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Adaptive Federated Learning for Real-time Anomaly Detection and Response in Large-Scale Distributed Networks

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ABSTRACT

The problem is the design of an adaptive, distributed anomaly detection system which protects privacy, and has the ability to evolve in real-time to identify and mitigate new threats while minimizing maximum detection delay and damage, in very large distributed environments. In this work, we propose an A-FCL (Adaptive Federated Collaborative Learning) architecture to enhance the separability of unknown anomaly patterns, adopt meta-learning approach (Meta-UAD) to decrease the false positive rate (FPR) and enhance adaptability, and develop a fully automated response architecture based on SOAR/SDN together with RL-AR (Reinforcement Learning with Adaptive Regulation) frameworks to dynamically and securely adapt low-latency response strategies. The relevance of this work is that it is the first to confront most challenging cybersecurity problems of the digital age and deliver an extremely high throughput autonomous security capability in large-scale environments slashing response times from minutes to milliseconds. The research methodology employed analytical, operational, and simulation methods, in which an advanced computer simulation environment was developed to evaluate the A-FCL framework —comprising contrastive learning as well as trust & reputation schemes to mitigate poisoning attacks—on extensive, heterogeneous (Non-IID) network datasets. The result was that the A-FCL model outperformed all the other models with an accuracy of 98.7% and the FPR was greatly reduced to 0.5% (a reduction of about 81.25%) by applying adaptive learning schemes. The system also exhibited excellent scalability, achieving a processing throughput of 22.1 GB/s for 50 edge nodes and an automated response time to critical attacks (such as DDoS) of no more than 45 milliseconds, representing a 96.6% reduction compared to manual response, while ensuring operational safety by reducing the safety violation rate by RL-AR to less than 0.4%.

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1. introduction

Massive distributed systems, such as multi-region cloud computing and industrial Internet of Things (IIoT) environments, are the foundation of today's digital infrastructure, but they are facing unparalleled security challenges stemming from an explosion of data, a non-trivial heterogeneity of data distribution (Non-IID), and very strict requirements of operational privacy and regulatory compliance. Conventional centralized anomaly detection systems are not sufficient for this purpose. They are not designed to handle high-speed data streams, they aggregate data in centralized points that can be attacked, and they require sending large volumes of data that violates users' privacy and consumes more bandwidth. Also, the rapid evolution of cyber threats (which increasingly manifest as slight anomalies or new attack patterns (Novel Anomalies)) results in Concept Drift causing static models to become outdated and unacceptably high level of FPR. This, however, requires a new approach for preserving scalability and privacy, while at the same time

being smart and responsive on the fly. The study introduces an Adaptive Federated Collaborative Learning (A-FCL) framework, based on Federated Learning (FL) to ensure the privacy and decentralization, and Contrastive Learning to improve the model's capability in identifying fine-grained anomalies in non-IID data. The proposed architecture extends detection with an automated real-time response capability leveraging Security Orchestration and Response (SOAR) In this paper, we considering the implication of Software-Defined Networking (SDN) empowered by structured reinforcement learning (RL-AR) to fulfill threat mitigation with minimum operational latency and safety constraints. The main novelty of the present work is to develop a unified model able to quantitatively tackle detection and response in large scale distributed scenarios and to present a thorough assessment of model correctness operational overhead and model security against.

Research problem and questions

Research problem: The critical challenge is to develop an anomaly detection system that is scalable, privacy-preserving, and can evolve to detect emerging threats (adapt to concept drift), and that operates in a manner with real time response to minimize operation latency and security compromise in massive and distributed networks

Research questions:

1. Can contrastive learning be effectively incorporated into a joint learning paradigm to enhance the performance of fine-grained anomaly detection in heterogeneous environments while preserving the privacy of the local data?
2. What are the potentials of meta-learning approaches on mitigating false positive rate (FPR) and handling drifts and data imbalance in distributed network flows?
3. What are the elements of the architecture design that provide low latency for the detection-to-automated response transition using SOAR/SDN techniques?
4. Do we have some insight on how RL could be used to promote real-time updates of a response policy while satisfying operational safety/security constraints?

Research Hypotheses

1. The results demonstrate the superiority of FCL-based models over centralized-based models (and autoencoder as a baseline) in worsening detection accuracy, while they also achieve a reduction in communication bandwidth consumption significantly.
2. Application of adaptive learning approaches (ALAC or Meta-Learning) leads to at least the 75% reduction in false positive rate (FPR) compared to static models, particularly in noisy and drifting environments.
3. In a SDN architecture, the detection system with SOAR platform integration minimizes the total response latency to critical anomalies to under 100 milliseconds.
4. Reinforcement learning with adaptive regulation (RL-AR) is capable of formulating dynamic mitigation policies which optimally balance the response effectiveness and the provision of NOP protection, with the violation rate of safety $\leq 0.5\%$.

Significance of the research

This paper is the first to tackle the most challenging issues that cybersecurity is currently confronted with in the digital era. It has theoretical contributions in that it closes the methodological gap of how to construct holistic learning models that are able to capture heavily heterogeneous data distributions, as well as temporal evolving anomaly patterns. We propose a novel framework that combines differential learning to learn distinctive feature spaces, which can be viewed as a pivotal theoretical contribution to the ability of FL to capture subtle anomalies. Furthermore, the research enriches the evaluation machinery by suggesting and employing measurement specific to groupware (e.g. Trust/Reputation based assessment of the integrity of the contributions). And its practical value is clear – to deliver a security mechanism that could run autonomously with high efficiency in large-scale environments, including financial institutions, health

networks, critical infrastructures, and so on. And since action through SOAR infrastructure can be automated so much faster via SDN architecture, response time can shrink from minutes to milliseconds with far less exposure of systems to attacks. Fewer false positive rates (FPR) also means less cognitive and operational workload for human security teams to deal with, so they can focus on strategic threats as opposed to random noise.

Research Objectives

1. Propose an A-FCL model to improve the discrimination of unknown abnormal patterns in multi-source data by effectively preserving data privacy.
2. Use meta-learning methods to decrease the number of false alarms and increase model's adaptability to unseen anomalies.
3. Propose a full-automated response framework based on security orchestration (SOAR) and SDN for low-latency and critical-threat network isolation.
4. Combine reinforcement learning and adaptive regulation (RL-AR) for the construction of dynamic and secure real-time response policies.
5. Assess accuracy (F1, AUROC), efficiency (latency, throughput) and model security (trust & reputation score) based on large-scale network datasets to measure the overall performance of the model.

Research Approaches

The study adopted a combination of three main approaches:

- **Analytical Methodology:** By applying an analytical methodology we make use of the first phase to analyze the existing scientific literature and understand the limitations of current collaborative detection systems (in particular with respect to heterogeneity and the protection of integrity from poisoning attacks).
- **Implementation Level:** The attention has been in the design and the implementation of the main element of the proposed model. This covered the design of the A-FCL architecture, the coding of the meta-learning techniques for adaptation, the software and hardware engineering for the integration of the SOAR system with an SDN controller utilizing fast protocols.
- **Simulation Approach:** The proposed method is applied to test quantitatively the performance of the model under a simulated realistic environment There are full comprehensive comparative experiments on both traditional and uniform learning with regard to both learning performance and robustness to demonstrate the validity of the proposed potential under the heterogeneous and non-stationary nature of time. 7. Adopted Research Methodology
- The methodology relies on the design of a sophisticated computer simulation environment that mimics the large-scale deployment of federated learning across multiple distributed data centers. The selected dataset (e.g., HIKARI-2021 or simulated CAIDA data) was divided into non-IID parts and distributed to hundreds of virtual clients to simulate a real FL scenario.
- **Data gathering:** We built on large-scale network traffic datasets for encrypted attacks and recent threat scenarios, focusing on data from sources in the academic and government sectors that share real traffic data after sanitizing.
- **Statistical analysis:** Sophisticated statistical methodologies were conducted, including One-Way Analysis of Variance (ANOVA) for comparing the mean performances of different models, Multiple Regression analysis to describe the relationship between various factors and latency, and Chi-Squared tests to assess disparities in the false alarm rates**.**
- **Implementation and evaluation:** Specific software environments (e.g., TensorFlow Federated, Pytorch) were adopted to realize the distributed deep learning models, while SDN simulation tools (e.g., Mininet) and open-source SOAR platforms were employed to assess the responsiveness in time.8. Research Boundaries

- **Spatial BoundariesOur** work studies macro-scale distributed networks, including cross-region cloud infrastructure and large-scale distributed industrial Internet of Things (IIoT) networks. The work is not considered for closed or small LAN stc that are not confronted with the same problems of heterogeneity and privacy. • TEMPO: TO is in real-time, based on overall latency (transaction time due to TC must be within the milliseconds, <500ms) which is a requirement for responsiveness in the face of modern threats. Analysis of non-critical threats that may involve longer response time has been omitted.B. Main body of the research: Analysis and quantitative evaluation

2. Research Methodology

1. Adaptive collaborative learning models for distributed network anomaly detection and response based on the prediction theory of information have been proposed

Developing an anomaly detection framework for large-scale distributed systems is challenging since it needs to address privacy protection, scalability, and non-IID nature of the data. To overcome these challenges, the Adaptive Fuzzy Convolutional Learning (A-FCL) framework is introduced. The model integrates the Federated Learning (FL) paradigm, which enables training a global model without moving raw data out of the client boundary, with the Contrastive Learning (CL) technique, which improves feature discrimination in the high-dimensional feature area. On the other hand, in the case of distributed networks, away from each other. subtle, and can be very different at various nodes (at one data centre you will detect the attack, at another you will not), making traditional FL models with simple aggregation (FedAvg) less effective. Differential learning counteracts this impact by competing embedding representations on local nodes, with the model to pull positive sample pairs (which are mostly normal and similar) away from each other and push negative (anomalous) sample pairs away from the normal representation. This selection method allows the integrated global model to acquire a more discriminative feature space and even identify subtle anomalies among different nodes [1].Besides the algorithmic level optimization, adaptive architecture calls for a shift from the conventional centralized server model to decentralized federated learning (DFL). Such a shift is needed to remove single points of failure and avoid threats to a centralized server, such as data tampering, or denial-of-service attacks. AG FL utilizes blockchain-based consensus, such as Proof of Attack Signature (PoAS), which is based on Proof of Stake (PoS) and ensures that model updates are hon est and un biased. Nevertheless, the decentralized and unpredictable trustworthiness of the nodes necessitates that a solid internal trust evaluation mechanism is incorporated. This amounts to a Trust and Reputation measure being calculated. The framework is inspired by a similar system that measures the accuracy of each node's contributions; it calculates the reputation (R-Score) of a node based on how well its historical updates align in expectations with the global model and the trust (T-Score) of a node that aims to determine whether the node is trustworthy enough to be involved in the current round of aggregation. This proactive defense form against evil nodes (e.g., poisoning attack that can be even launched by them) is necessary to secure the soundness and working availability of the overall model. The combination of A-FCL, DFL underpinned by consensus mechanisms, and the trust and reputation method constitutes a solid paradigm, capable to exceed the boundaries of faithful detection and protect model security and integrity in a malicious distributed setting [2].

Table 1: FCL Based Anomaly Detection models performance analysis in Distributed Networks.

Basic FL-DP (percentage)	Traditional AutoEncoder (percentage)	Proposed FCL (percentage)	Metric
96.1	94.2	98.7	Detection Accuracy
93.5%	89.8	97.4	Recall
0.947	0.919	0.981	F1 score
1.8	3.2	0.5	False Positive Rate (FPR)

Source: Simulation data based on the HIKARI-2021 dataset, one-way analysis of variance (ANOVA) for comparisons, Python (TensorFlow Federated, Scikit-learn).Table 1 demonstrates that the proposed FCL model far surpasses the classic AutoEncoder based model and the baseline FL-DP model. This superior performance is not only a slight improvement in accuracy with 98.7%, but also a conclusive extension of

such importance in cyber security. The F1 score (0.981) is also a good measure of the harmonic mean of precision and recall, which implies a great potential in capturing the true anomalies as well as reducing false alarms. Most importantly, the large reduction of the false positive rate (FPR) to 0.5%, compared with 3.2% of the classical model, is an indicator of the capability of differential learning in constructing more discriminative decision boundaries. This decrease in FPR is vital in large operating environments with a potential for high false alarms to cause desensitization to alerts and missed true threats. This improvement is methodologically justified by FCL being able to learn a feature space where normal data representations lie closely and compactly in both within-class (cohesion) and between-class (separation) via the variance loss function, and anomalous data representations are separated far away. This enables to minimize the intersection of heterogeneous data spaces which dominate the traditional FL setting, leaving the disparity in data distribution across nodes to impede the generalized capability of the model. By imposing a well-defined demarcation between the positive and negative samples at the node level (positive nodes contain only positive samples, negative nodes contain only negative samples), , the overall model becomes more robust and reliable in identifying subtle anomalies across the distributed system, which is a prerequisite for deployment in critical security systems. These results confirm that contrastive learning is not merely an improvement, but an algorithmic necessity for addressing the challenge of heterogeneous data in unified learning for anomaly detection [3].

Table 2: Analysis of communication efficiency and model convergence in distributed unified learning architectures

Model convergence rate (number of rounds)	Average communication latency (milliseconds/round)	Model update size (MB)	Aggregation Architecture
150	450 ms	25.5 MB	Traditional centralized (FedAvg)
185	680 ms	18.2 MB	Decentralized (DFL - PoAS)
110	310 ms	12.1 MB	Adaptive (A-FCL with mitigation)

Source: Simulation analysis of a distributed network with 500 nodes, logistic regression analysis of convergence, MATLAB. Table 2 offers a comprehensive description of the challenges, solutions, and architecture for collaborative learning on the large-scale distributed networks, considering communication efficiency and convergence speed as two major real-time application factors. The significance of our proposed adaptive model (A-FCL) can be seen in the largest compression in the model updates size (12.1 MB) over the FedAvg model (25.5 MB). Such a decrease of approximately 52% is a result of applying the update compression strategies (Model Quantization and Pruning) that are incorporated within the adaptive method that enables for sending the basic model information more efficiently through the limited bandwidth of wide area network (WAN). Reducing the size of updates is essential because communication overhead is the largest bottleneck in large-scale FL systems, particularly when hundreds or thousands of clients are involved in the training process. The communication latency of the proposed A-FCL model was the lowest (310 ms/round), outperforming the decentralized one (DFL-PoAS) with 680 ms. High latency of DFL is a consequence of having to run complicated consensus protocols, (e.g. PoAS) to ensure data integrity and contract reliability, which adds processing latency in each aggregation round. In comparison, the adaptive scheme, by means of intelligent client selection and dropout strategies, reduces the number of nodes that participate in aggregation without sacrificing quality, thus leading to a reduction on the overall latency and an acceleration on the convergence rate of the model in 110 rounds only. The fast convergence rate implies that the model gains the required information more quickly, which is indeed an implication of the strength of variational learning when learning robust feature representations. This study proves that the improvement in bandwidth efficiency and delay is a key ingredient of the success of FL in practice. [4]

Table 3: Assessment of trust and reputation in decentralized collaborative learning (DFL)

Malicious Node Detection Rate (Percentage)	Average Reputation Score (R-Score)	Average Trust Score (T-Score)	Node contribution rate (percentage)	Node type
0.0	0.95 (stable)	0.99 (reliable)	85.0	Normal Node
98.5	0.45 (volatile)	0.15 (Unreliable)	10.0	Poisoning Node

Malicious Node Detection Rate (Percentage)	Average Reputation Score (R-Score)	Average Trust Score (T-Score)	Node contribution rate (percentage)	Node type
N/A	0.70 (Moderate)	0.50 (questionable)	5.0	Silent/Inactive Node

Source: FedAD-Bench performance study, time series analysis of R-Score evolution, Spark MLLib.

In Table 3, the significance of trust and reputation-based metrics in decentralized federated learning (DFL) setups for safeguarding a global model from both insider and outsider disruptions, is emphasized, with poisoning, being atthe present moment a most challenging threat vector against FL. The reputation score (named as R-Score) is a cumulative metric determining how much a node's updates were consistent with the majority (or the assumed global model) in the past periods, while the trust score (named as T-Score) is the current estimation on the trustworthiness of a node in terms of its aggregation participation. The built-in trust mechanism is confirmed effective by the above to detect 98.5% of attackers who try to poison the model, as shown in Table 2. The malevolence of these nodes is so well pronounced on the confidence (T-Score 0.15) and reputation (R-Score 0.45) scores that their updates tend to be far from the mean of the normal distribution or opposed to the updates submitted by the healthy nodes. In addition, the scores remain very high for the regular nodes (T-Score = 0.99 and R-Score = 0.95) showing that the system can effectively differentiate between natural deviations (due to local heterogeneity) and adversarial malicious attacks. The ability to differentiate out these is what ensures the quality of the global model, Going one step further, by culling malicious contract updates, or weighting them down at the aggregation. the total detection rate and the distributed system stability are guaranteed. The use of these metrics is a necessary step for the definition of node actions within the cooperative framework, in that it turns FL from a simple privacy protection tool to a robust and reliable security system for internal attacks. [5]

2. Adaptive learning schemes for the enhancement of accuracy and the reduction of false alarms in anomaly detectors

Maintaining a low false positive rate (FPR) with high accuracy in a non-stationary and imbalanced data stream also lies at the core of anomaly detection because anomalies are rare by nature in high-speed and time-varying data streams. Here, adaptability is relevant, through methodologies that enable the model to learn in few-shot settings to mitigate concept drift - i.e., changes in formerly normal/anomalous data distributions over time, which results in model obsolescence. The methodological answer is to go for meta-learning, e.g., UAD-Meta which* allows the model to learn “prior knowledge” on how to learn faster and more effectively from unseen anomaly patterns. Instead of optimizing for a single task, the meta-learning procedure optimizes over “a distribution of tasks”, allowing the model to quickly adapt to a new anomaly class with only a few iterations and a few labeled examples. The method drastically decreases retraining burden and increases update efficiency that is imperative at resource bound edge environment**.** Besides of meta-learning to handle the drift in concepts and imbalanced data, there are adaptive post-processing procedures to mitigate the effect of random noise that result in false alarms. such as Adaptive Alert Classification (ALAC), that is a learner to classify alerts generated by a first-level anomaly detector. The ›ALAC alert classification model/completely human-secured ‹ that is constantly updated with feedback from a human security analyst (Human-in-the-Loop Distillation). For instance, when an analyst dismisses a certain alert as a false positive several times, the system knows to ignore it in the future with a high degree of confidence, eliminating some of the they workload. The noise induced by measurement errors or normal traffic variations, which are often misinterpreted as anomalies can also be filtered by exploiting Adaptive Multivariate Smoothing. This combined strategy, through adaptation of the algorithm at the detection stage and intelligence filtering at the post-processing stage, guarantees detection to be not only accurate but also operation-ally reliable, because a crucial tradeoff between high sensitivity and severe false alarm reduction is achieved. [6]

Table 4: Analysis of the reduction in false positive rate (FPR) using meta-learning (Meta-UAD) compared to basic methodologies

FPR reduction ratio (compared to AE)	F1 score on novel anomalies	False Positive Rate (FPR)	Detection Methodology
N/A	0.65	4.8	Basic automatic encoding (AE)
27.0	0.72	3.5	FL-AE (unified learning)
81.25	0.88	0.9	Proposed Meta-UAD (Meta-UAD)

Source: Simulation results on data containing intentional conceptual bias, Chi-Squared Test for significance of differences in FPR rates, Python (Pytorch).

Table 4 quantitatively emphasizes the qualitative shift caused by the use of adaptive meta-learning (Meta-UAD) in mitigating the problem of false positives (FPR) and the capacity of identifying new ones, an issue that plagues dynamic distributed network systems, among others. One of the most notable findings is a substantial decrease in the false positive rate of 81.25% over the baseline automatic encryption (AE) approach with the FPR going down from 4.8% to 0.9%. This substantial reduction is a consequence of the fact that the Meta-UAD method can learn complex and dynamic decision boundaries, which are not influenced by random noise or samples close to the boundary, which are the main sources of false alarms in conventional statistical methods. Meta-learning, by its nature, enables confidence mechanisms to be incorporated into samples, where low confidence weights are given to samples near the decision boundaries, preventing these samples from having an excessive influence on model training. In addition, the high performance on new anomaly detection (F1-Score 0.88) further supports the meta-learning premise, as the model can be trained on prior knowledge acquired from a set of meta-tasks and generalized to a new class of threats with only limited data snapshots. This result serves to further prove that Meta-UAD not only brings better accuracy but also the operational pliability that is certainly crucial when security systems need to face ever-increasing sophisticated and mutating attacks. [7]

Table 5: Impact of training data size and heterogeneity on accuracy metrics in adaptive learning

Recall (percentage)	Precision (percentage)	Data divergence (Jensen-Shannon Divergence)	Training Data Size (Percentage)	Data scenario
96.1	96.5	0.12	100	Homogeneous data (Baseline)
97.8	98.2	0.45 (High)	100	Adaptive learning (A-FL) - Full
96.9	97.5	0.45 (high)	25	Adaptive Learning (A-FL) - Diluted

Source: Model efficiency comparison, paired T-test for performance means, ,: R Studio.

Table 5 shows the intricate co-dependence of training sizes, data heterogeneity (Jensen-Shannon entropy), and accuracy/recall measures over adaptive learning (A-FL) in the FL scenario. The results demonstrate that A-FL not only can maintain satisfactory performance in extremely divergent scenarios (Divergence 0.45), but also enjoys fantastic data-level efficiency. Even though the adaptive model (A-FL) was trained on so divergent data, it yielded a higher precision (98.2%) and recall (97.8%) than the homogeneous reference case (96.5% and 96.1%, respectively). This result reaffirms that FL can naturally tap into distributed knowledge to make up for the deficiency of individual data, and even perform better than centralized models. The reason is that differential learning compels local models to learn the most discriminative features, and the overall model is less likely to rely on the exact statistical distribution of local data and more likely to be generalized to heterogeneous environment. What is even more surprising is that in the "A-FL - diluted" case, the training data was reduced by 75%, yet the model still preserved its full performance (, Precision 97.5%, and Recall 96.9%), with a similar AUC score. This quantitative evidence establishes that the model can be trained with a substantially reduced size and require less training, thus

allowing retraining and frequent updates to counteract concept drift. And it can be efficiently run on edge devices with constrained computing resources. [8]

Table 6: Statistical analysis of concept drift metrics

Readjustment time (seconds)	Accuracy loss rate before adaptation (percentage)	Deviation detection time (seconds)	Approved Methodology (A-FL)	Type of drift
1.2 seconds	12.5	5.1 seconds	Meta-Learning	Sudden drift
3.5 seconds	8.9	25.8 seconds	Weighted Aggregation	Gradual Drift
2.1 seconds	9.5	10.3 seconds	Contrastive Loss Tuning	Recurrent Drift

Source: Analysis of model behavior in a non-stationary time series environment, hybrid LSTM-ARIMA model for drift prediction, Jupyter Notebook (Pandas, Statsmodels).

Table 6 is about the most basic difficulties on real-time anomaly detection: the model stability against concept drift, which is the distribution of network data is time-variant. This drift makes pre-trained models obsolete and useless. The results show that the proposed adaptive solution (A-FL) empowers distinct mechanisms for different types of drifts. For sudden drift, which can be caused by a novel and fast spreading attack, the meta-learning approach detects the drift in just 5.1 seconds. This is through Meta-Learning's capacity to rapidly reorient an "approximation" to the optimal model using a limited set of new tasks, capping the accuracy loss to 12.5%. More significantly, the model can be readapted in 1.2 s. The rate of readjustment is the key to a robust detection in a high-speed environment. In the scenario of gradual drift where patterns evolve slowly, the introduction of weighted aggregation schemes in FL allows up-to-date (hence more relevant) nodes to get larger weights, and the impact on accuracy loss will be reduced to 8.9%. Besides, advanced statistical methods like hybrid forecasting models (LSTM-ARIMA) are applied to aid in identifying the time when key performance indicators (KPIs) start to drift from their expected values. This result analysis confirms that the generalization capability of the A-FL model is not only for detection accuracy but also for maintaining the model robustness under operating environment variations, making the model can be used to provide a real-time reaction to network dynamic changes. [9]

3. Real-time response mechanisms and mitigation of detected anomalies

Response at the edge to mitigate attacks is an essential part of a distributed security system and the handoff from anomaly detection to action must be as frictionless as possible. Real-time response is enabled by interfacing high confidence detection results (produced by A-FCL) with security orchestration, automation and response (SOAR) systems. SOAR creates a platform through which different security products can be integrated and complex playbooks automatically executed, for instance quarantining infected endpoints, updating firewall rules or rerouting suspicious traffic. Automation on its own brings down response time when compared to human intervention, so security personnel can prioritize on more strategic objects of their work. Mitigation responses must be conducted over a programmable infrastructure to provide a dynamic and reactive response, which is realized by software-defined networking (SDN). SDN allows the central point (Controller) to control the entire network promptly and dynamically by installing the flow rules (Flow Rules) on each switch, and can achieve very fine-grained isolation or limitation policies through flow information obtained from the detection system.For improving response intelligence, reinforcement learning with adaptive regulation (RL-AR) has been employed. In a high traffic network, there might be more than one feasible mitigation options, thus the system must find the best policy? to maximize the trade-off between the attack stop effectiveness and the# action cost(e.g., service disruption). The policy of best action (policy) in RL algorithm is learned by interacting with the environment. Yet because reinforcement learning is based on trial and error, it is risky to use in critical systems where testing a bad policy could violate operational safety constraints. RL-AR resolves this dilemma by combining the RL policy with a safety regularizer that enforces pre-defined security constraints, guaranteeing that exploration does not violate critical system functions while simultaneously learning response policies. This

design integration results in extremely low latency absent human intervention and leads to automated responses that are not only fast but also secure and reliable.

Table 7: Statistical comparison of response latency in distributed SOAR systems versus manual response

Total latency reduction (percentage)	Automatic response time (milliseconds)	Average Detection Time (ms)	Response scenario
96.6% (compared to manual)	45 ms	120 ms	DDoS attack (IP isolation)
94.7% (compared to manual)	90 ms	210 ms	Data leakage (flow stop)
N/A	4500 ms	120 ms	Manual policy update (reference)

Source: Experimental results from the ITU-T network simulation lab, multiple regression analysis of latency, R Studio (ggplot2 package).The game changer of SOAR in turning distributed network defense from a slow reactive method to a proactive, instant mode is presented in Table 7. The manual response baseline (4500 ms) corresponds to the conventional duration that it takes a security analyst to receive an alert, validate it, decide on a course of action, and carry out that course of action on multiple machines. On the other hand, this table clarifies that the integration of automated detection (detection time, 120–210 ms) with a scripted SOAR response results in remarkable automated response times (45–90 ms). For the total automated response time against the manual time, the total latency decreases by more than 94% in both cases, which demonstrates that SOAR effectively mitigates the "human latency" introduced by routine tasks. The reduction is critical in large-scale networks, where a fast attack (i.e. DDoS) necessitates taking measures in a few seconds, or it may result in devastating consequences. A automated response time of 45 ms to a DDoS attack enables the system to pinpoint the source of the attack before it substantially drains the network resources, especially since each TCP/IP connection in distributed systems can bring about 600 ms of delay. These results show that the real-time response can be realized by engineering efficiency and automation coordination with SO. [10]

Table 8: Effectiveness of reinforcement learning algorithms in applying safety constraints during network policy updates

Response efficiency in mitigation (percentage)	Safety constraint violation rate (percentage)	Average reward	Learning Algorithm
88	15.3	0.85	Deep Q Network (DQN) - Traditional
85	0.4	0.82	RL with adaptive regulation (RL-AR)
82	10.1	0.79	Policy Gradient - Traditional

Source: Simulation of security policy enforcement in an SDN network, Markov Decision Process Analysis, Python (Stable Baselines).The introduction of SOAR in transforming distributed network defense from a slow reactive approach to a proactive, instant mode is articulated in Table 7. The manual response baseline (4500 ms) represents the traditional time for a security analyst to get an alert, confirm it, make a determination of what to do, and then actually perform that on a handful of boxes. Conversely, this figure also reveals that when an automated detection (detection time: 120–210 ms) is combined with an scripted SOAR response, the resulting handling time (45–90 ms) is truly phenomenal. For the overall automated response time over the manual one, the overall latency is reduced more than 94% in either case, meaning that SOAR can successfully alleviate the "human latency" caused by mundane tasks. This decrease is vital in large-scale networks, where speedy attack (i.e. DDoS) requires responding in seconds, or it can bring severe results. 45 ms of automated response time to a blinding DDoS attack causes the system to identify the source of the attack prior to that occurring to a significant degree of network resources being used up, especially with the fact that in distributed systems each TCP/IP connection can result in an about 600 ms delay. These findings indicate that engineering efficiency and automation coordination with SO enable the realization of real-time response. [11]

Table 9: Analysis of flow rule update time in an SDN architecture in response to high-risk anomalies

Total update latency (milliseconds)	Rule activation time on the switch (milliseconds)	Command transmission time to the unit (milliseconds)	Method of Implementation	Required action (response)
8.3 ms	5.8 ms	2.5 ms	OpenFlow Protocol	Isolating the source of the attack (Blackholing)
4.9 ms	3.1 ms	1.8 ms	P4 Protocol	Rerouting traffic
19.3 ms	15.1 ms	4.2 ms	REST API (reference)	QoS adjustment (bandwidth throttling)

Source: Performance measurement in a simulated SDN environment using OpenDaylight Controller, Markov chain model for flow state estimation, Wireshark (for control packet tracing).In what follows, we provide in Table 9 critical information on the inner working of real-time response with emphasis on the measurement of update times of flow rules in software defined networks (SDN), which is the underpinning real-time mitigation enabler. We observe that the response within SDN is executed fast, since the update times are in milliseconds, which upholds the real-time response hypothesis as illustrated in the table. Most notably, modern programming protocols (e.g., P4) clearly show a latency advantage over legacy protocols (OpenFlow) or even slow REST API interfaces. In the process of killing the source of the attack, in a traffic redirection scenario, the P4 protocol reached a total update latency of 4.9 milliseconds, whereas the OpenFlow recorded 8.3 milliseconds. While this time difference is minute, it becomes critical when considering high velocity streams of data that can wreak havoc in a matter of seconds or less. The total latency, is composed of two main times: the time to send the command from the controller to the switch (the), and the time to enable the rule on the switch. Activation time (3. I (1 milliseconds for P4) demonstrates the efficiency of programmable switches, suggesting that they are designed optimally for dynamic policy enforcement. This high performance demonstrates that SDN can serve as the enforcement point of a distributed SOAR framework, so that the detection decision (A-FCL) is enjoined to perform physical actuation on the network at a rate well beyond the conventional real-time response demands of tens-to-hundreds of milliseconds. [12]

4. Performance Evaluation and Future Challenges in Large-Scale Distributed Network Environments

#Humanized response

Indeed, achieving this in such environments calls for an all-encompassing set of criteria that extend beyond the traditional accuracy metric to include system operational efficiency and security in distributed systems. Operational efficiency is tied to scalability and the ability of the system to process large amount of data, which is a difficulty for conventional detection algorithms because of their high computational complexity and high velocity of data. In the context of distributed systems, the issue of scalability is even more challenging due to higher network latencies introduced by interconnections among different continents. The assessment should give emphasis to edge computing approaches, where decentralized processing takes place in close proximity to the data generation point, in order to minimize propagation and process time. Furthermore, the assessment of federated learning must take into account particular metrics such as trust and reputation, which evaluate the dependability of contributions from nodes, a crucial factor in maintaining the model's integrity against poisoning attacks. [13]As for the challenges ahead, work is concentrated in three areas. among the first is dealing with data heterogeneity at the extreme end, since these systems need to evolve new aggregation tactics that are more fair and robust to the presence of extreme data heterogeneity across statistical data distributions. Secondly, there is a need to provide standardized benchmarking protocols, since up to now research has utilized different experimental setups and used different metrics on the performance, which hamper the trustful comparison of models This work aims at tackling these two issues. Such frameworks should rely on real (rather than synthetic) up-to-date data, and should provide (at least) with quality, privacy, and scalability metrics. Third, deep RL is being

combined with more traditional planning to form the top-down neural network paradigm, as a way to progressively relax model assumptions and bridge the gap between planning and learning. This will also entail enhancing trust and transparency机制 to guarantee that AI decisions in critical systems are interpretable and can be reviewed by humans. [14]

Table 10: Scalability Analysis via Throughput (GB/s) per Distributed Node

Latency increase rate with node increase (ms/node)	Average processing throughput (GB/s)	Number of active nodes	Processing Methodology
N/A	0.8 GB/s	1	Traditional Centralized (Batch Processing)
1.2 ms	15.4 GB/s	5	Distributed unified learning (A-FCL) - Cloud computing
0.4 ms	22.1 GB/s	50	Distributed Federated Learning (A-FCL) - Edge Computing

Source: System stress testing on large-scale virtual environments, time series analysis of performance variables, Grafana/Prometheus.

Table 10 in this section presents the results of the scalability test of the proposed system under a very high pressure of data flow, which is an important factor on the detection system to be deployed on large-scale network environments. The most important result is that the transition to a single distributed edge computing architecture leads to a processing throughput on the order of magnitude of 22.1 GB/s with 50 nodes, which significantly outperforms traditional centralized cloud processing (0.8 GB/s). It is consistent with the demands of the current days system, which must be capable to run on flows of 20 gigabytes per second. The reason for such superiority is the local process of data on edge devices ( ), drastically eliminating the size of required data being sent to the center. This distribution also slows down the rate that the latency increases with more nodes. Although each new node in a cloud computing environment increases latency by 1.2 milliseconds causing inter-region connectivity issues, in edge computing it is only 0.4 milliseconds. This mitigation of extra latency is indicative of the fact the A-FCL paradigm, enabled by model compression, load distribution and local data processing, is able to address the congestion and latency challenges associated with increased scalability in d-EEs, thereby enabling that performance does not degrade in a linear manner with network size growth

Table 11: Overall performance evaluation (AUROC, F1-Score) of the proposed model on large-scale benchmark datasets

FCL model without adaptation (FL-CL)	Basic RBM model	Proposed model (A-FCL)	Dataset
AUROC: 0.942	AUROC: 0.812	AUROC: 0.985	NSL-KDD (simulation)
F1-Score: 0.937	F1-Score: 0.782	F1-Score: 0.967	HIKARI-2021 (distributed)
Precision: 0.926	Precision: 0.784	Precision: 0.971	CICIDS-2017 (high heterogeneity)

Source: Comparative analysis using standard FedAD-Bench frameworks, ROC curve and area under the curve (AUROC),: Weka. Table 11 represents the detailed analysis of the impact of the adaptive collaborative learning (A-FCL) approach in terms of its size on real-world standard datasets, to the best of our knowledge which is well-known for its size and complexity was used to make the results comparable and rigorously academically documented. The robustness of A-FCL can be seen by its nearly optimal performance in terms of AUROC and F1-Score, even in the presence of non-IID data. For a complex distributed environment, such as the NSL-KDD dataset, the AUROC of the proposed method was 0.985, which indicates that the proposed method has a good discrimination ability for abnormal and normal instances. More significantly, it is also better than the non-adaptive FCL model (AUROC 0.942) and the baseline RBM model (AUROC 0.812). This result indicates that long-term robustness is enhanced by incorporating adaptive elements (which compensate for conceptual drift) into the model. A-FCL also performed well on the HIKARI-2021 dataset, which is large and distributed, with a F1 score of 0.967 higher than the non-adaptive FCL (0.937).. In addition, a precision score of 0. 971 on the highly heterogeneous CICIDS-2017 dataset demonstrates that the variance-based approach used in A-FCL

produces robust feature representations even when the data at each node follows different statistical distributions. These numbers rank A-FCL as one of the best models for real deployment in large scale cyber security systems, since it achieves superb trade-off between capturing real threats and producing false alarms [15].

Table 12: List of challenges classified in collaborative learning (FL) with quantitative measures of the impact of each challenge

Proposed Adaptive Strategy	Quantitative Impact (Average F1-Score Reduction)	Description/Operational Impact	Challenge category
Fuzzy Learning (FCL) and Weighted Aggregation	15.5	Decreased model generalization	Data Heterogeneity
Trust & Reputation Analysis	21.3	Deterioration of model safety and fairness	Poisoning Attacks
Quantization	18.0	High aggregation latency and training time	Communication Overhead Challenges
Meta-learning	12.5	Model obsolescence and loss of detection accuracy	Concept drift

Source: A systematic review of challenges and future trends in unified learning for anomaly detection, Sensitivity Analysis, KNIME Analytics Platform.

Table 12 lists and describes the structural and operational difficulties in implementing collaborative learning in real environments and quantifies the impact of each on the critical performance metric (F1-Score), as well as the adaptive strategies addressed by the research work in this document. This table can be considered a "roadmap" of challenges, which undoubtedly any highly distributed security system will have to face. Poisoning attacks introduce the largest quantitative effects, inducing an average f1-score reduction of 21.3%. Such huge impact motivates the necessity of defense mechanisms like trust and reputation based systems to filter or reduce the contribution of malicious nodes information, as depicted by the Table 3. After the bandwidth problem, with (18.0% decrease in impact order), the challenge arises when engineering solutions are required (e.g., quantization) to decrease the size of the updates sent. The heterogeneity challenge (15.5 percent performance degradation) is addressed by Federated learning (FCL) that increases generalization so that natural variations of local data do not taint the global model. This quantitative assessment of the challenges clearly identifies the objectives that should be the focus of future research and points to a solution that is best summarized by as a multi-pronged one that incorporates security defenses (trust), operational efficiency (compression), and algorithmic flexibility (machine learning) for the best performance possible under environmental constraints [16]

3. Results

1. The A-FCL model obtains the accuracy of 98.7% and f1 score of 0.981 which is 4.5% higher than traditional models.
2. The false positive rate (FPR) was decreased as low as to 0.5% through adaptive learning and meta-UAD schemes, an 81.25% reduction over baseline schemes.
3. The system throughput was 22.1 GB/s on 50 edge computing nodes, demonstrating strong scalability for large-scale networks.
4. By integrating the detection system with the SOAR platform, the automatic response time to DDoS attacks was shortened to 45 milliseconds, which accounted for 96.6% reduction of the total latency of manual response.
5. We demonstrate safe deployment of the RL-AR with less than 0.4% safety violation rate with dynamic network policy updates.
6. The Trust & Reputation based analysis engine successfully identified 98.5% of the nodes engaging in the poisoning attacks while keeping the unified model intact.
7. With the native compression techniques, the unified model update size was compressed by 52%, the connection latency per training round was reduced to 310 ms.

4. Recommendations

1. One may consider unified learning models with contrastive loss to enhance feature discrimination in high contrast settings.
2. Supervised learning techniques need to be incorporated into the distributed detection architecture to allow fast learning on novel anomalies and minimize alert fatigue of security operators.
3. The throughput rates (□20 GB/s) must be guaranteed with the investment on the edge computing infrastructure, with the reduction of operation delay.
4. It is recommended that automated detection outputs be integrated with SOAR platforms and SDN infrastructure to maintain detection-to-mitigation latency less than 100ms.
5. Reinforcement learning-augmented reinforcement learning (RL-AR) should be used to synthesize automated response policies which are guaranteed to around optimum effectiveness w.r.t.
6. Motivation: Metrics of trust and reputation should also be included as pre-conditions in the unified aggregation protocols to strengthen the robustness of models in facing internal malicious attacks.
7. It is suggested to use more advanced model quantization schemes to alleviate the computation load on the bandwidth of the distributed network.

5. Conclusion

This study has shown that the ACL solution is a significant paradigm shift for anomaly detection and response in extremely large, distributed networked systems, which feature very high data heterogeneity, rigorous privacy constraints and real-time execution. The technical aims were achieved by developing a novel integrated framework, which circumvents the well-known drawbacks of centralized approaches and basic unified learning techniques. The adaptive federated learning (A-FCL) approach showed evident quantitative improvement in detection performance (Accuracy 98.7%, F1 0.981), validating the F1 assumption and the potentiality of adaptive learning to generate distinguishable feature space even in the case of severe data heterogeneity. In particular, adaptation UAD (Meta-UAD), a representative of the adaptive learning paradigm, was able to effectively cope with conceptual drift with a false positive reduction (FPR) of only 0.5%, a more than 81% increment compared to the reference models, thus supporting hypothesis F2 and contribute in a direct way to reduce operational burden for security staff.As for the response, an auto response time to critical attacks (DDoS.. Latency of 45 ms is achieved, a 96.6% reduction in the total latency of manual response, confirming the F3 hypothesis that real-time response is guaranteed when SOAR is combined with SDN architecture. Most significantly, on the security aspect and during the formulation of dynamic response policies, reinforcement learning with adaptive regulation (RL-AR) significantly decreased the rate of safety violations to 0.4%, which lends support to hypothesis H4 and guarantees high-speed automation without endangering the safety of mission-critical systems. The trust and reputation system also improved the overall unified model integrity by identifying 98.5% of malicious contracts. The results for scalability show that by leveraging edge computing, the processing throughput can be raised up to 22.1 GB/s with its latency per node reduced, which open the door for deploying the scheme in large scale infrastructures. Therefore, this research proposes an abstract and quantifiable theoretical and practical framework, , enables to harmonize privacy and accuracy within the context of a spaced-out scientific process (i.e., operational efficiency), serving to bolster cyber security resilience for distributed systems.

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