology, the proposed method can audit and track data. Even if one AS acts maliciously and leaks the updates, it does not leak the direct business relationship information. Besides, since the method uses AS triples, the complex relationships such as mutual transit can also be handled.

3.1 Problem description

As introduced in Section 2.1, we can conclude that the route learned from one provider or peer cannot be exported to another provider or peer. For example, as illustrated in Fig. 1, AS4 leaks the route learned from its provider AS1 to its another provider AS2; b) Type2: AS2 leaks route P learned from its peer AS1 to its another peer AS5; c) Type3: AS4 leaks route P learned from its provider AS1 to its peer AS6; d) Type4: AS2 leaks route P learned from its peer AS1 to its provider AS3. The p2p represents peer-to-peer relationship and c2p represents customer-to-provider relationship.

Fig. 1: Route leak examples of Type1 to Type4 route leaks: a) Type1: AS4 leaks route P learned from its provider AS1 to its another provider AS2; b) Type2: AS2 leaks route P learned from its peer AS1 to its another peer AS5; c) Type3: AS4 leaks route P learned from its provider AS1 to its peer AS6; d) Type4: AS2 leaks route P learned from its peer AS1 to its provider AS3. The p2p represents peer-to-peer relationship and c2p represents customer-to-provider relationship.
locally and uploading the updates of trained local models instead of AS triples. As a result, we further transform the problem from sharing AS triples into sharing local model updates.

### 3.2 Overview of solution framework

The solution framework is shown in Fig. 2. In the framework, each AS deploys a blockchain node called ASChain Manager. Assuming most ASes are honest but curious. ASChain Manager is responsible for managing the blockchain network and federated learning tasks. As shown in Fig. 2, each AS chain Manager has at least two stages in one task. The first phase is to train its local model with local training data and upload updates of the local model to the blockchain network. The local training data is generated by local routing policies and the details about the generation will be introduced in Section 3.3. The second phase is to aggregate the received updates to a global model update, and upload the aggregated updates to make consensus. After the consensus, the winner of the consensus committee has the third phase, which is to store the global model update in the blockchain. In light of numerous studies [19], [31], [32] have made achievements on the consensus mechanism and other security issues of blockchain-based federated frameworks, we move our focus on customizing the framework for learning inter-domain routing policies.

The specific training process is illustrated in Fig. 3. In the initial state, assuming that an authorized organization publishes a learning task in the blockchain network and each ASChain Manager in the network can obtain all re-
requirements of the learning task, such as initial training model and training epoch. (step 3) When the task starts, ASChain Managers retrieve the task information from the blockchain. (step 2) ASChain Managers use local training data to train their local models. The local training data is composed of AS triples with labels generated using local routing policies. (step 3) In each global training epoch, the ASChain Manager encrypts the update of a local model and propagates it to the network. Other ASChain Manager decrypt and verify the received local update. (step 4) After all local updates are verified, the ASChain Manager begins to aggregate these local updates to a global model update and (step 5) propagates it to the network to make consensus with others. (step 6) The winner of the consensus generate a new block and store the final global update to blockchain. (step 7) If the training is not finished, the ASChain Manager updates the local model using the agreed global model update and repeats the step 2 to 6.

3.3 Data processing

In the next step, we process the original local data of ASes to training data that consists of AS triples and labels indicating whether they are malicious or not. The labels are generated according to local routing policies, which include AS business relationships and stable Routing Information Base (RIB) of AS. The RIB contains the information about the selected routes. The combination of an AS triple and its label is defined as a sample. Therefore, for each AS, the training data can be divided into two components, direct samples based on relationship information and inferred samples based on stable RIB.

Please note that in practice, in addition to the valley-free rule, other routing strategies can also be used to label AS triples. For instance, for an AS triple \((a, b, c)\) where \(a\) is a customer of \(b\) and \(b\) is a customer of \(c\), AS \(b\) may not allow the route learned from \(a\) to export to AS \(c\) even it does not break valley-free rule. However, as the confidentiality of other individual routing policies and common use of the valley-free rule, we mainly consider labeling AS triples based on valley-free rule in the experiment.

In a direct sample \((v_i, v_{i-1}, v_{i+1})\) of AS \(v_i\), the possible leaker is \(v_i\), and the \(v_{i-1}, v_{i+1}\) are both direct neighbors of \(v_i\). The \(\omega\) is the label of direct AS triple \((v_{i-1}, v_i, v_{i+1})\). In a inferred sample \((v_{i+1}, v_{i-1}, v_i, \omega)\) of AS \(v_i\), the possible leaker is \(v_{i-1}\), and the \(v_{i+1}, v_{i-1}\) are both direct neighbors of \(v_i\). The \(\omega\) is the label of inferred AS triple \((v_{i+1}, v_{i-1}, v_i)\). The direct samples are based on the known business relationship with neighbors. The inferred samples are based on the permutations of known neighbors and are used to broaden the vision of AS \(v_i\) because direct samples can only include the scenarios about the one-hop vision of \(v_i\) and the inferred samples contain part of two-hop vision. The main difference of the two types of triples is that in the direct triples the possible leaker is AS itself \(v_i\) and in the inference triples the possible leaker is the neighbor of \(v_i\). Details about the process for labeling AS triples are described below.

**Triple Labeling**

1) For each triple \((v_{i-1}, v_i, v_{i+1})\) in the direct triples \(DiT\) of \(v_i\):
   a) If \(v_i\) is a customer or peer of \(v_{i-1}\), and \(v_{i+1}\) is the provider or peer of \(v_i\), then the triple breaks the valley-free rule and the label \(\omega\) for \((v_{i-1}, v_i, v_{i+1})\) is set as malicious.
   b) Otherwise, the label \(\omega\) for \((v_{i-1}, v_i, v_{i+1})\) is set as regular.

2) For each triple \((v_{i+1}, v_{i-1}, v_i)\) in the inference triples \(InT\) of \(v_i\):

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**Algorithm 1 Data Processing**

1: **Input:** deployed AS \(m\), RIB \(S_m\), neighbors \(N_m\), business relationship \(R_m\).
2: **Output:** Training data \(D_m\)
3: \(D_m \leftarrow \oslash\)
4: for \(\forall n_i \in N_m\) do
5: for \(\forall n_j \in N_m\) do
6: if \(n_i = n_j\) then
7: Continue
8: end if
9: // Direct triples
10: if \(R_m(m, n_i) = c2p\) or \(R_m(m, n_i) = p2p\) then
11: if \(R_m(m, n_j) = c2p\) or \(R_m(m, n_j) = p2p\) then
12: /* AS triple \((n_i, m, n_j)\) is labeled as malicious */
13: \(D_m \leftarrow D_m \cup \{(n_i, m, n_j, 0)\}\)
14: end if
15: end if
16: /* AS triple \((n_i, m, n_j)\) is labeled as regular */
17: \(D_m \leftarrow D_m \cup \{(n_i, m, n_j, 1)\}\)
18: // Inference triples
19: if link \((n_i, n_j)\) in \(S_m\) then
20: \(D_m \leftarrow D_m \cup \{(n_i, n_j, m, 1)\}\)
21: /* Reverse triple pattern */
22: \(D_m \leftarrow D_m \cup \{(m, n_i, n_j, 1)\}\)
23: else
24: \(D_m \leftarrow D_m \cup \{(n_i, n_j, m, 0)\}\)
25: end if
26: end for
27: end for
Reverse Triple Pattern. For each triple \((v_{i+1}, v_{i-1}, v_i)\) in inference triples InT of \(v_i\):

1) If the link \((v_{i+1}, v_{i-1})\) appears in the stable RIB:
   a) if the triple’s label is regular, then the reverse triple \((v_i, v_{i-1}, v_{i+1})\) of \((v_{i+1}, v_{i-1}, v_i)\) is labeled as regular.
   b) if the triple’s label is malicious and \(v_{i-1}\) is a peer or customer of \(v_i\), then the reverse triple \((v_i, v_{i-1}, v_{i+1})\) of \((v_{i+1}, v_{i-1}, v_i)\) is labeled as malicious.

2) Otherwise, break.

Using the reverse triple pattern, we extend more triples from the initial generated triples. These triples and their labels are combined as local training data for federated learning. For a clear expression, the use of the 

| Triple Labeling and Triple reverse pattern | are summarized in Algorithm 1 |

3.4 Model sharing and storing during the blockchain

In the solution framework, except for avoiding single-point failure in traditional federated learning, the blockchain is used to share and store model updates, such as securely exchanging information between participants and auditing uploaded data.

Model sharing: For example, AS participants in the blockchain can be authorized a public/private key pair (or a set of key pairs) with their Autonomous System Number (ASN) by authorities (i.e., RIPE NCC, APNIC or large ISPs) and use the key pair to sign/validate the updates. In this way, the framework can verify the identities of AS participants that generated the updates. To guarantee the security of the transmitted updates, HTTPS connections can be built between two participants to prevent attackers accessing the updates. For meeting privacy requirements, many methods are proposed for the blockchain-based federated learning framework, such as [33] use threshold Paillier algorithm, [19] use Shamir’s secret sharing scheme, and [35] use differential privacy.

Model storing: Through the non-tamperable feature of blockchain, we can track(validate the uploading records and ensure the integrity of records. The initial block records the initial training model and task information. The consensus procedure is used to ensure that the global model update obtained by aggregation is unique, which can be implemented by Proof of Work (PoW) or Proof of Stake (PoS). After the consensus procedure, the results of each global training epoch are stored as a transaction of the block in the blockchain. For instance, the \(k\)th global training results can be defined as \(Y_k = [\text{Hash}(Y_{k-1}), T_s, T_{exp}, \Gamma, M_k, SIG_x(Y_k), x]\), where \(\text{Hash}(Y_{k-1})\) is the hash of previous block. Blocks in the blockchain are stored in a chain structure. The \(T_s\) and \(T_{exp}\) are the block generation time and expired time respectively. The \(\Gamma\) is the global model update. The \(SIG_x(Y_k)\) is the block signature of the winner participant \(x\) and \(M_k\) records the ASN of participants. Therefore, once a global epoch is finished, participants can download the global model update from the blockchain to update their local models.

Algorithm 2 FL-RLD Training

1: \textbf{Input}: deployed ASes \(M\), model \(Q\), local training epoch \(ce\), global training epoch \(e\)
2: \textbf{Output}: global model update \(\Gamma\)
3: \textbf{for} \(k = 1\) to \(ge\) \textbf{do}
4: \textbf{for} \(\forall m\in M\) in Parallel do
5: Obtaining local training data \(D_m\) using algorithm 1
6: local model \(Q^0_m\leftarrow Q\)
7: for \(i = 1\) to \(ce\) do
8: \textcolor{red}{/* Training model */} \textcolor{green}{\textcolor{blue}{Q^i_m\leftarrow modelTraining(Q^{i-1}_m, D_m)\textcolor{red}{/}}}\textcolor{green}{\textcolor{blue}{\textcolor{red}{/}}}
9: \textcolor{red}{/* Obtaining local model update */} \textcolor{green}{\textcolor{blue}{\gamma^i_m\leftarrow modelGetUpdate(Q^{i-1}_m, Q^i_m)\textcolor{red}{/}}}\textcolor{green}{\textcolor{blue}{\textcolor{red}{/}}}
10: end for
11: Uploading local model update \(\gamma^c_m\)
12: end for
13: for \(\forall m\in M\) in Parallel do
14: Aggregating all local updates \(\textcolor{red}{/*\textcolor{green}{\textcolor{blue}{\Gamma^k_m\leftarrow modelAggregate\{\gamma^c_m|\forall m\in M\}\textcolor{red}{/}}}\textcolor{green}{\textcolor{blue}{\textcolor{red}{/}}}}\)
15: end for
16: Making consensus and obtaining global model update \(\textcolor{red}{/*\textcolor{green}{\textcolor{blue}{\textcolor{red}{\textcolor{red}{\gamma^k_m\leftarrow consensus\{\Gamma^k_m|\forall m\in M\}\textcolor{red}{/}}}\textcolor{green}{\textcolor{blue}{\textcolor{red}{/}}}}}}\)
17: Storing \(\Gamma\) in the blockchain
18: end for

3.5 Theoretical cost analysis

Combining the training process in Fig 3 and training algorithm shown in Algorithm 2, the total cost of a training task can be divided into three parts: local computation cost (step \(\mathcal{A}, \mathcal{B}, \mathcal{C}\)), global communication cost (step \(\mathcal{D}, \mathcal{E}\)) and storing cost (step \(\mathcal{F}\)).

Local computation cost: Let \(L^i(D_m)\) be the local training cost of the participant \(m\in M\) in \(i\)th local training epoch where \(D_m\) is the local training data of \(m\) and \(a_k\) be the model aggregation cost in \(k\)th global training. So, the local computation cost is \(\sum_{ce} L^i(D_m) + a_k\) where \(ce\) is the local training epochs, \(D_m\) is the local dataset of \(m\).

Global communication cost: The global communication cost includes two parts, exchanging local updates and making consensus about aggregated global updates. First, let \(\delta^k_m\) be the local update of \(m\) in the \(k\)th global training epoch. Assuming the communication cost between any two participants for \(m\) is \(\Delta(\delta^k_m)\). Thus, the cost of broadcasting the local model update for \(m\) is defined as \((|M|-1)\Delta(\delta^k_m)\) where \(|M|\)
is the number of participants. Then, let \( \zeta^k(\card{M}) \) be the consensus cost of the global model training epoch. Finally, the total global communication cost is \( \sum_{l=1}^{ge} \sum_{m \in M} (\card{M} - 1) \Delta(\delta^k_m) + \zeta^k(\card{M}) \) where \( ge \) is the global training epochs.

**Storing cost:** The global updates in each global training epoch are stored in blocks. The storing cost is related to the size of model updates, so the storing cost is \( \sum_{k=1}^{ge} f(T^k) \) where the \( T^k \) is the global model update in \( k \)th global training epoch.

Therefore, the total cost of a training task can be presented as following:

\[
\text{total\_cost} = \sum_{k=1}^{ge} \sum_{m \in M} \left( (\sum_{i=1}^{ce} L^i(D_m)) + a_k \right) + \left( \sum_{k=1}^{ge} \sum_{m \in M} \frac{\Delta(\delta^k_m)}{\zeta^k(\card{M})} \right) + \sum_{k=1}^{ge} f(T^k)
\]

(1)

The parameters used in the Equation (1) are summarized in Table 1.

**TABLE 1: List of notations used in Equation (1)**

| Parameter | Meaning |
|-----------|---------|
| \( ge \) | Global training epochs |
| \( ce \) | Local training epochs |
| \( M, |M| \) | Deployed AS set, the number of M |
| \( D_v \) | Training data of deployed AS m |
| \( L^i(D_m) \) | Training cost of m in \( i \)th local training epoch |
| \( a_k \) | Aggregation cost in \( k \)th global training epoch |
| \( \delta^k_m \) | Local model update of m in \( k \)th global training epoch |
| \( \Delta(\delta^k_m) \) | Cost of broadcasting \( \delta^k_m \) between any two participants |
| \( \zeta^k(\card{M}) \) | Consensus cost |
| \( T^k \) | Global model update in \( k \) the global training epoch |
| \( f(T^k) \) | Cost of storing global model update in the blockchain |

### 3.6 Factors affecting deployment

Here, to promote the deployment, we discuss which factors can affect the detection effectiveness of the proposed method. The Internet is modeled as a graph \( G(V, E) \) where \( V \) is a set of all ASes in the Internet and \( E \) represents the direct links between ASes. In the graph, \( M \) is a set of ASes that have deployed the proposed detection system, where \( M \subseteq V \). For each AS \( \vhi \in M \), the local training data of \( m \) is represented as \( D_v \) where \( |D_v| \geq 0 \). Thus, the shared local training data of \( M \) can be defined as \( \mathbb{D} = \{ D_v \mid \vhi \in M \} \) and is used to federate train a global model to identify whether the input AS triple is malicious or regular. Thus, the aim of the global model is to memorize the mappings of AS triples and their label of local training data as much as possible. The accuracy that the global model’s can correctly identify a malicious AS triple in \( \mathbb{D} \) is set as \( \theta \), where \( 0 \leq \theta \leq 1 \).

**Lemma 1.** If \( \theta = 1 \), consider AS \( v_{k+1} \in M \) receives a leaking announcement \( R = \{ v_1, ..., v_{k}, ..., v_k \} \) and the leaking AS is \( v_h \). If \( v_h \in M \), then the AS triple \( (v_{h-1}, v_h, v_{h+1}) \) and its label are in \( \mathbb{D} \). Therefore, AS \( v_{k+1} \) can identify that \( R \) is a malicious announcement. For \( v_h \notin M \), if \( v_{h+1} \in M \) and AS triple \( (v_{h-1}, v_h, v_{h+1}) \in \mathbb{D} \), then AS \( v_{k+1} \) can identify that \( R \) is malicious.

When \( \theta = 1 \), the global model can identify every AS triple in \( \mathbb{D} \) is malicious or not. So, once AS \( v \in M \) receives an announcement with a malicious AS triple in \( \mathbb{D} \), it will correctly detect the malicious announcement. If \( \theta < 1 \), then the number of malicious AS triples that the global model can identify is \( \theta \cdot \card{\mathbb{D}} \).

Therefore, it can be concluded that the performance of route leak detection depends on two parts, accuracy of the global model and the number of malicious AS triples. Under the same accuracy of the global model, more route leaks will be detected as the number of malicious AS triples in \( \mathbb{D} \) increases.

### 4 Experiments and analysis

In this section, we give a description about experiment setup and show the experiment results. To learn more about the possible route leaks, we first explore the features regarding generated triples, such as the proportion of malicious triples and regular triples, and how the two types of triples have changed over the past four years. Then, experiments are conducted to evaluate the performance of the proposed detection method.

#### 4.1 Experiment setup

**Topology:** The BGP topology data used in the evaluation is collected from the CAIDA January 2021 AS relationship dataset [56] of IPv6, which has 12,721 ASes and 173,462 AS links. We use the method introduced in Section 3.3 to generate triples and their labels for ASes in the network.

**Implementation details:** The proposed method is implemented by Python and Keras [37], and the initial training model is a simple LSTM network. It includes a LSTM layer with input size (1, 96) and output size (1, 128), a hidden layer with output size (1, 64) and ReLU activation function, and an output layer with output size (1, 2) and Softmax activation function. For each 2-bit vector of the output layer, if the first bit is larger than the second one, then it is predicted as a regular triple. Otherwise it is predicted as a malicious triple. The model uses Adam optimizer [39] as the optimization process and the batch size is 32. The learning rate of the model is set as 0.001 and the FedAvg algorithm [40] is used to aggregate local updates. In the training data, each ASN in the generated triples is embedded as a 32-bit vector by converting decimal to binary. The local training epoch is set as 2 and the global training epoch is around 70 to 100.

**Training data details:** In our experiments, we consider two aspects of local training data that may influence the results, balanced/unbalanced data size and balanced/unbalanced class distribution. We select 4 groups of federated learning participants to test. Each group has 5 participants. We represent each participant of a group with Client1, Client2, Client3, Client4, and Client5. The details about the groups are illustrated in Table 2. The data size refers to the number of triples of the participant. For example, in group 1, participants have different sizes of local training data, and the number of malicious and
and Recall the single AS learning method with participant Client1, respectively.

The True Positives (TP) and False Positives (FP) are the number of true regular triples that the model predicts as anomaly and regular respectively. The True Negatives (TN) and False Positives (FP) are the number of true regular triples that the model predicts as malicious triples that the model predicts.

Accuracy, Precision, Recall, F1score are used as evaluation metrics for detection performance. Accuracy shows the ratio of correctly predicted triples to the total triples. Precision and Recall display the ratio of correctly predicted malicious triples and regular triples respectively. F1score is the average of Precision and Recall. Their definitions are as follows.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}
\]
\[
\text{Precision} = \frac{TP}{TP + FP}
\]
\[
\text{Recall} = \frac{TP}{TP + FN}
\]
\[
\text{F1score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

where True Positives (TP) and False Positives (FP) are the number of true malicious triples that the model predicts as anomaly and regular respectively. The True Negatives (TN) and False Positives (FP) are the number of true regular triples that the model predicts as regular and anomaly respectively.

Comparative methods: We use FL-RLD to represent the proposed method, and CL to represent the central learning method. The difference between CL and FL-RLD is that CL transports all local training data of participants of a group to a single server for model training while FL-RLD keeps the data training local. The C1, C2, C3, C4, and C5 represent the single AS learning method with participant Client1, Client2, Client3, Client4, and Client5 respectively. So, the single learning method can only utilize the local training data of a single AS to train the model. For example, the training data of C1 in group 1 uses the local training data of corresponding AS is \(D_{1,1}\) and the training data of CL is \(\{D_{i,j}\}_{i = 1, \ldots, 5}\). The training model of FL-RLD, CL and C1/C2/C3/C4 are all the same.

Traditional detection methods work by storing AS business relationships in various ways and filtering out routes that aren’t matched (i.e., building a RPKI-like repository to store the routing customer-provider authority objects [26], marking the “Down-only” routes [16] to prevent forwarding routes to upstream providers or peers). Hence, we modeled three different methods ML-random, ML-0, ML-1 based on the above analysis to compare with FL-RLD. In these three methods, they all build a global repository that all participants of a group directly share their AS relationships. Ideally, if all relationship information of the AS triple in test data is in the global repository, output the correct result. Otherwise, they respond differently: 1) ML-random will randomly output a result. 2) ML-0 will mark this AS triple as malicious. 3) ML-1 will mark this AS triple as regular.

### 4.2 Performance

Multiple ASes vs. Single AS: First, a comparison of a global model trained by multiple ASes and a model trained by a single AS is carried out. The results are shown in Fig.4. The Fig.4a and Fig.4b are results under datasets with unbalanced class distribution, while Fig.4c and Fig.4d are results under datasets with balanced class distribution. In Fig.4a, FL-RLD performs better than C1, C2, C3, C4 and C5 in all evaluation metrics under different groups of datasets, which provides an incentive for ASes to join federated learning. For example, in Fig.4b, the Accuracy of C1 to C5 are all lower than 0.8 but when they join the federated learning, the Accuracy is more than 0.95. The results also show that the difference of FL-RLD and CL in the performance is small (e.g., less than 0.06 Accuracy in group 1).

| Group 2 (balanced data size + unbalanced class distribution) | Data size | Anomaly | Regular | Anomaly % | Regular % |
|-------------------------------------------------------------|-----------|---------|---------|-----------|-----------|
| Client1 (19.77%)                                            | 63468     | 51066   | 12402   | 80.46%    | 19.54%    |
| Client2 (20.69%)                                            | 12549     | 12099   | 450     | 96.41%    | 3.59%     |
| Client3 (19.25%)                                            | 13134     | 12158   | 976     | 92.57%    | 7.43%     |
| Client4 (19.49%)                                            | 12218     | 7606    | 4612    | 62.25%    | 37.75%    |
| Client5 (20.79%)                                            | 13265     | 8998    | 4200    | 68.18%    | 31.82%    |

| Group 3 (balanced data size + balanced class distribution)  | Data size | Anomaly | Regular | Anomaly % | Regular % |
|-------------------------------------------------------------|-----------|---------|---------|-----------|-----------|
| Client1 (17.88%)                                            | 35712     | 17856   | 7856    | 50.00%    | 50.00%    |
| Client2 (35.93%)                                            | 149580    | 74790   | 74790   | 50.00%    | 50.00%    |
| Client3 (43.45%)                                            | 180904    | 90452   | 90452   | 50.00%    | 50.00%    |
| Client4 (10.40%)                                            | 43316     | 21658   | 21658   | 50.00%    | 50.00%    |
| Client5 (1.64%)                                             | 6836      | 3418    | 3418    | 50.00%    | 50.00%    |

| Group 4 (balanced data size + balanced class distribution)  | Data size | Anomaly | Regular | Anomaly % | Regular % |
|-------------------------------------------------------------|-----------|---------|---------|-----------|-----------|
| Client1 (20.58%)                                            | 3418      | 1761    | 1657    | 51.52%    | 48.48%    |
| Client2 (20%)                                               | 3418      | 1767    | 1746    | 49.92%    | 51.08%    |
| Client3 (20%)                                               | 3418      | 1724    | 1694    | 50.44%    | 49.56%    |
| Client4 (20%)                                               | 3418      | 1679    | 1739    | 49.12%    | 50.88%    |
| Client5 (20%)                                               | 3418      | 1676    | 1742    | 49.04%    | 50.97%    |
Fig. 4: The Performance of FL-RLD method compared with single AS learning method (C1, C2, C3, C4, C5) and Central Learning (CL) method

Fig. 5: The performance comparison of FL-RLD and other methods.

Global repository vs. FL-RLD: In Fig. 4, we compare FL-RLD with ML-random, ML-0 and ML-1, where these three comparative methods are based on sharing a global repository of business relationships. As introduced previously, the main difference of these three methods is that they respond differently when the AS relationship information is not in the training data. The results in Fig. 4 show that the performance of FL-RLD and ML-0 is better than others and FL-RLD performs better on average than ML-0. The ML-1 performs the worst because the number of triples marked as malicious is higher than that of regular triples, while the ML-1 classifies all unknown triples as regular, thus making the Recall low. The ML-0 classifies all unknown triples as malicious, so its performance is better than ML-1. However, the Precision of ML-1 is low, which makes high false alarms. Thus, the FL-RLD that performs well on both Precision and Recall is more recommended.

4.3 Deployment analysis

As analyzed in Section 3.6, the higher number of malicious AS triples are contained in the training data, the more route leaks can be detected by FL-RLD. Thus, to facilitate the deployment, we first analyze the distribution of AS triples over time and study the relationship between the number of deployed ASes and the number of route leaks that can be detected under different deployment strategies if the accuracy \( \theta \) of the global model is 1.

Malicious AS triples vs. Regular AS triples: Except for the 2021 topology used above, we also collect other three topologies, 2020, 2019, 2018, to study the distribution of AS triples over time. They are also from CAIDA AS relationship dataset of IPv6. Fig. 5 shows the proportion of malicious and regular triples of the local training data under different topology data grouped by year. As we can see, the results show that the number of malicious triples (around 60%-70%) are more than regular triples (around 30%-40%) in the local training data. This is because the number of peer-to-peer relationships is more than provider-to-customer relationships, which makes extensive possible route leaks. Please note that even the number of malicious AS triples are higher than regular AS triples, but actually most of ASes in the network act normally and only a small number of ASes act maliciously. Therefore, there are not so many malicious AS triples in the actual routing announcements.

Direct AS triples vs. Inference AS triples: Fig. 5 depicts CDFs of the percentage of inference triples to total triples. In the about 80% ASes, around 30% triples are inference triples where neighbors are the possible leakers. The data of the past four years from 2018 to 2021 show a similar result. It indicates that our generation method can enrich training data well by extending properly proportioned AS triples based on the known routing policies.

Deployment strategies: Fig. 5 shows the distribution of malicious triples in the training data to total malicious triples under different deployment strategies, where Peer/Customer/Provider selects ASes with the largest number of peers/customers/providers to deploy first. The results show that Peer deployment strategy can cover the most number of malicious triples than other two strategies with the same deployment rate. For example, in the data of 2021, if using Peer deployment strategy, it only needs to deploy 875 ASes (0.06878 deployment rate) to cover 99% total malicious triples while Customer deployment strategy can only reach 72% coverage rate with the same deployment rate. It also indicates that ASes with a large number of peers
have a large number of possible malicious triples.

5 CONCLUSION

This paper studied the problem of route leak detection in the inter-domain network and proposed a privacy-preserving method using blockchain-based federated learning to collaboratively train models with accurate routing policy information for route leak detection. Compared with traditional route leak detection methods, the proposed method considers the privacy of AS business relationships. To solve the lack of a ground truth problem in route leaks, it provides a self-validation scheme by labeling AS triples as malicious or regular using local routing policies. The evaluation results show that the proposed method can improve the performance of a single AS in detecting route leaks, and there is slight differences in results (e.g., around 0.06 in Accuracy) between the federated learning method and the central learning method, in which all local training data are gathered and trained together. In the analysis of FL-RLD deployment, it is found that AS with more peers are more likely to have more possible route leaks and can contribute more on route leak detection if they join the federated learning.

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