Interpretable Federated Transformer Log Learning for Threat Forensics

Abstract—**Threat detection and forensics have become an imperative component in every digital forensic triage. Supervised approaches have been proposed for inferring system and network anomalies; including anomaly detection contributions using syslogs. Nevertheless, most works downplay the importance of the interpretability of a model's decision-making process. In this research, we are among the first to propose an interpretable federated transformer log learning model for threat detection supporting explainable cyber forensics. The proposed model is generated by training a local transformer-based threat detection model at each client in an organizational unit. Local models at each client learn the system's normal behavior from the syslogs which keep records of execution flows. Subsequently, a federated learning server aggregates the learned model parameters from local models to generate a global federated learning model. Log time-series capturing normal behavior are expected to differ from those possessing cyber threat activity. We demonstrate this difference through a goodness of fit test based on Karl-Pearson's Chi-square statistic. To provide insights on actions triggering this difference, we integrate an attention-based interpretability module. We implement and evaluate our proposed model using `HDFS`, a publicly available log dataset, and an in-house collected and publicly released dataset named `CTDD`, which consists of more than 8 million syslogs representing cloud collaboration services and systems compromised by different classes of cyber threats. Moreover, through different experiments, we demonstrate the log agnostic capability and applicability of our approach on a real-world operational setting. Our interpretability module manifests significant attention difference between normal and abnormal logs which provide insightful interpretability of the model's decision-making process. Finally, we deem the obtained results as a validation for the appropriate adoption of our approach in achieving threat forensics in the real world.**

I. Introduction

The 2019 global coronavirus pandemic (COVID-19) led companies to shift activities from their conventional office model work-place to a work-from home model en-masse. This shift was enabled by the radical advancement of communication technology, online software services, and increased bandwidth services to perform work remotely. Despite the flexible benefits, this work modality introduces new cyber security threats to computing systems and infrastructures used by corporations and individuals [47].

During the increase in COVID-19 cases, cyber attacks targeting healthcare organizations increased by 45% compared to an overall 22% increase in cyber attacks across all other industries around the world [1]. Cyber attacks such as the one launched against Britain's National Health Service [10], Brno University Hospital [6], and another related to a Ransomware attack on the University of Düsseldorf (UKD) in Germany shows that these cyber attacks involve a range of attack vectors including Ransomware, Distributed Denial of Service (DDoS), Botnets, and other malicious attacks. In response to these attacks, a joint cyber security advisory was issued by the Cyber security and Infrastructure Security Agency (CISA), the Federal Bureau of Investigation (FBI), and the Department of Health and Human Services (HHS) advising on an increased and imminent cybercrime threat to U.S. hospitals and health care providers [2].

That said, one important aspect of threat forensics is to acquire attack provenance. For instance, the presence of a Ransomware attack on a particular organizational machine exhibit system behavioral changes in which the attack openly notifies the user of the infection [20]. By employing advanced deep learning-based threat detection models on system logs (syslogs), cyber security analysts can better differentiate normal system behaviors from their counterparts to ultimately achieve anomaly detection [12, 31, 45]. Indeed, syslog analysis is highly needed to understand the inner working and behavior differences of an Operating System (OS). Such logs offer valuable information about significant occurrences that explain how the system operates in terms of software, hardware, system processes, and system components which all can be leveraged to detect any abnormal activity occurring within a system.

Moreover, syslogs contain sensitive information that can provide insights on security weaknesses that are hidden from outside scans and may disclose information about vulnerable targets, login credentials, and security associations between entities [39]. Therefore, exposing syslogs containing sensitive information to a third party leads to the compromise of data privacy. To address this liability, various anonymization techniques, such as generalization and suppression, have been employed by the industry to safeguard the user's data privacy and the system as a whole. A drawback of applying such techniques is the decreased data usefulness for analysis and understanding the system's behavior. Maintaining a balance between data usefulness and privacy preservation, therefore, remains an important challenge when dealing with syslogs.

In addition, most proposed works also fail to include imperative elements for the development of effective threat detection models. These include: (1) producing, collecting, and open-sourcing novel representative datasets, (2) adopting techniques to ensure user data privacy during the training process to prevent the violation of data protection [41] and data jurisdiction laws [26], and (3) provide visibility to the model's decision making process for identifying system activity triggering post-incident detection.

To address this gap, we propose the first interpretable federated transformer log learning model for threat forensics. Unlike other works that exclusively focus on anomaly detection in syslogs, our proposed model incorporates the concept of Federated Learning (FL), a machine learning setting where multiple entities collaborate in solving a machine learning problem under the coordination of a federated server. We leverage the distributed nature of this concept to generate a robust model that offers a privacy preserving solution with a high level of security [4].

The proposed model is segmented into two main stages. In the first stage, a local transformer-based model trained at each client using the system's local dataset composed of syslogs files. Log event sequences are mapped to log keys sequences using a parser. The mapped time-series are then embedded and fed to a local model using stochastic gradient descent (SGD) for learning the underlying patterns of each given sequence. In the second stage, the learn parameters from all local models are passed to the FL server. These are aggregated to generate a global federated learning model. The global FL model is then shared with all participating clients. Multiple rounds of this cycle are executed for improving the performance of threat detection. In the last cycle, the interpretability module at each client computes the interpretability attention-based weights using the latest global FL model. Clients then share the weights with the FL server who aggregates them to generate the federated interpretable attention-based weights. All clients receive an updated version of the global FL model for inference and the federated interpretable attention-based weights used for comparing it's attention distribution against the one from a specific log sample, Algorithm 1.III. In addition, the intrepretability module provides forensic investigators the means to backtrack the log keys triggering a cyber threat detection. To the best of our knowledge, our work is the first to offer such benefit in a federated setting to support cyber forensics and digital triage.

In summary, this work makes the following contributions:

- We designed and implemented the first interpretable federated transformer log learning model for cyber threat detection in syslog with the capability of revealing actionable information triggering the model's outcome.
- We validated our model's performance by training it using two datasets while comparing it against State-Of-The-Art (SOTA) works.
- We discovered a strong correlation between log messages carrying indicators of the executed threat sample and the attention given to the corresponding mapped input sequence triggering the threat detection.
- We generated a cyber threat detection dataset consisting of 8,448,715 syslogs collected during the second half of 2020 from a production-level environment comprised of 62 instances running uncompromised cloud collaboration services and 16 cloud instances running threat samples.

The rest of this paper is organized as follows: In Section II, we present the background and related work. Section III covers our proposed model design. Section IV present our experimental evaluation. Section V explore the capabilities of the model's interpretability module. We present our discussion in Section VI. Finally in Section VII, concluding remarks are noted and a few future endeavors are pinpointed.

II. Background and Related Work

In this section, we introduce existing approaches adopted in syslog analysis and their corresponding limitations. In addition, we discuss the concept of federated learning and attention-based interpretability in the field of cyber security. Furthermore, we present a brief overview of the datasets used for threat and anomaly detection.

A. Existing Approaches for Syslog Analysis

During routine system operations, syslogs are generated from various sources in a computer system and consist of textual messages describing the activity throughout the global system. Such messages provide an abundance of information linked to the system's behavior. That said, threat forensics rely on periodic syslog scrutiny to unveil abnormal system behavior originating from suspected attacks. Due to a large number of generated logs, the examination of syslogs is not a trivial task and can be hard if not impossible to manually track, analyze, detect, and diagnose system problems. In what follows, we highlight previous, as well as, emerging log-based analysis approaches adopted in the literature and discuss their limitations along with the newly adopted approaches:

Rule-based approaches: Early research on log-based analysis proposed rule-based detection techniques. Such approaches rely on predefined rule-sets or dynamic rules which can be created, superseded, or deleted by existing rules at run time to accommodate for system behavior changes and thus limit and avoid unnecessary alert reporting. More precisely, rule-based approaches employ regular expressions to parse and recognize events and trigger predefined actions based on matched rules [15, 37, 38]. For instance, Swatch [15] is a monitoring log file system that filters unwanted data and take predefined actions based on detected log patterns. One of its main capabilities is to ignore duplicate entries in addition to performing rule changes based at the time of arrival. Moreover, Logsurfer [37], a log file analysis software, is designed to detect signatures of complex interactions and is capable of updating its rule-set at run-time and act accordingly.

However, two main foreseen fall-backs related to rule-based approaches are characterized by the need for continuous rule-sets maintenance and their significant specificity to application scenarios. Such ongoing maintenance requires domain expertise to define rules that describe system behaviors. Nonetheless, possible bottlenecks could occur during expert involvement in defining the rules. Accordingly, the literature has taken new directions and proposed further approaches to perform log analysis, which we discuss in the sequel.

Causality-based approaches: Causality analysis on logs gained much attention for comprehending system activities and to detect potential risks. These approaches leverage backward and forwards causal graphs to identify multi-hop attacks [24]. In addition, causality analysis utilizes dependency graphs [23] and action history graphs [22] which provide a detailed dependency graph describing the system execution sequences that occur during an intrusion. Moreover, provenance-aware system approaches are introduced in [34] and [36] to facilitate the integration of provenance across multiple levels of abstraction. For example, such an approaches can help determine malware provenance and find the source of anomalies. Moreover, whole system simulation such as TaintBochs [9, 14] is being used to analyze sensitive data handling at a whole system level and to help to recover legitimate file system data after an attack occurs.

Despite the so many credits of causality analysis in time series problems, many concerns were related to the non-trivial lifetime and iterative input and output processing of processes which can cause the well-known problem of dependency explosion [27]. Many research addressed the problem of dependency explosion by adopting data reduction techniques [14, 24, 27]. These approaches include Binary-based execution partitioning and TaintBochs simulation. Nonetheless, it is not certain that reducing the data volume of irrelevant dependencies can lead to a decrease in attack investigation time [30]. In addition, such data reduction can unintentionally eliminate unnoticed important data which highly affects the results of the analysis.

AI-based approaches: Current literature presents two main approaches for log analysis, namely, (1) log event indices-based and (2) log template semantics-based. In this paper, we follow the log event indices-based approach. Both approaches first employ a log parser to identify log templates from a time-series of log events. Subsequently, log templates are mapped into a time-series of vectors representing the original sequence of log events. In contrast, log template semantics-based approaches employ word embeddings to convert the extracted log templates into vectors.The generated vector time-series is then used for training supervised and unsupervised AI-based models that learn the underlying patterns within the vector time-series using different methods. Such methods include Principal Component Analysis (PCA) [49], Support Vector Machine (SVM) [16], Bi-LSTM [52], LSTM [12, 33], and Transformers [18, 46]. Some of these works incorporate methods to control unseen log events via human intervention or by applying semantic vectorization techniques such as Term Frequency-Inverse Document Frequency (TF-IDF).

Nonetheless, SOTA methods fail to preserve user data privacy, as they are based on centralized training approaches, and lack methods for revealing the level of influence that each element in the time-series had over the model's prediction.

B. Federated Learning and Attention-based Interpretability

Federated learning [32] addresses the fundamental problems of privacy, ownership, and data locality. Federated Stochastic Gradient Descent (FedSGD) and Federated averaging (FedAVG) [32] are two methods used for aggregating the parameters of local models trained at each client. Previous works on federated learning has been applied in the cyber security domain. These include (1) a multi-task deep neural network in federated learning (MT-DNN-FL) for network anomaly detection, traffic recognition, and traffic classification [53], (2) an autonomous self-learning distributed system for detecting anomalies in IoT devices [35], and (3) DeepFeed [28] which applies federated deep learning to detect cyber threats against industrial cyber physical systems. To the best of our knowledge, no works in the cyber forensic space has integrated federated learning and interpretability for threat inference using syslogs.

Model interpretability in cyber forensic applications has been explored using LSTM-based models with attention [5] by calculating the weighted sum over the attention value vectors. Other LSTM works, where no attention mechanisms are used, have employed anomaly score decomposition [43] to provide visibility on the model's decision making process. Such works, nonetheless, do not integrate interpretability in a federated learning setting.

C. Datasets for Threat and Anomaly Detection

Most cyber security datasets focus on network traffic [13, 21] while the few public datasets which consist of syslogs [50] are mostly collected from distributed systems [48] or high performance computing infrastructure with a relatively low number of unique log messages and data structure, in contrast to those seen in Operating System (OS) logs. On the other hand, datasets for cyber threat analysis have been created using synthetic data generators [29] or using real systems but limited to authentication events in Windows-based systems [19].

Different from these works, our Cyber Threat Detection Dataset (CTDD) [3] is the first publicly available dataset consisting of syslogs produced by real user activity and synthetic threat scenarios in a modern cloud-based operational system. The syslogs were captured from 62 virtual machines (VMs) running uncompromised cloud collaboration services. Synthetic threat scenarios were emulated in 16 additional VMs. Our approach has the advantage that future research groups can produce additional real or synthetic threat samples using the same cloud image which is publicly available at Jetstream Cloud [40, 42].

III. Proposed Model Design

In this section, we present the proposed interpretable federated transformer log learning model supporting threat forensics. The proposed model is designed considering the following assumptions: (1) Federated server and clients are trusted. (2) The FL model is implemented without additional privacy protection or security mechanisms beyond preserving data locally at each client and the inherited privacy benefits of FL. (3) Only offline learning is considered for training the proposed model with homogeneous Independent and Identically Distributed (IID) data. (4) Distributed optimization follows a synchronous approach where all clients are available at all times. (5) A typical horizontal FL architecture [51] is followed were local datasets present different samples but share the same feature space. The training process of our interpretable

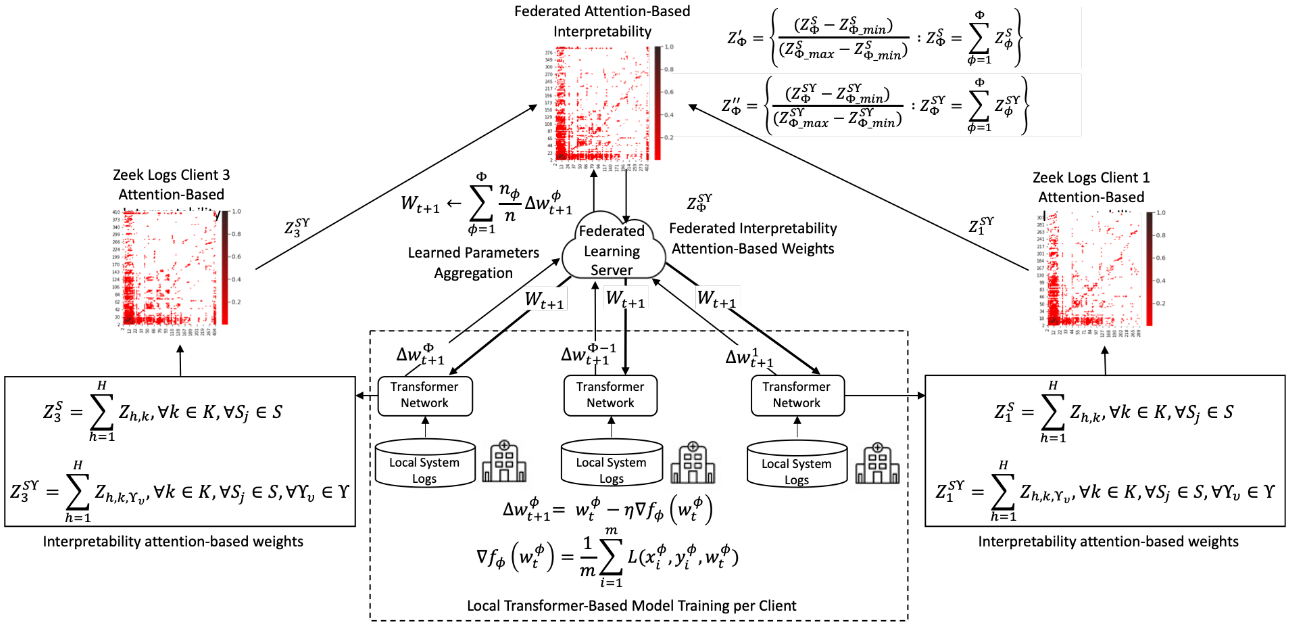

Federated Attention-Based
Interpretability
$Z'_{\Phi} = \left\{ \frac{(Z_{\Phi}^{S} - Z_{\Phi\_min}^{S})}{(Z_{\Phi\_max}^{S} - Z_{\Phi\_min}^{S})} : Z_{\Phi}^{S} = \sum_{\phi=1}^{\Phi} Z_{\phi}^{S} \right\}$
$Z''_{\Phi} = \left\{ \frac{(Z_{\Phi}^{SY} - Z_{\Phi\_min}^{SY})}{(Z_{\Phi\_max}^{SY} - Z_{\Phi\_min}^{SY})} : Z_{\Phi}^{SY} = \sum_{\phi=1}^{\Phi} Z_{\phi}^{SY} \right\}$
Zeek Logs Client 3
Attention-Based
Z_3^{SY}
$W_{t+1} \leftarrow \sum_{\phi=1}^{\Phi} \frac{n_{\phi}}{n} \Delta w_{t+1}^{\phi}$
Learned Parameters
Aggregation
Federated
Learning
Server
Z_{ϕ}^{SY}
Federated Interpretability
Attention-Based Weights
Zeek Logs Client 1
Attention-Based
Z_1^{SY}
W_{t+1}
W_{t+1}
W_{t+1}
Δw_{t+1}^{Φ}
$\Delta w_{t+1}^{\Phi-1}$
Δw_{t+1}^{1}
Transformer
Network
Transformer
Network
Transformer
Network
Local System
Logs
Local System
Logs
Local System
Logs
$Z_3^S = \sum_{h=1}^{H} Z_{h,k}, \forall k \in K, \forall S_j \in S$
$Z_3^{SY} = \sum_{h=1}^{H} Z_{h,k,Y_v}, \forall k \in K, \forall S_j \in S, \forall Y_v \in Y$
Interpretability attention-based weights
$Z_1^S = \sum_{h=1}^{H} Z_{h,k}, \forall k \in K, \forall S_j \in S$
$Z_1^{SY} = \sum_{h=1}^{H} Z_{h,k,Y_v}, \forall k \in K, \forall S_j \in S, \forall Y_v \in Y$
Interpretability attention-based weights
$\Delta w_{t+1}^{\phi} = w_t^{\phi} - \eta \nabla f_{\phi}\left(w_t^{\phi}\right)$
$\nabla f_{\phi}\left(w_t^{\phi}\right) = \frac{1}{m} \sum_{i=1}^{m} L(x_i^{\phi}, y_i^{\phi}, w_t^{\phi})$
Local Transformer-Based Model Training per Client

Fig. 1. The architecture of the proposed Interpretable Federated Transformer Log Learning for Threat Detection. A set of clients Φ contributing to the global FL model receive a set of hyperparameters and initial model parameters W_0 for training local transformer-based models using their local data. Additionally, the interpretability module uses the model's calculated attention by key to compute $Z_{\phi}^{S\Upsilon}$. $Z_{\phi}^{S\Upsilon}$ is computed for normal and cyber threat case scenarios. Each client sends the learned model parameters Δw_{t+1}^{ϕ} and their computed interpretable attention-based weights $Z_{\phi}^{S\Upsilon}$ to the FL server. The FL server aggregates the learned parameters to generate an updated global FL model W_{t+1}. Afterwards, the interpretability module at the FL server aggregates $Z_{\phi}^{S\Upsilon}$ to generate the federated interpretable attention-based weights $Z_{\Phi}^{S\Upsilon}$. Finally the FL server shares W_{t+1} and $Z_{\Phi}^{S\Upsilon}$

federated transformer log learning model for threat forensics is presented in Algorithm 1.

The starting point of our proposed model's training process, presented in Fig. 1, takes place at client devices from each organization unit producing log files (i.e., auth.log, syslog, kernel, and audit.log). Log messages are processed using a log parser that maps the time-series of log messages into a sequence of log keys. These sequences are embedded into vectors used for training a local model at each client that learns the underlying patterns from the log key sequence. Each client passes the local model's learned parameters to the FL server. The FL server aggregates the parameters from the participating clients to generate the global FL model which is shared back to the clients. Finally, an interpretability module is offered to provide insights to the model's decision making process by aggregating the calculated attention given to each unique element in the input sequence. Details of each component are described in the following.

A. Distributed Federated Learning Architecture

In Algorithm 1, we integrate the FedAvg algorithm presented by [32]. More specifically, we leverage this algorithm on the federated learning server depicted in Fig. 1. In this process, the FL server collaborates with Φ clients $c_1, \ldots, c_{\Phi-1}, c_{\Phi}$ for generating an updated global FL model. Each client trains a local model using their local data and share exclusively the locally computed gradients or learned model parameters $\Delta w_{t+1}^{1}, \ldots, \Delta w_{t+1}^{\Phi-1}, \Delta w_{t+1}^{\Phi}$ with the FL server.

Initial hyperparameters and model parameters W_0 are passed by the FL server to each client. FederatedSGD (FedSGD) is an algorithm used for generating a global model in a federated setting. In this process, the client computes the average gradient $g_{\phi} = \nabla f_{\phi}(w_t^{\phi})$ using its local data at the current model w_t^{ϕ}, Algorithm 1.I. Afterwards, clients pass g_{ϕ} to the FL server who aggregates them $\nabla F(W_t) = \sum_{\phi=1}^{\Phi}(\frac{n_{\phi}}{n})g_{\phi}$. The aggregated average gradients are used for computing an updated global FL model $W_{t+1} \leftarrow W_t - \eta \nabla F(W_t)$ where n_{ϕ} denotes the number of data points for client ϕ. FedAvg is an equivalent algorithm used for updating the global FL model. In this approach, the learned model parameters from each client are aggregated by the FL server. Given that $\forall \phi, \Delta w_{t+1}^{\phi} \leftarrow w_t^{\phi} - \eta g_{\phi}$, the updated global FL model can be computed as $W_{t+1} \leftarrow \sum_{\phi=1}^{\Phi}(\frac{n_{\phi}}{n})\Delta w_{t+1}^{\phi}$ Algorithm 1.II. Afterwards, the updated global FL model is sent to all clients.

B. Log Parser

Our decentralized federated transformer log learning model requires vector representation for the time-series of log messages to learn the extensive and convoluted patterns and correlations embedded within log sequences. `Spell`, a public log parser [11, 17], is used for identifying log templates within a log time-series. Given a subset of log files l where $l \in L$, each log file (i.e., audit.log, auth.log, kernel.log, sys.log) is composed of a finite unstructured sequence of log messages $l = \{m_i : m_i \in M, i = 1, 2, \ldots\}$ where m_i denotes the message at index position i, and M denotes all the log messages in l.

Mapping log messages to log keys requires the log parser to first identify the event template and variable elements from each log message. The mathematical representation of the mapping function is $\beta : m_i \rightarrow (e_i, v_i) \forall i, e_i \in E, i = 1, 2, \ldots$ where $E = e_1, e_2, \ldots, e_n$ represents all the identified distinct event templates in the log file l, e_i represents the event template identified in m_i and v_i is the corresponding list of variables. Each distinct template in E is assigned a unique log key κ_i using the mapping function $\psi : e_i \rightarrow \kappa_i \forall i, e_i \in E, \kappa_i \in K, i = 1, \ldots, n$, where K represents the set of all unique key values. The time-series of the mapped log keys S is presented in the formula below:

$$\begin{aligned} S = \{\kappa_1, \kappa_2, \ldots, \kappa_n\} \leftarrow \psi(e_i) \leftarrow e_i \leftarrow \beta(m_i) \forall i, \\ m_i \in M, e_i \in E, \kappa_i \in K \end{aligned} \tag{1}$$

After all parsing operations are finished, S is segmented into sub-sequences S_j based on defined window frames Λ as presented in the following equations:

$$\begin{aligned} S_j &= ((\kappa_{(j-1)\Lambda+p})_{p=1,\ldots,\Lambda})_{j=1,\ldots,n/\Lambda} \\ &= ((\kappa_{(j-1)\Lambda+p})_{p=1}^{\Lambda})_{j=1}^{n/\Lambda} \\ &= \{S_1, \ldots, S_{n/\Lambda}\} \end{aligned} \tag{2}$$

C. Local Log Learning: Transformer-Based Model

Our proposed model integrates the work presented by Vaswani et al. in [44]. Local models are composed by a set of stacked encoder modules, a set of stacked decoder modules, and the interconnections between them.

Encoder: The encoder is composed by a multi-head attention and a feed-forward sub-layer. A residual connection is employed for each sub-layer followed by layer-normalization. The elements in log key sequence are embedded to form a vector list $X = (x_1, x_2, \ldots, x_n)$ where the vector size is defined as d_m. A positional encoding vector is added to each input embedding to provide context of their corresponding position in the sequence. The resulting vector list is passed to the self-attention layer.

Self-attention, used to define the relationships between every key and the other elements in the sequence, is calculated using 3 vectors, namely, query(Q), key(K), and value(V) generated by multiplying every vector x_i with 3 matrices W^Q, W^K, W^V. The resulting vectors Q, K, V have the corresponding dimensions d_q, d_k, d_v; all being smaller than d_m. The output of the self-attention layer Z_s is calculated as follows:

$$Z_s = Attention(Q, K, V) = softmax(Q \cdot K^T / \sqrt{d_k})V \tag{3}$$

To improve the performance of the attention layer, we implement the multi-headed attention mechanism which linearly projects the Q, K, and V matrices H times, where H represents the number of attention heads to be used. This approach allows the model to jointly address information from each

Algorithm 1: Interpretable Federated Transformer Log Learning Algorithm.

```
Input: Hyperparameters for local models defined by
       the federated server, number of clients $\Phi$,and
       number of rounds $R$.
Output: Updated Federated Transformer Log Learning
        Model $W_{t+1}$ and Interpretability
        attention-based weights $Z_{\Phi}^{S}$ and $Z_{\Phi}^{S\Upsilon}$.
Initialization:
FL server defines the hyperparameters for the federated
  model including encoder/decoder layers $N$, attention
  heads $H$, and clients $\Phi$.
Procedure:
while $Round \neq 0$ do
    (I). For clients in business unit:
    for all $\phi \in \Phi$ do
        Local Transformer-based Model Training:
        Log parser maps all log messages $M$ to log
        sequences $S_j$:
        $S_j \leftarrow M$
        Log key sequences $S_j$ are embedded:
        $X_j \leftarrow S_j$
        Compute the average gradients with current
        model $w_t^{\phi}$:
        $g_{\phi} = \nabla f_{\phi}(w_t^{\phi})$
        Update the model parameters:
        $\Delta w_{t+1}^{\phi} \leftarrow w_t^{\phi} - \eta g_{\phi}$
        Send the learned model parameters $\Delta w_{t+1}^{\phi}$ to
        the Federated Learning (FL) server.
        Interpretability Module:
        Compute interpretability attention-based weights
        by $Z_{\phi}^{S}$ and $Z_{\phi}^{S\Upsilon}$ and share them with the FL
        server.
    end
    (II). For Federated Learning Server:
    Global Model Update:
    $W_{t+1} \leftarrow \sum_{\phi=1}^{\Phi}(\frac{n_{\phi}}{n})\Delta w_{t+1}^{\phi}$
    Interpretability Module:
    Generate the federated interpretability
    attention-based weights:
    $\mathrm{Z}_{\phi}^{S} = \sum_{h=1}^{H} Z_{h,\kappa}$
    $\mathrm{Z}_{\phi}^{S\Upsilon} = \sum_{h=1}^{H} Z_{h,\kappa,\Upsilon_{\upsilon}}$
    Share $Z_{\Phi}^{S\Upsilon}$ with clients.
    (III). For clients in business unit:
    for all $\phi \in \Phi$ do
        Update local model:
        $w_t^{\phi} = W_{t+1} \leftarrow \mathrm{FederatedServer}(\phi, W_{t+1})$
        Compute goodness of fit test for $Z_{\phi}^{S\Upsilon}$:
        $D_i = \sum_{i=1}^{\upsilon} \sum_{k=1}^{K} \frac{Z_{\phi}^{S\Upsilon_i} - Z_{\Phi}^{S\Upsilon_i}}{Z_{\Phi}^{S\Upsilon_i}}$
        Update interpretability attention-based weights:
        $Z_{\phi}^{S\Upsilon} \leftarrow Z_{\Phi}^{S\Upsilon}$
    end
end
```

log key from different representation sub-spaces at different positions in the sequence. The resulting process is a multi-head $Z_{cn} = Concat(Z_1, Z_2, ..., Z_H)$ matrix generated by the concatenator of individual Z_h matrices resulting from each attention-head. The Z_{cn} matrix is then multiplied with a weight matrix W^O, trained jointly with the model, resulting in a matrix Z that captures the information from all attention heads. The output matrix Z is finally passed to the feed-forward sub-layer and then to the input of the next encoder in the stack.

$$\begin{aligned} Z &= Multi - head(Q, K, V) \\ &= Concat(Z_1, Z_2, ..., Z_H)W^O \\ where & \\ Z_h &= Attention(QW_h^Q, KW_h^K, VW_h^V), \\ & h = 1, \ldots, H \end{aligned} \tag{4}$$

Decoder: Similar to the encoder module, the decoder module is composed by a stack of decoders. The decoder shares the same components of the encoder with the addition of a encoder-decoder attention sub-layer positioned between the self-attention and feed-forward sub-layers. Matrices K and V, resulting from the enconder's module output and the Q matrix shared by the previous decoder in the stack are used for allowing every position in the decoder to attend all positions in the log key input sequence. In addition, the auto-regressive decoder module adds the output of each step, the predicted log key, with a positional encoding. In contrast with the encoder, the self-attention layer of the decoder is only permitted to attend earlier positions in the output sequence; this is achieved by masking future positions before the softmax calculation takes place.

After the multi-head attention, each encoder and decoder has a pointwise feed-forward layer. This is applied separately and identically to each element in the log key sequence. The feed-forward layer consists of two linear transformation which use ReLu activation function and is formally expressed as:

$$FFN(x) = max(0, xW_1 + b_1)W_2 + b_2 \tag{5}$$

The logits vector is ingested by softmax layer that transforms the logits vector into probabilities. The element in the vector with the highest probability is selected and the log key associated with it is set as the output of this specific time step.

The training data consists of sequences of mapped keys from syslogs collected from uncompromissed systems. Sequences of log keys within a window frames Λ are used for training the local model. The local model is trained to predict a list of candidate log keys given previous log keys. The transformer neural network architecture creates a multi-classification model, each type of log key representing a class. As stated before, this SOTA architecture uses attention to gain context from previous inputs when predicting the next log key. With structured data and built model, the log key anomaly detection model is trained to predict the next log key which represents the next log entry. The generated prediction is fed to the model to continue generating predictions.

After training the model, new logs are processed to generate a new prediction of log keys. First, a log key sequence, based on a window frame Λ, is fed to the model. Based on this input, the model predicts the top g candidates. If the ground truth key G_j (which follows the input sub-sequence S_j) matches one of the top g candidates, then S_j is classified as a normal sequence. Otherwise, the input sub-sequence S_j is classified as abnormal. A sequence S is classified as a cyber threat if the number of sub-sequences classified as abnormal is greater than or equal to a threshold τ defined by the user.

In order to backtrace the source of detected anomalies, the interpretability module presents the sequence of log keys that triggered the detection of an anomaly and the attention for each key in the input sequence. If a log key is classified as abnormal, the sequence of log keys that initiated the incident can be tracked down. The sequence that triggered that anomaly is considered as a risk pattern. Risk patterns are then extracted from the sequence to generate new test cases.

D. Model Interpretability

The interpretability module at each client provides insight to the level of influence each unique log key $\kappa \in K$ has in a particular sequence of log keys S. The federated transformer log learning model $W_t + 1$ is used by the interpretability module to evaluate a given sequence S. While the federated transformer log learning model is trained using log key sequences S from uncompromised systems, the interpretability module at each client and at the FL server can be used for log key sequences collected from compromised or uncompromised systems.

Initially, each client uses their currently available data from their uncompromised systems. As the federated model ingests each sub-sequence $S_j \in S$, it calculates the attention for each key $k_i \in S_j$. After processing all sub-sequences $S_j \in S$, the interpretability module aggregates the attention of each unique log key $\kappa \in K$ across all S_j. We refer to this influence as the interpretability attention-based weights. This operation is reflected in the following equation:

$$Z_\phi^S = \sum_{h=1}^{H} Z_{h,\kappa}, \forall \kappa \in K, \forall S_j \in S \tag{6}$$

Additionally, the model computes the normalized version of Z_ϕ^S for generating a bar chart. This provides the user with visibility to the influence each unique key has for all input sub-sequences.

$$Z'_\phi = \frac{(Z_\phi^S - Z_{\phi\_min}^S)}{(Z_{\phi\_max}^S - Z_{\phi\_min}^S))}, \forall \phi \in \Phi \tag{7}$$

Furthermore, the interpretability module provides additional granularity by aggregating the attention of every unique key $\kappa \in K$ across all input sequences S_j for each ground truth key G_j. G_j is also an element of Υ which denotes the list of unique ground truth keys $|G_j|$ from all clients. We denote υ

as the index for each unique key in Υ. The weight calculated by aggregating the attention of every unique key κ for all sequences S_j influencing each Υ_v is denoted by the following equation:

$$Z^{S\Upsilon}_{\phi} = \sum_{h=1}^{H} Z_{h,\kappa,\Upsilon_v}, \forall \kappa \in K, \forall S_j \in S, \forall \Upsilon_v \in \Upsilon \qquad (8)$$

Similarly to equation 7, the model computes the normalized version of $Z^{S\Upsilon}_{\phi}$ and generates a saliency map for visualization purposes.

$$Z''_{\phi} = \frac{(Z^{S\Upsilon}_{\phi} - Z^{S\Upsilon}_{\phi\_min})}{(Z^{S\Upsilon}_{\phi\_max} - Z^{S\Upsilon}_{\phi\_min}))}, \forall \phi \in \Phi \qquad (9)$$

Each client sends the interpretability attention-based weights Z^{S}_{ϕ} and $Z^{S\Upsilon}_{\phi}$ to the FL server. The FL server aggregates the computed weights from each client ϕ and computes the corresponding normalized analog as presented in the following equations:

$$Z'_{\Phi\_norm} = \frac{(Z'_{\Phi} - Z'_{\Phi\_min})}{(Z'_{\Phi\_max} - Z'_{\Phi\_min}))} : Z^{S}_{\Phi} \quad = \sum_{\phi=1}^{\Phi} Z^{S}_{\phi} \qquad (10)$$

$$Z''_{\Phi\_norm} = \frac{(Z''_{\Phi} - Z''_{\Phi\_min})}{(Z''_{\Phi\_max} - Z''_{\Phi\_min}))} : Z^{S\Upsilon}_{\Phi} \quad = \sum_{\phi=1}^{\Phi} Z^{S\Upsilon}_{\phi} \qquad (11)$$

The FL server shares the federated interpretability attention-based weights Z^{S}_{Φ} and $Z^{S\Upsilon}_{\Phi}$ with each client. The same process is followed for logs from compromised systems; as an example, multiple users can send to the FL server the Z^{S}_{ϕ} and $Z^{S\Upsilon}_{\phi}$ computed from log sequences S from compromised systems to generate a federated interpretability attention-based weights for cyber threats Z^{S}_{Φ} and $Z^{S\Upsilon}_{\Phi}$.

After the client receives Z^{S}_{Φ} and $Z^{S\Upsilon}_{\Phi}$ for uncompromised and/or compromised systems from the FL server, the interpretability module conducts a multinomial distribution goodness of fit test based on Chi-Square for $Z^{S\Upsilon}_{\phi}$ with respect to $Z^{S\Upsilon}_{\Phi}$ for uncompromised and/or compromised systems to quantify their corresponding statistical distribution difference. The interpretability module tests if the interpretability attention-based weights for a sequence of interest $Z^{S\Upsilon}_{\phi}$ has a specific distribution by computing the Karl Pearson's chi-square statistic as follows:

$$D_i = \sum_{i=1}^{v} \sum_{k=1}^{K} \frac{\left(Z^{S\Upsilon_i}_{\phi} - Z^{S\Upsilon_i}_{\Phi}\right)^2}{Z^{S\Upsilon_i}_{\Phi}}, \forall v \in \Upsilon, \forall \kappa \in K \qquad (12)$$

Using the multinomial, we can then test if the given sample $Z^{S\Upsilon}_{\phi}$ has a similar distribution to $Z^{S\Upsilon}_{\Phi}$ by testing:

$$\begin{aligned} &H_0 : Z^{S\Upsilon}_{\phi} = Z^{S\Upsilon_1}_{\phi}, \ldots, Z^{S\Upsilon_v}_{\phi} = Z^{S\Upsilon}_{\Phi} \qquad VS \\ &H_1 : Z^{S\Upsilon}_{\phi} \neq Z^{S\Upsilon}_{\Phi} \end{aligned} \qquad (13)$$

Datasets	Duration	# of logs	# of Anomalies
HDFS	38.7 hours	11,175,629	16,838 (blocks)
CTDD	235 days	8,448,715	2,501 (logs)

TABLE I
STATISTICS OF HDFS AND CTDD DATASETS

Given an observation $\left(Z^{S\Upsilon}_{\phi} = Z^{S\Upsilon_1}_{\phi} \ldots Z^{S\Upsilon_v}_{\phi}\right)$, the valid p-values are calculated:

$$p-value = P\left(\chi^2(v-1) > \sum_{i=1}^{v} \sum_{k=1}^{K} \frac{\left(Z^{S\Upsilon_i}_{\phi} - Z^{S\Upsilon_i}_{\Phi}\right)^2}{Z^{S\Upsilon_i}_{\Phi}}\right) \qquad (14)$$

The interpretability module uses the p-value to fail to reject the hypothesis H_0 or reject the hypothesis H_1 that the distribution of the interpretability attention-based weights for the given sample $Z^{S\Upsilon_v}_{\phi}$ shares the same distribution as $Z^{S\Upsilon_v}_{\Phi}$. The test rejects the null hypothesis because the cyber threat induces a perturbation in the space from the joint distribution point of view, making the test statistics able to account for the difference between both cases as Chacon et al. [8] exhibited in his research.

IV. Experimental Evaluation

A. Datasets Considered

Our experiments were conducted using the two datasets presented in Table I. The HDFS dataset [48] is composed of 11,175,629 logs collected from a cluster of 200 Amazon virtual machines running Hadoop-based jobs which can easily be obtained from Zenodo [7]. The original work labeled all logs in this dataset using handcrafted rules to classify them between normal and abnormal. Abnormal samples in this dataset are identified by matching a set of block ids listed as abnormal to their appearance in the log messages. The list of abnormal logs amount to 16,838 blocks ids.

Our CTDD dataset is composed of logs registering system activity running uncompromised cloud collaboration services. This environment consists of a cluster of virtual machines deployed across multiple networks in the Jetstream educational cloud that offer interactive computing in the cloud such as Jupyter Lab. The normal operation syslog samples presented in this dataset were collected from 62 VMs, each operated by different users. No user was allowed to access a VM assigned to another user. The threat samples from our dataset were collected from 16 VMs running malicious software samples.

Syslogs from uncompromised VMs running cloud collaboration services were collected from 3 clusters, all of them hosted Ubuntu 18.04 operating systems. Each VM was assigned to a student to perform a variety of data analytics and machine learning activities. *"Sudo"* privileges were restricted for *"Ubuntu"* user in the Practicum 2020 cluster while the IS 7033 and ITESM 2020 clusters had unrestricted *"root"*

Attack Case	Description of Scenario	References	# of logs
GonnaCry	GonnaCry is an academic Ransomware program that allows users to infect a client to encrypt files, peripheral devices, and destroy original files. It does not have all the features of WannaCry2.0	S0366	129
ech0raix	A ransomware family that targets QNAP Network Attached Storage (NAS) devices. Devices are compromised by bruteforce attacks or exploiting known vulnerabilities. The ransomware executes a malicious payload that encrypts targeted file extensions on the NAS.	T1486	27
ACK Flood	An attack that exhausts OS finite TCP connections by sending a flood of ACK packets for non existing connections and leveraging the stateful nature of the TCP protocol.	T1499.001	114
NTP DDoS Amplification	A DoS Reflection Amplification Attack. The attack send packets to a third-party server with the spoofed address of a target.	T1498	406
SYN Flood	An attack that exhausts OS finite TCP connections by sending excessive amounts of SYN packets where the 3-way TCP handhake is never completed	T1499.001	132
malaria	An injection attack that injects malicious code via ptrace system calls. The trace system call injection is usually executed by writing arbitrary code into a running process.	T1055-008	182
nemox	A half-virus for infecting any ELF files in a specific directory.	T1027-001	109
nf3ct0r	A virus for infecting ELF files. Also know as an ELF infector.	T1027-001	135
utrojan	Universal trojan for accessing an unauthorized system.	T1036-004	221
Lin Blackhole	A malicious program created using C programming language which on infecting the victim client provides a backdoor to the attacker.	T1587-001 and T1588-001	74
Lin Ovason	A malicious program created using C programming language which on infecting the victim client provides a password protected backdoor to the attacker.	T1587-001 and T1588-001	101
Python Backdoor	A malicious program written using Python programming language infects the victim client to serve a backdoor to the attacker. The attacker can obtain a simple reverse shell using tools like netcat or socat	T1587-001 and T1588-001	179
Binom ASM	A computer virus that is written using assembly language searches for ELF files in the victim client and injects malicious payload. This computer virus requires admin level access for successful infection. It target the files located in the bin directory in the victim's machine	T1027-001	292
Eternity ASM	A computer virus that is written using assembly language that infects a target ELF file in the victim's machine.	T1027-001	152
Dataseg Code Injector	A malware that injects unwanted/malicious code into the data segment of the binaries mainly for defense evasion purposes.	T1027-001	202
Bash Spyware	A simple bash script that uses built-in tools for harvesting internal system data and send it to a compromised mail server	T1119	46

TABLE II
MALICIOUS SAMPLES OF CYBER THREAT DETECTION DATASET

privileges. Furthermore, VMs in the IS 7033 clusters were safeguarded by a firewall that allowed access to user specific IP addresses while the Practicum 2020 and ITESM 2020 clusters were assigned to security groups that restricted ingress traffic to most network ports. In addition, a total of 2,501 syslogs were collected from 16 compromised VMs running malicious threat samples presented in Table II. This set of experiments were conducted with the same cloud image used in Practicum 2020.

B. Training and Testing Details

Local models at each client are based on the transformer-model architecture presented in [44]. Local log files are parsed with `Spell` [11] to map the sequence M of log messages into multiple log keys sequences S_j using a sliding window frame approach of size Λ. The embedded vector representation X_j of log key sequences S_j are fed to the corresponding client's local model for training. In our study, we train the interpretable federated transformer log learning model for threat detection using the datasets in Table I. In our experiments, the following hyper-parameters were set to the following fixed values: model size $d\_model = 512$ for each hidden layer, $epochs = 5$, $dropout = 0.2$, confidence interval $g = 10$, window size $\Lambda = 10$, and number of rounds $R = 10$. Given that the learning rate does not present much variance as a function of other parameters, as shown in [32], we fixed the learning rate $\eta = 0.01$. We experimented by varying the number of layers in the encoder and decoder stacks $N = \{1, 4, 6\}$, the number of attention heads $H = \{1, 2\}$, and the number of clients contributing to the update of the global FL model $\Phi = \{1, 2, 4, 8, 10\}$.

After finishing training the global FL model, we tested the model using previously unseen non-malicious samples and the logs collected from the compromised systems. cyber threats are detected by comparing the ground truth key G (the key following currently input sequence S_j) against the top $g = 10$ predicted candidates. In the event where G is not listed within the top g predicted candidates, the model labels the prediction as an anomaly else it labels it a normal event. The user dictates the maximum anomaly threshold (number of sequences S_j labeled as abnormal) to classify S as a cyber threat. In our experiments, we set maximum anomaly threshold to 1, instructing the model to classify S as a cyber threat in the event that a single sequence S_j with S is labeled as an anomaly by the model.

All training and testing tasks were implemented using Pytorch 1.7.1+cu110, Python 3.6.9, and OpenNMT [25] base model implementation. The model was trained in a virtual machine with a V100 GPU (CUDA 11.0) provided by Jetstream Cloud [40, 42].

C. Experimental Results

We are motivated by the existing model's performance and interpretability features for cyber threat detection tasks. Although each training run for an individual client local model is relatively small, we trained over 1,200 individual models in this experiment. In this subsection, we will first present the results obtained with the HDFS dataset. Afterwards, we present our proposed model's performance with our CTDD dataset. We compare the experimental results achieved by our proposed model with those presented by SOTA unsupervised centralized methods, namely, LogRobust [52], DeepLog [12], LogAnomaly [33], and HitAnomaly [18]. As SOTA methods used a centralized training approach, we used standard stochastic gradient descent training on the full training dataset with no client partitioning (a model built by a central entity) $\Phi = 1$ to make the intended comparison.

First, with the HDFS dataset, our model's parsing process identified 31 distinct event templates from the full dataset. Table III shows that our model's best performance, achieving an F-score of 0.9384 with one encoder layer, one decoder layer, and 2 attention heads. Deeplog who identified $E = 29$ distinct event templates which showed a better performance as the model learns from log event templates and parameter values. LogRobust identified $E = 29$ distinct event templates and showed to benefit from learning semantic information from log events and contextual information from log sequences. While their F-score performance showed to be slightly better than our results (0.9500 and 0.9384 respectively), it shows the lowest recall between all the compared works. Our model achieved an F-score of 0.9384 while LogAnomaly, which learns the semantic and syntax information from log templates, achieved an F-score of 0.9000. With an f-score of 0.9970, HitAnomaly achieved the best performance of all compared models. We attribute this achievement to the larger number of identified event templates (46 events parsed with Drain), a positive impact introduced by the log parser the approach taken for learning from sequences of event templates and parameter values. HitAnomaly, LogAnomaly, and LogRobust also introduce automatic approaches to deal with unstable log data while DeepLog requires human intervention to deal with new templates. Our model it's limits to learning exclusively the sequential patterns from log sequences. Yet, it takes advantage of the transformers' ability to learn from longer sequences and the attention given to specific log keys within the sequence.

The second set of experiments were performed also with the HDFS dataset using a federated learning setting. The federated model was evaluated using a range of different clients $\Phi = 2, 4, 8, 10$, number of layers $N = 1, 4, 6$, and attention heads $H = 1, 2$. The experiments demonstrated that the proposed model outperforms models built by a central entity $\Phi = 1$ for most cases. Moreover, we noted that the performance stabilizes as the number of rounds R is increased from 1 to 10. We also noted that when fixing the number of rounds R, the performance improves as the number of clients contributing to the global FL model is increased. In other words, the model converges faster with a lower number of rounds R as the number of contributing clients Φ increases. This trend is also observed in [32]. As shown in Table IV, our model achieved its peak performance (accuracy=0.9307, precision=0.8867, recall=0.9706, f-score=0.9268) when setting the hyperparameters to $\Phi = 10$, $N = 4$, $H = 1$, and 10 epochs. We also observed a stable increase in performance when using 2 attention heads instead of 1. The exception was observed when setting the number of encoder/decoder layers to 6.

Methods	Dataset	Precision	Recall	F-score
DeepLog	HDFS	0.9500	0.9600	0.9600
LogAnomaly	HDFS	0.8400	0.9700	0.9000
HitAnomaly	HDFS	0.9910	0.9850	0.9970
LogRobust	HDFS	1.0000	0.9100	0.9500
Proposed Method Centralized	**HDFS**	**0.9375**	**0.9393**	**0.9384**
Proposed Method Federated	**HDFS**	**0.8867**	**0.9706**	**0.9268**
Proposed Method Centralized	**CTDD**	**0.7733**	**0.7733**	**0.7733**
Proposed Method Federated	**CTDD**	**0.7922**	**0.8133**	**0.8026**

TABLE III
PERFORMANCE OF SOTA MODELS ON HDFS AND CTDD DATASETS.

The third set of experiments were performed with the CTDD dataset. In this dataset, the parser identified 447 unique event templates E. The higher log diversity is an indicator of the increased complexity of our dataset over the HDFS dataset. We can observe this complexity impacts our model's performance across all metrics. Yet, it shows our model's capability to detect cyber threats in a real-world operational setting. We also used a standard stochastic gradient descent training on the full training dataset with no client partitioning $\Phi = 1$ to show the transformer model's performance in a centralized training approach. In contrast with our findings in the HDFS dataset, the performance achieved with one client or two clients showed a similar performance for all cases. The peak performance (accuracy=0.7939, precision=0.7733, recall=0.7733, F-score=0.7733) in a centralized setting was achieved with 1 encoder/decoder layer and 1 attention head. Finally, the fourth set of experiments were performed using a federated learning approach with the cyber threat dataset. Throughout these experiments, we observed an improved performance stability as the number of contributing clients increased. We also observed a greater performance with 2 attention heads and a slight improvement when increasing the number of encoder/decoder layers with clients contributing to the global model $\Phi = 10$. The best performance using a federated learning setting (accuracy=0.8181, precision=0.7922, recall=0.8133, F-score=0.8026) was achieved with 4 and 6 encoder/decoder layers, 10 clients, and 2 attention heads. The experimental results are shown in detail in Table IV.

Φ	N	H	HDFS				CTDD			
			Accuracy	Precision	Recall	F-score	Accuracy	Precision	Recall	F-score
1	1	1	83.986	92.524	70.240	79.857	**79.394**	**77.333**	**77.333**	**77.333**
2			90.508	84.219	97.211	90.250	73.939	74.242	65.333	69.504
4			89.642	83.063	96.823	89.417	78.788	77.027	76.000	76.510
8			83.054	87.229	73.223	79.615	80.606	77.922	80.000	78.947
10			85.487	76.612	97.720	85.888	80.606	76.543	82.667	79.487
1		2	**94.432**	**93.755**	**93.936**	**93.845**	79.394	78.873	74.667	76.712
2			83.986	92.524	70.240	79.857	78.788	77.778	74.667	76.190
4			89.685	83.938	95.440	89.320	79.394	77.333	77.333	77.333
8			91.242	89.143	91.802	90.453	81.212	77.500	82.667	80.000
10			92.634	88.285	96.507	92.213	80.606	77.215	81.333	79.221
1	4	1	89.883	85.492	93.476	89.306	78.788	72.000	65.333	75.524
2			93.051	90.788	94.179	92.452	78.182	76.712	74.667	75.676
4			88.096	80.063	98.084	88.162	78.788	77.027	76.000	76.510
8			93.072	88.711	97.017	92.678	80.606	78.667	78.667	78.667
10			**93.072**	**88.677**	**97.065**	**92.682**	78.788	77.027	76.000	76.510
1		2	92.820	89.249	95.634	92.331	78.182	78.261	72.000	75.000
2			91.209	85.504	96.992	90.886	74.545	76.190	64.000	69.565
4			89.762	82.534	98.108	89.650	79.394	78.873	74.667	76.712
8			92.776	88.285	96.871	92.379	80.000	79.167	76.000	77.551
10			92.842	88.300	97.017	92.453	**81.818**	**79.221**	**81.333**	**80.263**
1	6	1	92.152	92.344	90.104	91.210	78.788	79.412	72.000	75.52
2			89.291	84.480	93.476	88.751	78.182	78.261	72.000	75.000
4			88.600	84.339	91.826	87.924	78.182	76.712	74.667	75.676
8			90.606	86.017	94.591	90.100	79.394	76.623	78.667	77.632
10			91.560	86.296	96.677	91.192	81.212	78.205	81.333	79.739
1		2	92.568	91.697	91.875	91.786	78.788	78.571	73.333	75.862
2			88.677	81.531	96.895	88.551	77.576	77.143	72.000	74.483
4			82.670	89.570	69.779	78.446	77.576	77.941	70.667	74.126
8			85.630	79.813	91.293	85.168	80.606	78.667	78.667	78.667
10			79.830	76.660	90.420	82.974	**81.818**	**79.221**	**81.333**	**80.263**

TABLE IV

Experimental results using the HDFS and CTDD datasets. Hyperameters used for this study include: $N = \{1, 4, 6\}$ encoder/decoder layers, $H = \{1, 2\}$ attention heads, and $\Phi = \{1, 2, 4, 8, 10\}$ clients. Our model's top performance on the HDFS dataset was achieved with 10 clients, 4 encoder layers, 4 decoder layers, and 1 attention head. On our CTDD dataset, the model's top performance was achieved with 10 clients, 2 attention heads, and with 4 and 6 encoder and decoder layers.

V. Model Interpretability

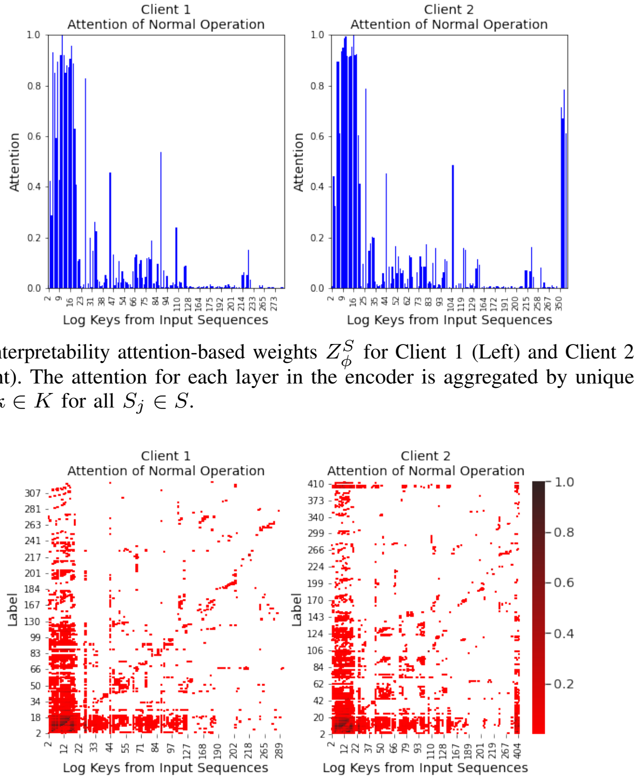
The attention-based interpretability module aggregates attention calculated in the transformer model, as shown in Section III-D, and generates visualizations presenting the difference attention distribution between normal operations and cyber threats. To demonstrate the applicability of our proposed model and the use case of our interpretability module, we present two case scenarios: (1) A real-world operational setting where multiple business units connecting multiple uncompromised systems are contributing to the generation of a global federated model, and (2) A organization being attacked with a DoS attack.

A. Cyber Threat Forensics in a Real-World Operational Setting

Lets us assume that an American Healthcare System with a network of providers and health facilities that offer a full range of healthcare services from preventative to post-acute care. The American Health System seeks to integrate a novel cyber threat detection system into the existing Security Information and Event Management (SIEM). The security analysts have identified specific facilities that have not been previously compromised by threat actors. The healthcare system has maintained HIPAA compliance and has stored system, event, and audit logs from the past 6 years. Training a module for cyber threat detection in a centralized setting would require to gather data from each provider and health facility into a single server. Nevertheless, as log files contain workforce members login, failed login attempts, software updates, downloaded programs, change of passwords, EHR logins, patient data access, changes to eHPI, among others, sharing logs to a central entity poses high security risks and potential violations to HIPAA. To prevent such risk scenario and facilitate the model to learn from log data across multiple health facilities, the security administrators decide to use our interpretable federated transformer log learning model for threat forensics.

After each care facility trains a local model using exclusively their local data, they use the interpretability module to visualize the main log keys (each associated with one log template) contributing to correct predictions. Each correct prediction matching the log key (ground truth) that follows the input sequence is influenced by the attention of each log key in the input sequence. As the model was trained with data from uncompromised systems, the aggregated attention computed by the interpretability module provides a representation of the attention distribution across all log keys during normal operations.

In Fig. 2a we present the aggregated attention from 2 clients computed by our interpretability module. We can observe the



(a) Interpretability attention-based weights Z_{ϕ}^{S} for Client 1 (Left) and Client 2 (Right). The attention for each layer in the encoder is aggregated by unique key $\kappa \in K$ for all $S_j \in S$.

(b) Interpretability attention-based weights $Z_{\phi}^{S\Upsilon}$ for Client 1 (Left) and Client 2 (Right). The attention of each layer in the encoder is aggregated by each $\upsilon \in$ (y-axis) and each unique key $\kappa \in K$ (x-axis) for all $S_j \in S$.

Fig. 2. Interpretability attention-based weights Z_{ϕ}^{S} and $Z_{\phi}^{S\Upsilon}$ computed by the client's corresponding interpretability module with their uncompromised data.

difference in attention distributed across all keys from all input sequences. In addition, we can observe that most of the attention concentrates on the log keys in the input sequences with lower value. Furthermore, in Fig. 2b the interpretability module breaks down the attention of every key in the input sequence influencing each correctly predicted log key (ground truth). The saliency map shows that lower keys highly influence most correctly predicted log keys (ground truths) following all input sequences.

B. Attack Scenario

In this scenario, an organization hires an ethical hacker to launch a cyberattack on its competitor with a motive to bring operational disruption and distraction of its competitor. In this case, the hacker/attacker intends to launch a volumetric DDoS attack against the target organization's web server. The attacker uses a popular scanning tool in the reconnaissance phase to find that the victim's organization is running Ubuntu 18.04 and is protected with a simple firewall. The attacker notices that an NTP amplification DDoS attack would be a perfect protocol to exploit as the victim's web server had its UDP port 123 open and the server seems to be an open resolver. As the attacker understands that the victim's organization is unable to detect the source of the attack, the attacker decides to carry out the NTP amplification DDoS attack over other volumetric DDoS attacks. The attacker aims to send high amount of spoofed requests to the NTP servers that has the monlist command enabled with the response pointing the victim organization's web server. The attacker who now controls the NTP server sends out large amount of UDP responses back to the victim's web server. This consumes the victim's network bandwidth, disrupting normal operation and service availability to the victim organization's clients. The successful attack allows the attacker to take down his victim for a desired amount of time.

The organization's forensic investigators use the interpretability module to backtrace the system activity, recorded in the syslogs, that triggered the detection of a cyber threat. Fig. 4 presents a series of sub-sequences S_j from the victim's syslog. The associated templates to each key κ in S_j is presented in Fig. 3. These are evaluated by the model to compute the attention for each log key and top g candidates for each sub-sequence. We can observe that the predicted candidates for sub-sequences S_2 and S_3 do not match their corresponding ground truth keys G_j, which are subsequently labeled as anomalies.

Additionally, forensic investigators can compare the saliency map of the NTP attack with the ones computed from interpretability attention-based weights computed for other attacks. In this case, the saliency map for previously known SYN Flood and BT DDoS attacks is shown in Fig. 5. By comparing the saliency maps of the NTP DDoS and SYN Flood attacks, we can observe their shared attention distribution. Also, the distribution similarity of each attack can be compared against a saliency map of the federated interpretability attention-based weights $Z_{\Phi}^{S\Upsilon}$ of the previously mentioned attacks. In Fig. 5, we present the interpretability attention-based weights of the NTP DDoS, BT DDoS, SYN Flood, and the federated interpretability attention weights aggregating the attention-based weight of the three. This along with the previous features presented provides forensic investigators with actionable information that leads to an efficient analysis of system operation.

VI. Discussion

In the previous two case scenarios we demonstrated how the attention distribution differed between uncompromised

```
Log Key − Log Template

  268      <*> <*> ctnetlink v0.<*> registering wit...
  269      link_config autonegotiation is unset or ...
  270      WARNING Unknown index <*> seen reloading...
  271      <*> Link UP
  164      time <*> <*>"" level info msg ""Loading ...
  168      time <*> <*>"" level info msg ""Docker d...
  169      time <*> <*>"" level info msg ""Daemon h...
  171      time <*> <*>"" level info msg ""API list...
  170      Started Docker Application Container Eng...
   11      ens3 Configured
    9      Started ntp−systemd−netif.service.
  420      Stopping Network Time Service...
  421      ntpd exiting on signal <*> Terminated
```

Fig. 3. Corresponding log templates of each key in evaluated sequence of NTP DDoS attack.

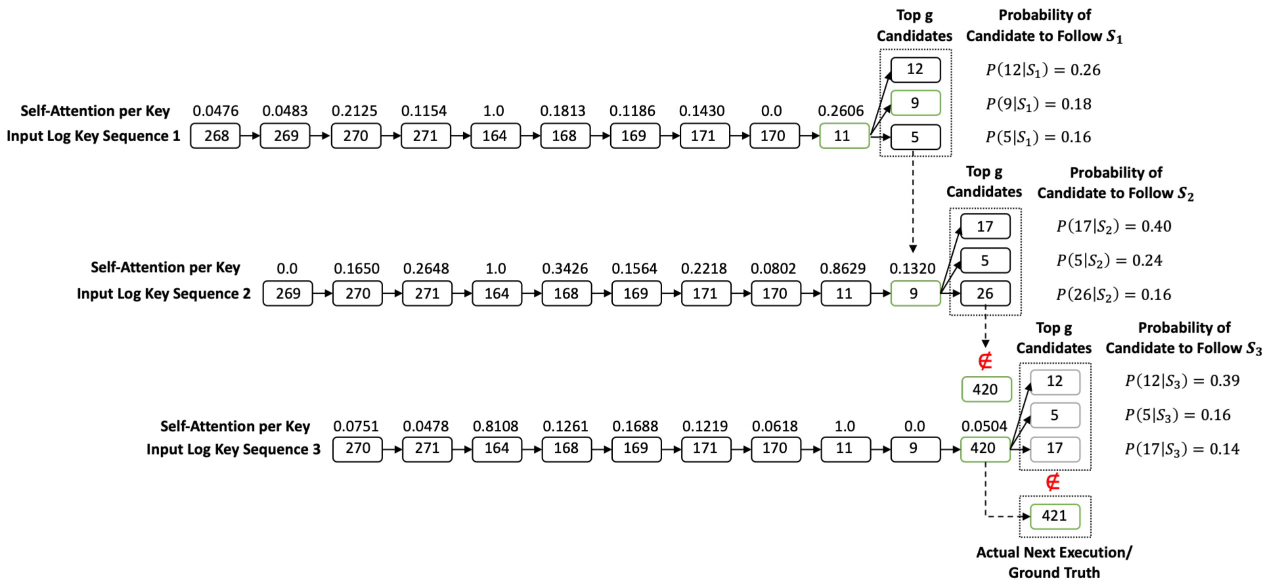


Fig. 4. Log key sub-sequences of NTP DDoS attack in sequence S processed by the federated model for predicting the g candidates. The "Ground Truth Keys" following sub-sequences $\{S_1, S_2, S_3\} \in S$ are compared against the corresponding predicted list of g candidates for identifying anomalies leading to cyber threats. The number of log keys for each sub-sequence is determined by the window frame parameter Λ. For every sub-sequence S_j, attention is calculated for every key in S_j. In the proposed transformer-based model, attention is ultimately passed to a fully connected layer and subsequently to a Softmax layer for predicting the top g candidates and the probability for each of them. For this case scenario, in sub-sequence S_1 the attention highly concentrates in keys 164, 168, and 11 to correctly predict the log key 9 that follows the sub-sequence. In contrast, the following two sub-sequences $S_2 and S_3$ shows the attention concentrated in keys 164, 169, and 11 where this last log key showed an attention 3 to 4 times larger than in S_1. This difference in attention across generates predictions of top g candidates that do not match the following ground truth keys, indicating a deviation from the normal system behavior that leads the detection of this cyber threat.

systems and systems targeted by a NTP DDoS attack. The same approach was followed to evaluate all log sequences from uncompromised and compromised systems included in our CTDD dataset. Fig. 6 (left) shows the aggregated attention for each log key in the input sequence from all uncompromised clients computed by our interpretability module. Similar to the previous results, when comparing with the attention computed from all sequences from compromised systems, we can observe the difference in attention distributed across all keys. In addition, we can observe that most of the attention in uncompromised systems concentrate in log keys with lower value while attention in compromised systems, shown in Fig. 6 (right), concentrate in log keys with higher value.

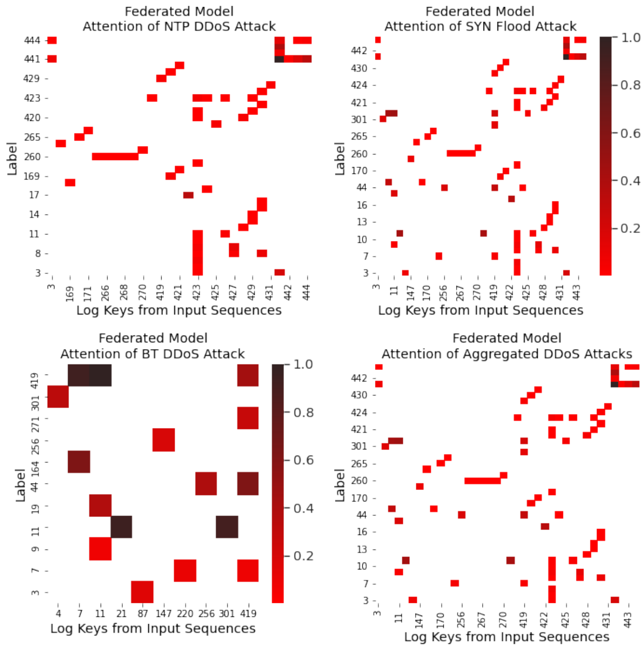


Fig. 5. Top Left: Aggregated attention by input log key of NTP DoS attack. Top Right: Aggregated attention by input log key of SYN Flood attack. Bottom Left: Aggregated attention by input log key of BT DoS attack. Bottom Right: Federated attention of NTP DDoS, SYN Flood, and BT DDoS attacks.

Fig. 6 (left) presents the saliency map with the attention of every log key in the input sequence influencing each correctly predicted log key (ground truth) following the input sequence. Fig. 6 (right) presents the saliency map with the attention of every log key in the input sequence influencing each detected anomaly which are ground truth label not matching any of the predicted top g candidates. The saliency map show that log keys in the input sequence with high values highly influence the detection of anomalies trigger by most log keys following the input sequence. In this case, we also observe the same difference in attention distribution between compromised and uncompromised systems.

To measure the distribution difference for a specific sample, the interpretability module performs a goodness of fit test of the corresponding $Z_{\phi}^{S\Upsilon}$ with respect to a given federated $Z_{\Phi}^{S\Upsilon}$. We computed $Z_{\phi}^{S\Upsilon}$ for the syslogs of the cyber threats listed in Table II. We calculated the Chi-square statistic for each $Z_{\phi}^{S\Upsilon}$ with respect to the federated $Z_{\Phi}^{S\Upsilon}$ of all cyber threats, shown in Fig. 6 (left). We performed the same comparison with respect to the federated $Z_{\Phi}^{S\Upsilon}$ of uncompromised systems,

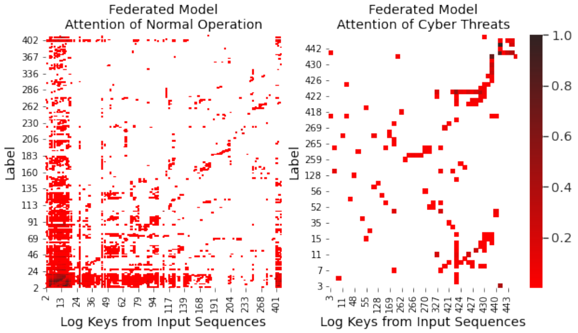


Fig. 6. On the left: Saliency map of aggregated attention of Clients 1 and 2 computed by the FL interpretability module. On the right: The saliency maps show a clear difference in the distribution of attention resulting from independent sample sets of data points representing different case scenarios (normal non-compromised environment and NTP DDoS cyber threat). The attention of client systems shows a higher concentration on $k_i \in K, i = 1, \ldots, 26$ while the attention of the NTP DDoS cyber threat concentrates on $k_i \in K, i = 424, \ldots, 444$.

shown in Fig. 6 (right).

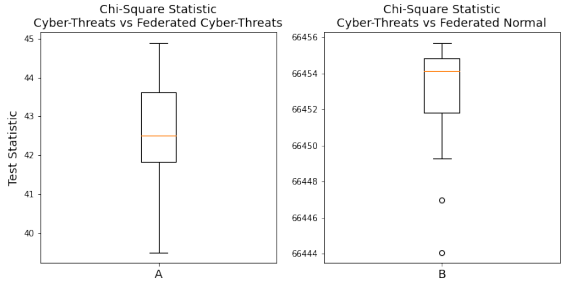
The Chi-square statistic $Z_{\phi}^{S\Upsilon}$ of each cyber threat with respect to the federated $Z_{\Phi}^{S\Upsilon}$ of compromised systems, shown in Fig. 7a (left), computed to an average of 42.664 and a $p-value = 1$. Given this results, we do not reject the hypothesis that the cyber threats share the same distribution as the federated $Z_{\Phi}^{S\Upsilon}$ of compromised systems. On the other hand, the Chi-square statistic of each cyber threat with respect to federated $Z_{\Phi}^{S\Upsilon}$ of uncompromised systems, shown in Fig. 7a (right), computed to an average of 66452.6871 and a $p-value = 0$. The Chi-square statistics for the latter comparison where far greater than the range within the chi-square statistic, shown in Fig. 7b, with 448 degrees of freedom. Given these results, we reject the hypothesis that the distribution of $Z_{\phi}^{S\Upsilon}$ for any cyber threat differs from the distribution of federated $Z_{\Phi}^{S\Upsilon}$ of uncompromised systems.

Such results support the effectiveness of our approach for using attention for interpretability purposes and show that our federated learning approach properly captures the aggregated knowledge from multiple clients for detecting cyber threats and evaluating distribution similarity.

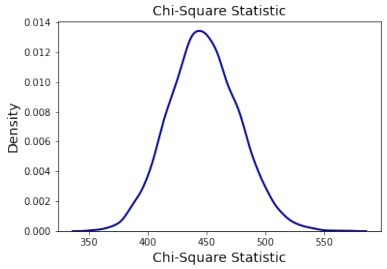
Some of the observed limitations of our work include the detection of cyber threats using fusion logs which combines multiple types of logs(i.e., syslogs, kernel logs, audit logs, authentication logs). Additionally, our current model is limited to learn only from known log templates. Integrating previously unseen logs for improving the performance for cyber threat detection is yet to be explored. Additionally, we observed that the performance for some SOTA models greatly improve when implementing log template semantic-based. These features will be explored in our future work.

VII. Conclusion

We proposed an interpretable federated transformer log learning model for detecting cyber threats with interpretability capabilities useful for threat forensics. Existing approaches consist of centralized anomaly detection models that overlook



(a) Box plot of Chi-Square statistic computed for $Z_{\phi}^{S\Upsilon}$ of each cyberattack in the CTDD dataset with respect to the federated$Z_{\Phi}^{S\Upsilon}$ of all cyber threats (left) and $Z_{\Phi}^{S\Upsilon}$ of all uncompromsed systems.



(b) Chi-Square distribution curve with 448 degrees of freedom.

Fig. 7. Goodness of fit test for the multinomial interpretability attention-based weights of each attack with respect to the federated interpretability attention-based weights of compromised and uncompromised systems.

data privacy and data jurisdiction laws. As of now, none of the existing works explore the interpretability of the model's predicted outcomes, obscuring the user's visibility into the model's decision-making factors. Thus, the techniques presented in this paper are an improvement over SOTA works. The proposed approach constructs a time-series vector from log sequences extracted from syslogs capturing system operational and user activity. Using an unsupervised approach, a transformer-based model at each client learns the underlying patterns of the time series. In addition, it integrates a federated learning approach for aggregating the learned patterns from local models to produce an updated global FL model. Furthermore, it uses the attention values to provide visibility to the model's decision-making process and highlights differences in attention between normal sequences and threat sequences.

Our approach demonstrated its log agnostic capability and applicability on high-dimensional time series. Our model's peak F-score (93.84%) in the HDFS dataset was achieved using two encoder and decoder layers, and 1 attention head. While it does not outperform SOTA works, it outclasses these by integrating data privacy and visibility into the model's decision-making process. In future work, we will be exploring the applicability of our approach on different types of multivariate time-series data including network and audit logs.

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