Symbolic analysis meets federated learning to enhance malware identifier

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ABSTRACT

The manual methods to create detection rules are no longer practical in the anti-malware product since the number of malware threats has been growing over past years. Thus, the turn to machine learning approaches is a promising way to make malware recognition more efficient. The traditional centralized machine learning requires a large amount of data to train a model with excellent performance. To boost the malware detection, the training data might be on various kind of data sources such as data on the host, network, and cloud-based anti-malware components, or even, data from different enterprises. To avoid the expenses of data collection as well as the leakage of private data, we present a federated learning system to identify malware through behavioral graphs, i.e., system call dependency graphs. It is based on a deep learning model including a graph autoencoder and a multiclass classifier module. This model is trained by a secure learning protocol among clients to preserve the private data against inference attacks. Using the model to identify malware, we achieve the accuracy of $\sim$ 85% for homogeneous graph data and $\sim$ 93% for inhomogeneous graph data.

KEYWORDS

Federated Learning, Symbolic Analysis, Malware Detection, Data Privacy

ACM Reference Format:
Charles-Henry Bertrand Van Ouytsel, Khanh Huu The Dam, and Axel Legay. 2022. Symbolic analysis meets federated learning to enhance malware identifier. In *The 17th International Conference on Availability, Reliability and Security (ARES 2022), August 23–26, 2022, Vienna, Austria.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3538969.3538996

1 INTRODUCTION

Since the number of malware threats has been growing over past years, the manual analysis methods to create detection rules are no longer practical in the anti-malware products. It therefore requires new advanced protection techniques which optimize the tasks of malware detection and classification. Hence, the turn to the machine learning (ML) approaches is a promising way to make the malware recognition more efficient, robust, and scalable [27, 46]. In the traditional centralized ML, a large amount of data is required to train a model with excellent performance. To boost the malware detection, it might train the model on various kinds of data sources such as data on the host, network, and cloud-based anti-malware components, or even, data from different enterprises since the amount of data on each side is insufficient. Although all data can be collected in a central server for training, it is too expensive as well as it might cause the leakage of sensitive data [1, 30].

To tackle this challenge, several works [29, 31, 35, 37, 41, 49, 50] implement the federated learning (FL) which pushes model training to the devices from which data originate. Each device uses local data to train a local model, and then, all the local models are sent to the server to be aggregated into a global model. This FL setting constitute a risk in preserving data privacy since the sensitive information of the local data may be revealed via the inference attacks to training model [33, 47, 51]. Hence, an additional privacy protection is setup to the FL with amount of differential privacy noise adding to the model parameters [1]. However, the work in [9] shows that relying on the differential privacy noise is insufficient to prevent the data leakage via the training model, as they explicitly trust the server with the crucial task of adding the differential privacy noise, and hence provide no protection against a semi-honest or untrusted server. In other hand, the more differential privacy noise is added to the model, the more degraded the performance of FL.

Taking into account these issues, we introduce a FL system that enables multiple participants to jointly learn an accurate deep learning model for malware detection and classification. They build this model without sharing their input datasets while preserving privacy of their local data against inference attacks. Our system consists of several clients which hold their own dataset, a key-client selected from the clients that holds the secret key to encrypt the model parameters and an aggregator which combines the local model parameters into a global model. To avoid inference attacks, we replace the key-client for every training round. Even if the aggregator or the clients take a snapshot of the training model, it is hard for them to infer the data from the others. In particular, each client holds its own classifier model which is trained to recognize malware at the clients' side. For this goal, we first characterize malware by the system call dependency graphs (SCDG) which represent the program behaviors. Following [5, 34, 44] , we use symbolic analysis to

ARES 2022, August 23–26, 2022, Vienna, Austria

ACM ISBN 978-1-4503-9670-7/22/08…$15.00
https://doi.org/10.1145/3538969.3538996

explore all possible execution paths of a malware, and then, its corresponding SCDG is built from these execution paths. Secondly, we propose a deep learning model including a graph autoencoder and a multi-classifier, to encode and classify the SCDGs. The graph autoencoder vectorizes the input SCDGs, and then, the multi-classifier identifies malware according to the output of the autoencoder. We evaluate the deep learning model on two datasets. The first dataset includes SCDGs computed by the same extraction strategy. The second dataset includes SCDGs computed by different strategies. In the experiments, we obtain significant results which are comparable to the *Centralized Learning*. The obtained accuracy is $\sim$ 85% for the homogeneous graphs and $\sim$ 93% for the inhomogeneous graphs.

Section 2 presents related works. Then, we recall the definition of system call dependency graph, and present the symbolic analysis to extract the graphs from malware in Section 3. Section 4 presents the deep neural network classifier which we propose for encoding and classifying the system call dependency graphs. Our secure learning approach to train the deep learning model is introduced in Section 5. Section 6 reports its evaluation results on our datasets. Finally, the conclusion is presented in Section 7.

2 RELATED WORK

Malware detection approaches are mainly categorized into signature based and behavioral based approaches. The signature-based approaches extract binary patterns and metadata from a malware family and use these patterns to detect all samples from that family [6]. The approach suffers from the necessity to build an extensive database of signatures within a short period of time. In addition, it is relatively easy to overtake this approach by rewriting or obfuscating the binaries [7].

In the latter more advanced approaches, malware are detected by analyzing their behaviors instead of the syntax of the program. The behavioral analysis is usually distinguished as dynamic or static analysis. In the dynamic analysis [17], malware are executed in an emulated environment (e.g.: sandbox) to seek for a malicious behavior [48]. However, it is sometimes challenging to trigger the malicious behavior since there are limitations in execution time and the context emulated by the sandbox.

On the other hand, static techniques allow to analyze the behaviors of malware on the disassembled code without executing it. The static code analysis is performed concretely or symbolically. In the concrete analysis [22], the execution trace is computed from the disassembled code by some contextual information. Therefore, it exhibits similar limitations to the dynamic analysis since the provided contexts cannot cover all the executions of the program.

The symbolic analysis performs a symbolic execution with symbolic input variables in place of concrete values. It allows exploring all the possible execution paths in the control flow graph [5, 16, 34, 44]. In this manner, the malicious behaviors are easily exposed in this analysis. We consider the symbolic analysis in this work to construct SCDGs as behavioral signatures of malware. This behavioral graph representation has been proved as an efficient approach for malware detection in the recent works [3, 5, 13, 14, 16, 18, 28, 32, 42].

[5, 14, 15] implement machine learning techniques on SCDGs for malicious behavior extraction as well as malware detection. The graph mining techniques are employed to find malicious patterns in SCDGs of malware in [16, 18, 28, 32, 42]. [13] identifies malware families by applying clustering algorithms on SCDGs. Those works obtain good results in the malware detection and classification. However, there are several challenges in training and updating the malware classifiers since malware detectors need to be updated consistently with a mass number of malware. In addition, collecting all data in a centralized manner are so expensive while the data on individual devices are insufficient for training the efficient machine learning model.

Therefore, the federated learning is proposed to handle those issues in the traditional machine learning [26]. More precisely, It implies that each device uses local data to train a local model. Subsequently, all the local models are uploaded to the server to be aggregated into a global model. This learning technique has been successfully applied to anomaly detection [20, 35, 40] as well as to malware detection [19, 23, 31].

[20, 35, 40] successfully employ the federated learning techniques for anomaly detection on IoT devices. [31] also demonstrates the positive efficiency of the federated learning for malware classification comparing to the traditional machine learning, i.e., Support Vector Machine (SVM). However, it is lack of the private data protection. Moreover, the privacy-preserving federated learning system is implemented in [19, 23]. [23] allows mobile devices to collaborate for training a SVM classifier with a secure multi-party computation technique. [19] implements an average weight model to preserve the data privacy. Enhancing the models in [19, 23], we implement a secure learning approach with the homomorphic encryption to avoid the data inference attacks. Additionally, we implement a federated learning on inhomogeneous SCDGs to exploit the computation power of devices as well as the various representations of malware behaviors.

3 SYSTEM CALL DEPENDENCY GRAPH

System call dependency graph (SCDG) is a directed graph consisting of nodes and edges, which represents the behaviors of a program. The nodes are (system) function calls. An edge represents information flowing between two system calls in execution traces. The execution traces are obtained through the symbolic execution of a binary. Each trace is a list of system calls and the relevant information of these calls, such as the arguments, the resolved address, and the calling address. Two system calls of the execution trace are data dependent if they have either argument relationship or address relationship. Two system calls have the argument relationship if they are using the same argument in an execution trace. The address relationship of two system calls is when the address of a system call is the argument (or return value) of another call.

Let S be a set of system calls. Formally, a system call dependency graph is a directed graph $G = (V, E, L)$ such that: V is a set of nodes, $L : V \rightarrow S$ is a labeling function which maps a node $v \in V$ to a system call $s \in S$ and $E : V \times V$ is the set of edges. $(v_1, v_2) \in E$ means that the system calls $L(v_1)$ and $L(v_2)$ are data dependent and the call to $L(v_1)$ is made before the call to $L(v_2)$, For example, the argument relationship of two system calls `GetModuleFilenameA(0,m)` and `CopyFileA(m,m',1)` is represented by an edge $(v_1, v_2) \in E$ in the

graph $G = (V, E)$ such as $v_1, v_2 \in V$, $L(v_1) =$ `GetModuleFilenameA` and $L(v_2) =$ `CopyFileA`.
In this work, we implement a symbolic execution to extract SCDGs from the binaries as follows. Initially, the symbolic execution is performed on malware binaries to explore all possible execution paths. Thanks to `ANGR` engine [45], the execution flows of the binary are recorded as states including the instruction addresses, register values, memory usages, etc. in a period of time. At each execution step, if a variable can accept several values, the symbolic value is replaced to keep track the execution and the related constraints. During the execution, new states are created according to the instruction by the `ANGR` engine. If a branch instruction is met, i.e., a conditional jump, the current state is forked into two states: the first is considered for taking the jump instruction, and the second is considered for the next instruction. Otherwise, the current state produces a single child state. Hence, the exploration will produce an enormous number of states during the symbolic execution. The state explosion can be controlled by using some constraint solvers, i.e., z3 or SMT solver, or heuristics to optimize the symbolic execution [8, 44]. Following [5], we consider three strategies to explore the state at each execution step to compute SCDGs:

(1) Custom Breadth-first search (CBFS) implements the Breadth-first search to construct the graph of possible shortest paths from the execution traces. It prioritizes non-visited instruction address which allows to increase the code coverage.
(2) Custom Depth-first search (CDFS) considers the possible longest paths in the Depth-first search on the execution traces. It also prioritizes non-visited instruction address which allows to increase the code coverage.
(3) Breadth-first search (BFS) explores all paths from the execution traces in the Breadth-first search manner.

After the state exploration, we obtain several execution traces from a binary. Each trace is a sequence of system calls with the arguments, the resolved addresses and the calling addresses.Then, a SCDG is built on these execution traces. Its nodes correspond to system calls. Its edges represent the information flow of pair of system calls and their order in the execution traces. An edge is built from two system calls if they possess either the argument relationship or the address relationship in the same execution trace. By using different exploration strategies, we may obtain various SCDGs to characterize the same binary. Hence, the study on such various SCDGs may enhance the performance of malware detection as well as malware family recognition.

4 DEEP LEARNING MODEL

Since the SCDGs correspond to the behaviors of malware, we construct a deep learning model to encode the SCDGs and classify the malware. The model consists in a graph autoencoder connected to a classifier module, shown in Figure 1. First, the graph autoencoder transforms a SCDG into a feature vector. Then, the classifier module takes the feature vector as input, and produces a predicted class of SCDG associated with this feature vector. They are presented in the following sections.

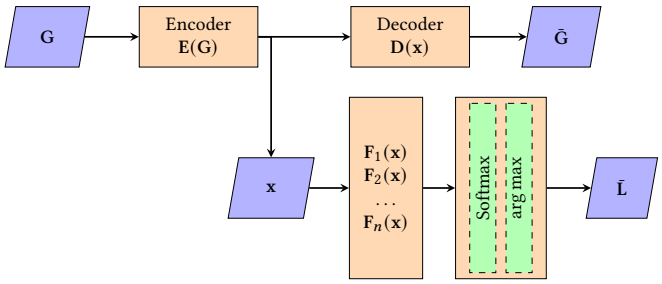


Figure 1: Deep neural network classifier

4.1 Graph autoencoder

The graph autoencoder [13] is equipped with Long Short Term Memory (LSTM) layers to embedding a SCDG into a feature vector. A LSTM layer is a recurrent neural network which is able to remember information for a long period of times through memory cells. Each cell has three connected gates to control the internal state: the input gate i_t is used to decide which part of information is stored in the memory cell; the forget gate f_t is used to decide which part of information is thrown away from the memory cell; and the output gate o_t which specifies the output. Given an input x_t and the output of previous cell h_{t-1}, the output h_t is computed by $h_t = o_t * \mathbf{tanh}(C_t)$. C_t is the internal state of the current cell is computed as follows:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

where $\tilde{C}_t = \mathbf{tanh}(W_C \cdot [h_{t-1}, x_t] + b_C)$ is a new candidate for the internal state. Over periods of time, the three gates of the memory cell are interacting with other layers through the sigmoid function $\sigma(\cdot)$ as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

where $\{W_f, W_i, W_o\}$ and $\{b_f, b_i, b_o\}$ are weights and biases of corresponding layers. These $\{W_f, W_i, W_o\}$ and $\{b_f, b_i, b_o\}$ are also called model parameters.

Let G_r be a SCDG. The graph autoencoder trains its LSTM layers through two modules: The encoder module $\mathbf{E}(\mathbf{G})$ transforms the graph structure, i.e., possible paths in $\mathbf{G}$, into a feature vector, i.e.,$\mathbf{x} = \mathbf{E}(\mathbf{G})$. The decoder module $\mathbf{D}(\mathbf{x})$ does an opposite way to reconstruct the original graph $\widehat{\mathbf{G}}$ from its feature vector $\mathbf{x}$ given by the encoder module, i.e., $\widehat{\mathbf{G}} = \mathbf{D}(\mathbf{x})$. This graph autoencoder is trained to optimize a reconstruction error Loss_1:

$$\text{Loss}_1(G_r, \widehat{\mathbf{G}}) = \frac{1}{2} \sum_{i=1}^{n} ||c_i - \hat{c}_i||^2$$

where $||c_i - \hat{c}_i||$ is the measure of the difference between the component c_i of the original graph Gr and its reconstructed component $\hat{c}_i$ in the graph $\widehat{\mathbf{G}}$. Using LSTM layers as its internal layers enables the graph autoencoder to manage arbitrary size graphs, i.e., SCDGs.

4.2 Classifier module

The classifier module is a combination of n single classifiers, i.e., $\{\mathbf{F}_i(\mathbf{x})\}_{i=1}^{n}$, $n > 0$. Each classifier i corresponds to a malware family. It is a fully connected neural network layer connected to the activation function softmax$(\cdot)$ [21]. These classifiers are connected to the graph autoencoder via the output of the encoder $\mathbf{E}(\mathbf{G})$. Let $\mathbf{x}$ be an output of $\mathbf{E}(\mathbf{G})$, the module is defined as follows:

$$\hat{y} = \text{softmax}([\mathbf{F}_i(\mathbf{x})]_{i=1}^{n})$$
$$\mathbf{L}(\mathbf{x}) = \arg\max_{i=1}^{n}(\hat{y})$$

where $\mathbf{L}(\mathbf{x})$ is the predicted label class of SCDG indicating the predicted malware family, $\mathbf{F}_i(\mathbf{x}) = \mathbf{W}_i \cdot \mathbf{x} + \mathbf{b}_i$. $\mathbf{W}_i$ and $\mathbf{b}_i$ are

respectively the weight and the bias values of the layer $\mathbf{F}_i$. The $\{(\mathbf{W}_i, \mathbf{b}_i)\}_{i=1}^{n}$ are model's parameters.
This module is trained to optimize the Binary Cross Entropy Loss:

$$\text{Loss}_2 = -\frac{1}{n}\sum_{i=1}^{n} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)$$

where y specifies the ground truth class of SCDG associated with $\mathbf{x}$. $y_i = 1$ if the SCDG is in the class i. Otherwise, $y_i = 0$.

To train the deep learning model, we use a stochastic optimization algorithm, i.e., the Adam optimizer algorithm [25], which recomputes the model parameters in every training step on the training data, in order to optimizing the total loss function. The total loss function Loss is the sum of losses from the graph autoencoder and the classifier module.

$$\text{Loss} = \text{Loss}_1 + \text{Loss}_2.$$

5 SECURE LEARNING APPROACH

In the previous section, we introduce the deep learning model to classify SCDGs. We present in this section a secure learning approach to train this model on different devices/clients using the concept of federated learning. We first recall the federated learning (FL) approach [26]. FL is a collaborative learning approach among $\mathbf{N}$ devices/clients with the help of a central server, e.g., an aggregator server. In the training process, clients use their private dataset to train their local model, and then, all the local models are sent to the aggregator server to be merged into a global model. Next, the parameters of the global model are sent to clients for updating to their local model. After a sufficient number of local training and updates exchanges between the aggregator server and the associated clients, the clients' models can converge to an optimal learning model. However, the FL is not always a sufficient privacy mechanism to protect the privacy of clients, i.e., the private dataset. It is easy to be exposed to the data inference attacks. As we have mentioned above, the popular technique, such as using differential privacy to protect the private data, is not strong enough to protect the leakage of private data [9]. That is why, using encryption algorithms, such as using homomorphic encryption [2, 38], multi-party computation (MPC) [10], constitute an interesting approach to preserve the data privacy. In the section, we implement a secure learning protocol with an average-weight aggregation using homomorphic encryption. It protects the private data from semi-honest clients and server. Note that the semi-honest (a.k.a honest-but-curious) model is that collaborators (clients/server) do follow the protocol but try to infer as much as possible from the values (shares) they get, also by combining their information. This protocol is presented in the following sections.

5.1 Communication setting

We implement an asymmetric encryption for the communication between clients and the server (Figure 2). Support a client want to send safely a message to the server. First, the server generates a key pair composed of a private key and a public key. The private key is hidden by the server. The public key is openly distributed to the client. The private key can decrypt what the public key encrypts and vice versa. Then, the client encrypts its message by using the server's public key. It openly sends this ciphertext to the server. This ciphertext is safe since any other cannot decrypts it without the private key from the server. The server receives the ciphertext and decrypts it with its private key. Thus, this setting ensures a secure communication between the client and the server.

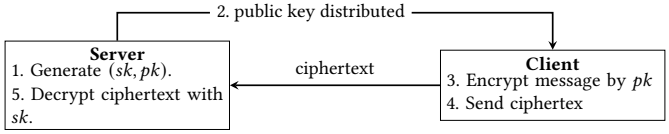


Figure 2: Client-Server communication

5.2 Homomorphic encryption for a secure training model

For a safe computation at the aggregator, we implement the homomorphic encryption to the model parameters. Let us recall the homomorphic encryption scheme [12, 24, 39]. Let $(\mathbf{sk}, \mathbf{pk})$ be a pair of secret and public keys, respectively. Given a numeric value $\mathbf{z}$. First, $\mathbf{z}$ is encoded into a plaintext. The public key $\mathbf{pk}$ is used to encrypt the plaintext of $\mathbf{z}_{plaintext}$ into a ciphertext $\bar{z}_{\mathbf{pk}}$. Let HEnc be a function which encodes a numeric value and encrypts its plaintext into a ciphertext with a public key, e.g., $\bar{z}_{\mathbf{pk}} = \text{HEnc}(\mathbf{z}, \mathbf{pk})$. Let HDecrypt be a function which decrypts a ciphertext by using a secret key and decodes its plaintext into a numeric value. Then, $\text{HDecrypt}(\bar{z}_{\mathbf{pk}}, \mathbf{sk})$ decrypts $\bar{z}_{\mathbf{pk}}$ to the plaintext $\mathbf{z}_{plaintext}$, and it decodes $\mathbf{z}_{plaintext}$ to the numeric value $\mathbf{z}$, i.e., $\mathbf{z} = \text{HDecrypt}(\bar{z}_{\mathbf{pk}}, \mathbf{sk})$.

The important property of homomorphic encryption is users can process and make calculations on encrypted data without revealing the original data. With the secret key, the user decrypts the processed data, which is exactly the expected result [11, 36]. Given numeric values $\mathbf{x}$ and $\mathbf{z}$, the multiplication of the ciphertext of $\mathbf{z}$, i.e., $\bar{z}_{\mathbf{pk}}$, and the plaintext of $\mathbf{x}$, i.e., $\mathbf{x}_{plaintext}$, is a ciphertext of $\mathbf{z} \cdot \mathbf{x}$, i.e., $\text{HEnc}(\mathbf{z} \cdot \mathbf{x}, \mathbf{pk}) = \bar{z}_{\mathbf{pk}} \cdot \mathbf{x}_{plaintext}$. The addition of two ciphertexts $\bar{x}_{\mathbf{pk}}$ and $\bar{z}_{\mathbf{pk}}$ is also a ciphertext of $\mathbf{z} + \mathbf{x}$, i.e., $\text{HEnc}(\mathbf{z} + \mathbf{x}, \mathbf{pk}) = \bar{z}_{\mathbf{pk}} + \bar{x}_{\mathbf{pk}}$.

With the homomorphic encryption, we implement a secure learning among $\mathbf{N}$ clients. The local updates are protected in the encrypted message. The global update is computing on encrypted data with respect to the addition operator of the homomorphic encryption. The Algorithm 1 describes the m training rounds of $\mathbf{N}$ clients. Each

client i holds a pair of $(\mathbf{pk}^i, \mathbf{sk}^i)$, and the *Key-client* holds a secret value $\mathbf{z}$. For each training round, the training process is as follows: First, the system selects a *Key-client* among clients. The selected client, i.e., *Key-client*, exchange the public key, i.e., $\mathbf{pk}^i$, and its encrypted value, i.e., $\bar{z}_{\mathbf{pk}^s} = \text{HEnc}(\mathbf{z}, \mathbf{pk}^s)$ with other clients. Meanwhile, each client locally trains their local model. When the training step is done, they use the ciphertext $\bar{z}_{\mathbf{pk}^s}$ of the *Key-client* to encrypt the parameters of their local model and send them to the *aggregator*. Then, the *aggregator* computes the sum of clients' parameters and sends to the *Key-client*. The *Key-client* decrypts the global updates from the *aggregator*, i.e., $\mathbf{w} = \frac{1}{\mathbf{z}\cdot\mathbf{N}}\text{Decrypt}(\bar{w}_{\mathbf{pk}^s})$ and sends the updates $\mathbf{w}$ to every client i. Finally, the clients receive and apply the updates to their local model. After these updates are done, a new round is started by choosing a new *Key-client* and training the local models at the clients' side.

Algorithm 1 Secure training in the federated learning

for each *round* $\in [1 \dots m]$ **do**
  Randomly choose a *Key-client* among clients.
  The clients send their public keys, i.e., $\mathbf{pk}^i$, to the *Key-client*.
  The *Key-client* sends its encrypted secret value $\bar{z}_{\mathbf{pk}^s} = \text{HEnc}(\mathbf{z}, \mathbf{pk}^s)$ to all clients.
  for each $i \in [1 \dots \mathbf{N}]$ **do in parallel**
    The client i trains the local model on its own data.
    The client i encrypts the model's parameters $\mathbf{w}^i$ using the secret value $\bar{z}_{\mathbf{pk}^s}$, i.e., $\bar{w}^i_{\mathbf{pk}^s} = \mathbf{w}^i \cdot \bar{z}_{\mathbf{pk}^s}$.
    The client i sends the update $\bar{w}^i_{\mathbf{pk}^s}$ to the *aggregator*.
  end for
  The *aggregator* computes the encrypted global weight

$$\bar{w}_{\mathbf{pk}^s} = \sum_{i=1}^{n} \bar{w}^i_{\mathbf{pk}^s}.$$

  The *aggregator* sends the encrypted global weight $\bar{w}_{\mathbf{pk}^s}$ to the *Key-client*.
  The *Key-client* decrypts $\bar{w}_{\mathbf{pk}^s}$ by its secret key $\mathbf{sk}^s$ and the secret value $\mathbf{z}$ to get the global weight $\mathbf{w}$.

$$\mathbf{w} = \frac{1}{\mathbf{z}\cdot\mathbf{N}}\text{HDecrypt}(\bar{w}_{\mathbf{pk}^s}, \mathbf{sk}^s)$$

  for each $i \in [1 \dots \mathbf{N}]$ **do in parallel**
    The *Key-client* encrypts the updates $\mathbf{w}$ by $\mathbf{pk}^i$, i.e., $\mathbf{w}_{\mathbf{pk}^i}$, and sends the updates to the client i.
    The client i decrypts $\mathbf{w}_{\mathbf{pk}^i}$ by its secret key $\mathbf{sk}^i$ and applies the updates to its local model.
  end for
end for

5.3 Application to malware identifier

We apply the secure learning protocol to train the deep learning model on N clients. Each client has its own malware which cannot be shared to others. To identify malware, the clients implement a classifier model at their side. They share the parameters of their local classifier model during the training phase. They get back the update from the *aggregator* after each training round. An example of the training process of three clients is shown in Figure 3: Clients keep their binaries/malware. Using the SCDG extraction, they generate SCDGs from their binaries, and the SCDGs are also kept in private. Then, they train the local model on the extracted SCDGs. The trained model's parameters are encrypted, and they are sent to *aggregator*. The aggregator safely computes the update on the encrypted parameters. Then, it sends the aggregated parameters to the *Key-client*, i.e., Client-2, for decryption. The *Key-client* decrypts the aggregated parameters and sends them to Client-1 and Client-3. The clients receive the aggregated parameters and update their local model. The communication channels among the aggregator and clients are implemented following the client-server communication in Section 5.1.

In this work, we consider two cases of sharing the model parameters as follow:

(1) Clients collaboratively learn the full model including the graph autoencoder $(\mathbf{E}(\mathbf{G}), \mathbf{D}(\mathbf{x}))$ and the classifier module $\{\mathbf{F}_i(\cdot)\}$, called *Full-Aggregation Learning*. This is a closed collaboration since all clients should have the same structure of their local model as well as they share their data labels.

(2) We decompose the model in Section 4 into two parts: the autoencoder $(\mathbf{E}(\mathbf{G}), \mathbf{D}(\mathbf{x}))$ and the classifier module $\{\mathbf{F}_i(\cdot)\}$. Clients share only a part of model, i.e., the encoder part $\mathbf{E}(\mathbf{G})$, with each other, called *Partly-Aggregation Learning*. It enables clients sharing their feature computing in the form of an encoder $\mathbf{E}(\mathbf{G})$. Thus, it keeps the private data classes. It then allows a flexible implement of learning paradigms at the client's side.

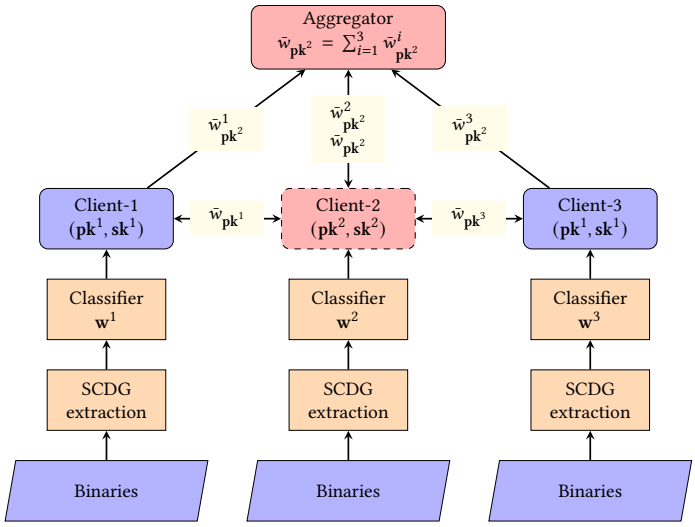


Figure 3: Secure learning among 3 clients and one aggregator. Client-2 is the *Key-Client* and it might be replaced by another after each training round.

6 EXPERIMENT

We will evaluate the performance of our deep learning system in this section. We first present our datasets and the data proportion on each client. Then, we present the implement of our learning

approaches on the homogeneous SCDGs and on the inhomogeneous SCDGs. The results also are compared to the *Centralized Learning* implement. The FL experiment is deployed on four virtual machines. Their resources are reported in Table 1. The evaluation is measured

	Physical CPU	Virtual CPU	Memory
Aggregator	4	8	24GB
Client-1	4	8	24GB
Client-2	8	8	20GB
Client-3	8	8	15GB

Table 1: Virtual Machines used in our experiment

by the accuracy of the trained malware identifier as follows:

$$\text{Accuracy}(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n} 1(y_i = \hat{y}_i)$$

where n is the number of samples, $1(\cdot)$ is the indicator function, $\hat{y}_i$ is the predicted value of the i-th sample and y_i is the corresponding true value.

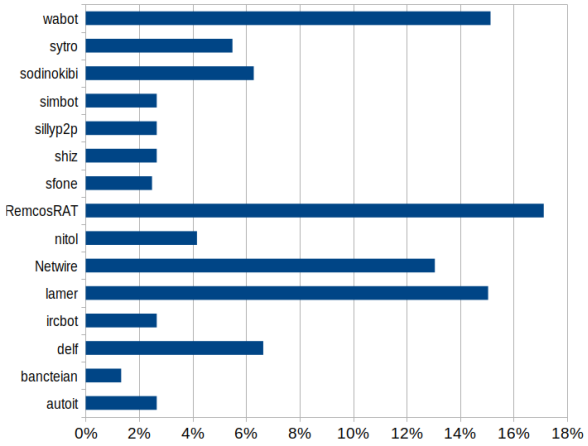
6.1 Dataset

We collect malware from Cisco and MalwareBazaar Database [1] to build two datasets: Dataset-1 and Dataset-2. Dataset-1 consists of 2260 malware from 15 families (Figure 4-a). It is randomly split into two sets: the training set of 2034 malware and the test set of 226 malware. The SCDGs in Dataset-1 are computed by the same strategy, i.e., CDFS which is presented in Section 3. Dataset-1 is used for the *Homogeneous-data* scheme. Dataset-2 is a collection of 1844 malware from 15 families (Figure 4-b). They are distributed to three clients. Each client implements its own strategy to compute SCDGs from binaries in Dataset-2. Particularly, Client-1 successfully extracts 1660 graphs by strategy BFS. Using strategy CBFS, Client-2 successfully extracts 1725 graphs. Client-3 obtains 1662 graphs by strategy CDFS. Since the clients implement different strategies, in a limit period of time, i.e., 20 minutes, the number of SCDGs extracted from Dataset-2 is different at each client. Thus, this challenges our secure learning model to deal with the context of inhomogeneous SCDGs. The data proportion of each dataset are detailed in Table 2.

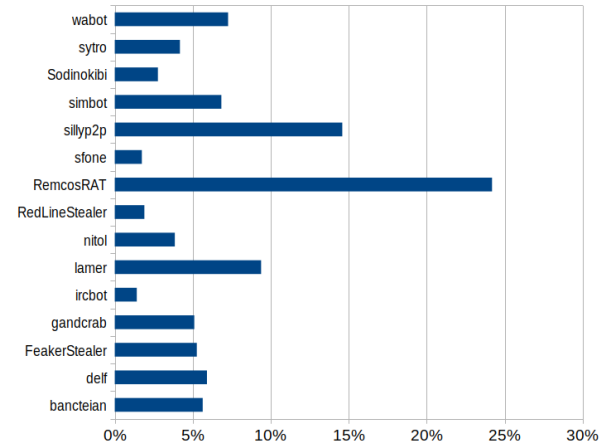
[1] https://bazaar.abuse.ch/

	Partitions	Training set	Test set
Dataset-1	Client-1	678	226
	Client-2	678	
	Client-3	678	
Total		2034	226
Dataset-2	Client-1	1245	415
	Client-2	1293	432
	Client-3	1246	416

Table 2: The distribution of data in FL



(a) Dataset-1



(b) Dataset-2

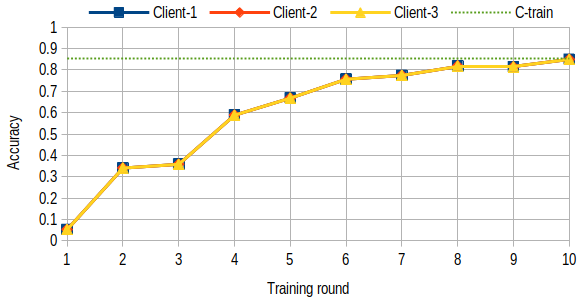
Figure 4: The malware distribution in the two datasets, showing the percentage of different categories with respect to the total number of malware files. The malware' labels are assigned by AVClass [43] according to VirusTotal reports.

6.2 Secure Federated Learning on SCDGs

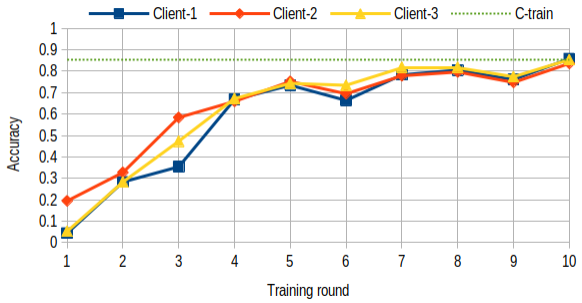
In this experiment, our approach is evaluated on a homogeneous dataset, i.e., Dataset-1. First, we evaluate the model on the centralized data of Dataset-1. Then, we compare this result to the implement of our secure learning approach where the data of Dataset-1 are split into 3 partitions of 678 malware, and they are distributed among the three clients. The data proportion at each clients is shown in Table 2.

Centralized Learning: We setup the classifier to take a SCDG as input, and it outputs the feature vector of size of 64. The classifier module is constructed according to number of malware families in the training partition, i.e., 15 classifiers which correspond to 15 malware families. We train the model for 10 epochs on the training set. Then, the trained model is used to identify malware from the test set. We obtain the accuracy of 85.4%.

Secure Federated Learning: We implement the secure training for three clients, using the library TenSEAL [4] for encrypting and aggregating the model parameters and RSA cryptosystem[2] for a secure communication. The local models are trained on the client's training set. The updated models are evaluated on the test set. Note that the client's training set is a part of the training set in the *Centralized Learning*, and the test set is used for both the *Centralized Learning* and the *Secure Federated Learning*. The proportion of data at clients is shown in Table 2.



(a) Full-aggregation learning



(b) Partly-aggregation learning

Figure 5: Accuracy of the secure federated learning. The dash-line (C-train) is the accuracy of the centralized learning.

Figure 5 shows that the performance of the local models is improved after 10 training rounds. For the *Full-Aggregation Learning* (Figure 5-a), the performance of all clients is similar, and their accuracy can reach 84.96% comparing to the accuracy of 85.4% in the *Centralized Learning*. Although the increment of accuracy is a bit different among clients in the *Partly-Aggregation Learning*, they are getting more converged at the end of the training phase. Comparing to the *Centralized Learning*, the performance of Client-1 and Client-3 in *Partly-Aggregation Learning* is equal to or even better than the ones in the *Centralized Learning*. Figure 6 shows the confusion matrix of the classifiers of three learning types. The classifier at Client-1 is chosen to represent the classifier of the *Partly-Aggregation Learning*. The results are also reported in Table 3.

[2] https://cryptography.io/

		Accuracy (%)
Centralized Learning		85.4
Full-Aggregation Learning		84.96
Partly-Aggregation Learning	Client-1	**85.84**
	Client-2	83.63
	Client-3	**85.4**

Table 3: Comparison of the centralized learning and the secure federated learning.

6.3 Secure Federated Learning on the inhomogeneous SCDGs

Since the computing power is different from devices, the features, e.g., SCDG, are extracted accordingly. The training graphs are computed in different techniques among clients even though that they are SCDGs. In this work, we consider three types of SCDG, that are extracted from binaries by the three different strategies in Section 3, i.e., BFS, CBFS and CDFS, at three clients. Particularly, Client-1 implements BFS, Client-2 implements CBFS, and Client-3 implements CDFS. The data proportion is reported in Table 2. In the scheme, the clients have their own training set and test set. The training sets are used to train their models. Then, the test sets are used to evaluate the performance of the models. Similar to previous experiment, we first implement the *Centralized Learning* in the client's side. Then, we compare the results to the secure learning approach with two aggregation cases.

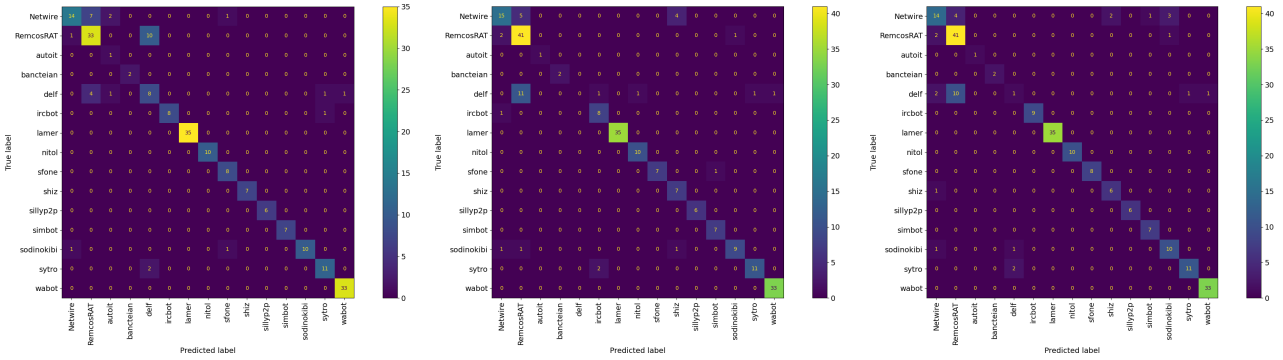
(1) For the *Centralized Learning*, the model is separately trained on its training set for each client in 20 epochs. Then, this model is evaluated on the client's test set.

(2) For the *Secure Federated Learning*, we implement two types of aggregations: *Full-Aggregation Learning* and *Partly-Aggregation Learning* (see Section 5.3). The secure training is applied to train the local model for 20 training rounds. In each training round, the client trains the local model on its training set, and then, it evaluates the updated model on its own test set.

		Accuracy (%)
Centralized Learning	Client-1	92.05
	Client-2	81.02
	Client-3	89.9
Full-Aggregation Learning	Client-1	87.4
	Client-2	**87.27**
	Client-3	88.22
Partly-Aggregation Learning	Client-1	**93.73**
	Client-2	**87.96**
	Client-3	89.18

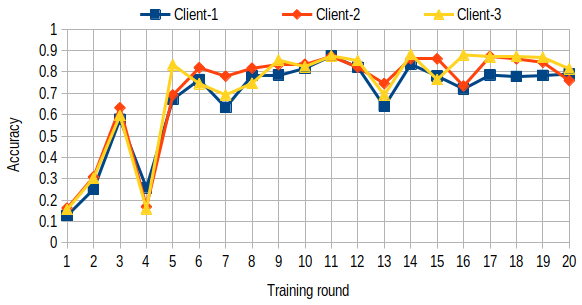
Table 4: Comparison of the centralized learning and the secure federated learning in the inhomogeneous-data scheme.

Figure 7-a shows that the performance of the local models are improved after 20 training rounds in *Full-Aggregation Learning*. Three clients can reach the accuracy of ~ 87% after 11 training rounds. Then, the performance of Client-1 goes down to 79% while Client-3 reach its peak, i.e., 88.22%, at the 14-th round. Compared

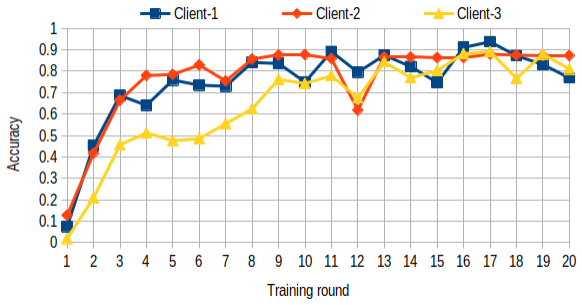


(a) *Centralized Learning* (b) *Full-Aggregation Learning* (c) *Partly-Aggregation Learning* at Client-1

Figure 6: Confusion Matrix of the classifiers on Dataset-1.



(a) Full-aggregation learning



(b) Partly-aggregation learning

Figure 7: Accuracy of the secure federated learning in the inhomogeneous-data scheme.

to the *Centralized Learning*, Client-2 in *Full-Aggregation Learning* can achieve the better performance at the 8-th round. It reaches 87.27% of accuracy, at the 11-th round while the accuracy in the *Centralized Learning* is 81.02%. The degradation at Client-1 in *Full-Aggregation Learning* is about 5.1% comparing to the *Centralized Learning*. For *Partly-Aggregation Learning* in Figure 7-b, Client-1 gets the accuracy of 93.73% after 17 training rounds while Client-2 and Client-3 get 87.96% and 89.18%, respectively. The performance of Client-1 and Client-2 overtake the ones in *Centralized Learning* while the degradation at Client-3 is about 0.72%. The confusion matrix of classifiers at Client-2 is shown in Figure 8. The results are also reported in Table 4.

Overall, our secure learning approach is able to train the deep learning model for an accurate malware identifier. Comparing to the *Centralized Learning*, the performance degrades slightly in some client. It is a side-effect of calculation on the encrypted data in the secure aggregation. Besides, the experimental results also show that the *Partly-Aggregation Learning* overtakes the *Full-Aggregation Learning* in our system. Hence, the *Partly-Aggregation Learning* should be considered in future implementations of the federated learning for malware classification since it allows the clients collaborate with each other while keeping their classifier model in private.

7 CONCLUSION

In this paper, we present a deep learning model for malware classification and a secure learning approach to integrate this learning model into a federated learning system. We validate the system to identify malware in our datasets. We obtain a significant result with the accuracy of ~ 85%. It is comparable to the *Centralized learning*. Moreover, we implement the system to learn SCDGs extracted from three various strategies. We can achieve the accuracy of ~ 88% in *Full-Aggregation Learning* and ~ 93% in *Partly-Aggregation Learning*, comparing to the accuracy of ~ 92% in *Centralized Learning*. According to the experimental results, the *Partly-Aggregation Learning* represent a promising option to develop collaborative learning for malware classification in the future.

ACKNOWLEDGMENTS

Charles-Henry Bertrand Van Ouytsel is FRIA grantee of the Belgian Fund for Scientific Research (FNRS-F.R.S.). We would like to thanks Cisco for their malware feed and VirusTotal for giving us access to their API.

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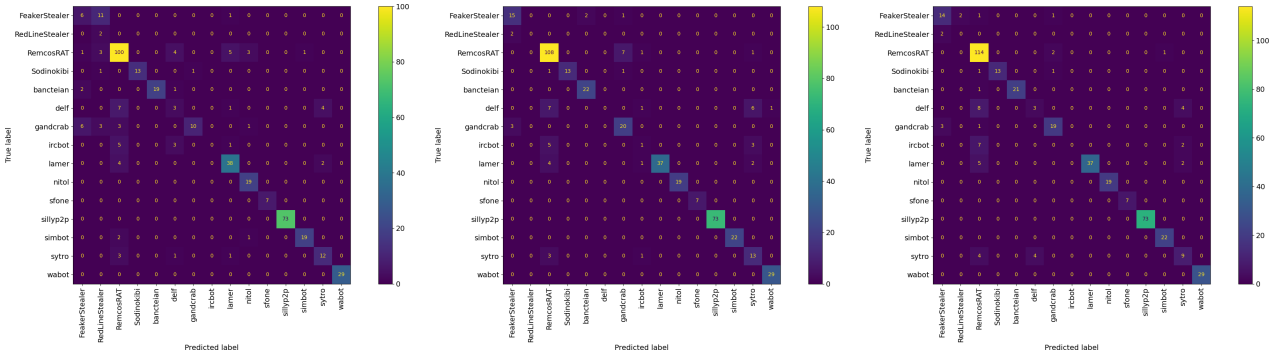

(a) *Centralized Learning* (b) *Full-Aggregation Learning* (c) *Partly-Aggregation Learning*

Figure 8: Confusion Matrix of the classifiers at Client-2 on Dataset-2.

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