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IOT SECURITY: FROM CONTEXT-BASED AUTHENTICATION TO SECURE FEDERATED LEARNING ANOMALY DETECTION

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IoT Security: From Context-based Authentication to Secure Federated Learning Anomaly Detection

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ERKLÄRUNG GEMÄSS §9 DER PROMOTIONSORDNUNG

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Darmstadt, 08.10.2024

Duc Thien Nguyen

ABSTRACT

We are witnessing a rapid deployment of Internet of Things (IoT) devices in our daily lives, e.g., in smart homes, offices, factories, and infrastructure. According to Statista, the number of IoT devices is expected to increase from 8.6 billion in 2019 to 29.4 billion in 2030, resulting in an annual growth rate of 12%[1]. This emphasizes the increasing demand for a new class of applications requiring smart connectivity and intelligent features, such as robotics, home automation, autonomous transportation, and intelligent manufacturing. Unfortunately, many IoT devices are vulnerable due to insecure design, implementation, and configuration, leading to a surge in cyberattacks on IoT applications. Statista reports that the number of cyberattacks on IoT surged by 36% annually, from 32 million in 2018 to 112 million in 2022, thus, multiplying the increasing number of IoT[2]. Existing attacks often exploit insecure authentication mechanisms or employ sophisticated IoT malware at a large scale. The first line of attacks aims to intercept device communication, allowing adversaries to manipulate device communication or access sensitive IoT data. However, implementing secure authentication for IoT device pairing faces significant challenges due to the heterogeneity of IoT devices, the variety of application scenarios, and the often cumbersome requirements for user involvement. This poses the need for new pairing schemes that are IoT vendor-agnostic and do not require human intervention. However, secure pairing is not enough to protect IoT devices against large-scale attacks caused by sophisticated IoT malware. For example, infamous IoT malware like Mirai and its variants have taken control of hundreds of thousands of IoT devices in a short time and used them as bots to run the largest Distributed Denial of Service (DDoS) attack at that time, resulting in the large-scale disruption of online services, e.g., from Amazon, Netflix, and GitHub[3]. Unfortunately, existing protection methods are ineffective in capturing such novel attacks. Thus, this introduces a new line of research focused on advanced technologies such as Machine Learning (ML) which can detect sophisticated and dynamic attacks in heterogeneous IoT settings. However, ML algorithms are also susceptible to severe security and privacy attacks, including model manipulation and training data leakage. Therefore, when employing ML for security applications, it is crucial to ensure the security of the ML algorithms used.

In this dissertation, we present four comprehensive solutions to secure IoT devices and Federated Learning (FL). We focus on FL because it is an emerging distributed learning paradigm used to build our IoT intrusion detection system. Firstly, we introduce a novel longitudinal context-based pairing scheme to establish secure communication be-

1 https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/

2 https://www.statista.com/statistics/1377569/worldwide-annual-internet-of-things-attacks/

3 https://en.wikipedia.org/wiki/Mirai_(malware)

tween IoT devices. Further, we propose an innovative anomaly detection system that utilizes FL to identify attacks caused by IoT malware. Since FL is vulnerable to inference and backdoor attacks, we present a secure and backdoor-resilient framework for FL-based applications. Unfortunately, the world faced the severe COVID-19 Pandemic during my studies. In response, we applied our context-based authentication research to Digital Contact Tracing (DCT), aiming to break infection chains. We propose a new DCT system designed to effectively identify potential encounters with SARS-CoV-2 infected users while being resilient against large-scale security and privacy attacks. In the following, we summarize these four solutions.

ConXPair2- a context-based pairing scheme. We introduce ConXPair2, a context-based zero-interaction approach for pairing IoT devices. Our approach continuously tracks changes in context modalities, such as ambient light and noise, to evolve secure pairing keys over time. Unlike existing methods, ConXPair2 does not require tight time synchronization and offers enhanced security against Man-In-The-Middle (MITM), context guessing, and replay attacks. We also develop an advanced fingerprinting extraction technique that generates high-entropy fingerprints, addressing the low entropy issue in longitudinal, passive context fingerprinting. Moreover, we conduct a systematic security analysis of context-based pairing systems, emphasizing their practical application through an empirical evaluation framework that measures security using min-entropy. This comprehensive analysis aids in understanding the robustness of context-based authentication systems in typical IoT environments.

TraceCorona - a digital contact tracing system in response to COVID-19 pandemic. Digital contact tracing plays an important role in identifying infection chains. We propose TraceCorona, a novel privacy-preserving contact tracing system based on the Diffie-Hellman key exchange, offering enhanced security and privacy compared to existing methods. The beta version of TraceCorona has been successfully used by over 2,000 users, demonstrating the effectiveness of our approach. Further, we systematically review the advantages and drawbacks of prominent DCT systems, focusing on their effectiveness, security, privacy, and ethical aspects. We identify significant security and privacy gaps in widely used systems like the Google and Apple Exposure Notification APIs.

DÏoT - a federated learning-based intrusion detection system for IoT. Addressing the surge in attacks on IoT devices caused by malware, we propose DÏoT, an anomaly detection system based on our advanced network modeling approach and FL. In particular, DÏoT employs natural language processing techniques and advanced neural network algorithms to learn normal traffic patterns of IoT devices and detect deviated patterns as abnormal traffic generated by malware. Moreover, DÏoT builds a specific detection model for each device type, reducing false alarms and increasing detection accuracy. DÏoT's effectiveness is further enhanced by utilizing FL, allowing collaborative model training of many participants without compromising participant data privacy.

FLAME - a secure and backdoor resilient federated learning framework. Tackling backdoor and inference attacks in FL, we design a backdoor resilient FL framework that employs our adaptive noising technique to neutralize poisoned model updates. Moreover, we propose two supplemented components, dynamic clustering and adaptive clipping, to boost poisoned update elimination while preserve model performance by reducing the required noise added to the models. Furthermore, we propose DeepSight to improve the accuracy of FLAME clustering component in non-iid data settings by analyzing models' internal structures to identify and remove potential poisoned updates. In addition, we develop *private* FLAME to prevent inference attacks by secure model updates from a semi-honest model aggregator that seeks to learn information about data training through model update inspections.

ZUSAMMENFASSUNG

Wir erleben eine rasche Verbreitung von Geräten des Internet-of-Things IoT in unserem Alltag, z. B. in Smart Homes, Büros, Fabriken und der Infrastruktur. Laut Statista wird die Zahl der IoT-Geräte voraussichtlich von $8,6$ Milliarden im Jahr 2019 auf $29,4$ Milliarden im Jahr 2030 steigen, was einer jährlichen Wachstumsrate von 12% entspricht[4]. Dies unterstreicht die steigende Nachfrage nach einer neuen Klasse von Anwendungen, die intelligente Konnektivität und Funktionen erfordern, wie z. B. Robotik, Hausautomation, autonomen Transport und intelligente Fertigung. Leider sind viele IoT-Geräte aufgrund von unsicheren Designs, fehlerhafter Implementierungeu und mangelhafter Konfigurationen anfällig gege Angriffe, was zu einem Anstieg der Cyberangriffe auf IoT-Anwendungen geführt hat. Statista berichtet, dass die Zahl der Cyberangriffe auf das IoT jährlich um 36% gestiegen ist, von 32 Millionen im Jahr 2018 auf 112 Millionen im Jahr 2022[5]. Diese Entwicklung verdeutlicht die steigende Zahl von Bedrohungen für IoT-Anwendungen. Bestehende Angriffe nutzen häufig unsichere Authentifizierungsmechanismen aus oder setzen ausgeklügelte IoT-Malware in großem Maßstab ein. Ein häufiger Angriffsvektor ist das Abfangen der Gerätekommunikation, wodurch Angreifer die Möglichkeit haben, diese zu manipulieren oder auf sensible IoT-Daten zuzugreifen. Die Implementierung einer sicheren Authentifizierung für die Kopplung von IoT-Geräten gestaltet sich jedoch aufgrund der erheblichen Heterogenität der Geräte, der Vielfalt der Anwendungsszenarien und der oft Schwierigen Benutzbarkeit als herausfordernd. Daher besteht ein Bedarf an neuen Kopplungsverfahren, die unabhängig von IoT-Anbietern sind und kein menschliches Eingreifen erfordern. Sicheres Pairing allein reicht jedoch nicht aus, um IoT-Geräte vor groß angelegten Angriffen durch ausgeklügelte IoT-Malware zu schützen. Ein berüchtigtes Beispiel ist die IoT-Malware Mirai und ihre Varianten, die die Kontrolle über Hunderttausende von IoT-Geräten übernommen und sie als Bots eingesetzt haben, um den bis dahin größten Distributed Denial of Service (DDoS)-Angriff auszuführen. Dieser Angriff führte zu großflächigen Unterbrechungen von Online-Diensten, darunter Amazon, Netflix und GitHub[6]. Leider sind bestehende Schutzmethoden nicht in der Lage, solche neuartigen Angriffe effektiv zu verhindern. Daher eröffnet sich eine neue Forschungsrichtung, die sich auf fortschrittliche Technologien wie maschinelles Lernen (ML) konzentriert, um ausgeklügelte und dynamische Angriffe in heterogenen IoT-Umgebungen zu erkennen. Allerdings sind ML-Algorithmen selbst anfällig für schwerwiegende Sicherheits- und Datenschutzangriffe, einschließlich Modellmanipulation und der Weitergabe von Trainingsdaten. Daher ist es beim Einsatz von ML für

4 https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/
5 https://www.statista.com/statistics/1377569/worldwide-annual-internet-of-things-attacks/
6 https://en.wikipedia.org/wiki/Mirai_(malware)

Sicherheitsanwendungen entscheidend, die Integrität und Sicherheit der verwendeten ML-Algorithmen zu gewährleisten.

In dieser Dissertation stellen wir vier umfassende Lösungen zur Sicherung von IoT-Geräten und Federated Learning (FL) vor. Wir konzentrieren uns auf FL, weil es ein aufkommendes, verteiltes Lernparadigma ist, das wir zum Aufbau unseres IoT-Angriffeserkennungssystems verwenden. Zunächst führen wir ein neuartiges, kontextbasiertes Kopplungsverfahren ein, um eine sichere Kommunikation zwischen IoT-Geräten zu gewährleisten. Des Weiteren schlagen wir ein innovatives System zur Erkennung von Anomalien vor, das FL nutzt, um Angriffe durch IoT-Malware zu identifizieren. Da FL anfällig für Inferenz- und Backdoor-Angriffe ist, stellen wir einen sicheren und Backdoor-resistenten Ansatz für FL-basierte Anwendungen vor. Leider wurde die Welt während meines Studiums von der COVID-19-Pandemie heimgesucht. Als Reaktion darauf haben wir unsere kontextbasierte Authentifizierungsforschung auf die Digital Contact Tracing (DCT) angewandt, um dabei zu helfen Infektionsketten zu durchbrechen. Wir schlagen ein neues DCT-System vor, das potenzielle Begegnungen mit SARS-CoV-2-infizierten Nutzern effektiv identifizieren kann und gleichzeitig gegen groß angelegte Sicherheits- und Datenschutzangriffe resistent ist. Im Folgenden fassen wir diese vier Lösungen zusammen:

ConXPair2 – ein kontextbasiertes Pairing-Verfahren. Wir stellen ConXPair2 vor, einen kontextbasierten Zero-Interaction-Ansatz für das Pairing von IoT-Geräten. Unser Ansatz verfolgt kontinuierlich Veränderungen der Kontextmodalitäten, wie Helligkeit und Geräusche, um im Laufe der Zeit sichere Pairing-Schlüssel zu entwickeln. Im Gegensatz zu bestehenden Methoden erfordert ConXPair2 keine enge Zeitsynchronisation und bietet verbesserte Sicherheit gegen Man-In-The-Middle (MITM)-, Context-Guessing- und Replay-Angriffe. Zudem entwickeln wir eine fortschrittliche Technik zur Fingerabdruck-Extraktion, die Fingerabdrücke mit hoher Entropie erzeugt und das Problem der geringen Entropie bei passiven longitudinalen Fingerabdrücken behebt. Darüber hinaus führen wir eine systematische Sicherheitsanalyse von kontextbasierten Pairing-Systemen durch, wobei wir ihre praktische Anwendbarkeit durch einen empirischen Bewertungsrahmen hervorheben, der die Sicherheit unter Verwendung der Min-Entropie misst. Diese umfassende Analyse hilft dabei, die Robustheit von kontextbasierten Authentifizierungssystemen in typischen IoT-Umgebungen zu verstehen.

TraceCorona – ein digitales Kontaktverfolgungssystem als Reaktion auf die COVID-19-Pandemie. Die digitale Kontaktnachverfolgung spielt eine wichtige Rolle bei der Identifizierung von Infektionsketten. Wir schlagen TraceCorona vor, ein neuartiges, die Privatsphäre wahrendes System zur Kontaktnachverfolgung, das auf dem Diffie-Hellman-Schlüsselaustausch basiert und im Vergleich zu bestehenden Methoden mehr Sicherheit und Privatsphäre bietet. Die Beta-Version von TraceCorona wurde bereits von über 2.000 Nutzern erfolgreich eingesetzt, was die Effektivität unseres Ansatzes beweist. Darüber hinaus überprüfen wir systematisch die Vor- und Nachteile bekannter DCT-Systeme und konzentrieren uns dabei auf ihre Effektivität, Sicherheit,

den Datenschutz und ethische Aspekte. Wir identifizieren signifikante Sicherheits- und Datenschutzlücken in weit verbreiteten Systemen wie den Google und Apple Exposure Notification APIs.

DÏoT – ein auf föderiertem Lernen basierendes Intrusion Detection System für das IoT. Um der Zunahme von Angriffen auf IoT-Geräte durch Malware zu begegnen, schlagen wir DÏoT vor, ein System zur Erkennung von Anomalien, das auf einem fortschrittlichen Netzwerkmodellierungsansatz und FL basiert. DÏoT verwendet insbesondere Techniken zur Verarbeitung natürlicher Sprache und fortschrittliche neuronale Netzwerkalgorithmen, um normale Verkehrsmuster von IoT-Geräten zu erlernen und abweichende Muster als durch Malware erzeugten, abnormalen Verkehr zu identifizieren. Darüber hinaus erstellt DÏoT ein spezifisches Erkennungsmodell für jeden Gerätetyp, wodurch Fehlalarme reduziert und die Erkennungsgenauigkeit erhöht werden. Die Effektivität von DÏoT wird durch den Einsatz von FL weiter erhöht, da ein kollaboratives Modelltraining vieler Teilnehmer ermöglicht wird, ohne die Privatheit der Daten der Teilnehmer zu gefährden.

FLAME – ein sicheres und gegen Backdoor-Angriffe geschütztes föderiertes Lernsystem. Zur Bekämpfung von Backdoor- und Inferenzangriffen in FL entwickeln wir ein Backdoor-resistentes FL-Framework, das adaptives Noisin einsetzt, um vergiftete Modell-Updates zu neutralisieren. Darüber hinaus schlagen wir zwei ergänzende Komponenten vor: dynamisches Clustering und adaptives Clipping, um die Beseitigung von vergifteten Updates zu verbessern und gleichzeitig die Modellleistung zu erhalten, indem das erforderliche Rauschen, das den Modellen hinzugefügt wird, minimiert wird. Wir schlagen zudem DeepSight vor, um die Genauigkeit der FLAME-Clusterkomponente bei nicht-idealen Datenverteilungen zu verbessern, indem die internen Strukturen der Modelle analysiert werden, um potenziell vergiftete Modellaktualisierungen zu identifizieren und zu entfernen. Darüber hinaus entwickeln wir eine Privatheiterhaltende variante von FLAME, um Inferenzangriffe zu verhindern, indem sichere Modellaktualisierungen von einem teilweise vertrauenswürdigen Modellaggregator durchgeführt werden, der versucht, durch Inspektionen der Modellaktualisierungen Informationen über das Training der Daten zu erfahren.

Let's walk together, mindfully.

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CONTENTS

ACRONYMS

BLE Bluetooth Low Energy

DCT Digital Contact Tracing

DDoS Distributed Denial of Service

DH Diffie-Hellman

ECDH Elliptic-curve Diffie-Hellman

DL Deep Learning

DP Differential Privacy

DSN Digital Sensor Networks

FL Federated Learning

FPRs False Positive Rates

GAEN Google and Apple Exposure Notification API

GPS Global Positioning System

GRU Gated Recurrent Unit

HDBSCAN Hierarchical Density-Based Spatial Clustering of Applications with Noise

IDS Intrusion Detection System

IDSs Intrusion Detection Systems

IID independent and identically distributed

IoT Internet of Things

kNN k-nearest neighbors algorithm

ML Machine Learning

MITM Man-In-The-Middle

PKI Public Key Infrastructure

PSI Private Set Intersection

PSK Pre-Shared Key

PSSA Pre-Shared Security Associations

RNN Recurrent Neural Network

STPC Secure Two-Party Computation

ZIP Zero-interaction pairing

Part I

SYNOPSIS

1 INTRODUCTION

Internet of Things (IoT) devices are increasingly deployed in smart homes, smart factories, and smart infrastructures, demonstrating the surging demand for smart connectivity and intelligent features. According to Statista, the IoT market is witnessing exponential growth and expected to rise from 9.76 billion devices in 2011 to 29.42 billion by 2025 [168]. However, many IoT devices have security vulnerabilities caused by insecure design, implementation, and configurations [6, 59, 71, 81, 99, 108, 117, 118, 127, 162, 167, 173]. As a result, various attacks have exploited IoT device vulnerabilities, such as attacks against device communication [34, 41, 117, 128, 151, 162, 166, 169], smart home applications [19, 55, 58, 59, 72, 81, 97, 106, 144, 171, 212], industrial IoT [95, 164], as well as massive large-scale DDoS attacks [71, 108, 173]. These attacks lead to serve consequences, e.g., making devices unusable [167, 176], leaking of sensitive data [40, 118, 166, 180], large-scale interruptions of internet and online services [71, 108, 165, 172, 173], or, disruptions of industrial and critical systems [88, 163, 164].

Existing attacks on IoT systems are often caused by two main issues: unsecured communication or authentication errors [34, 41, 55, 59, 67, 81, 106, 117, 128, 151, 152, 154, 162, 166, 169] and IoT malware (i.e., the malware that specifically targets IoT devices) [66, 71, 84, 127, 167, 173]. However, conventional device pairing schemes and malware detection mechanisms are insufficient to mitigate ever-increasing threats and dynamic attack landscapes [44, 71, 108, 117, 128]. Conventional pairing often requires human intervention [38, 94, 102, 211, 213] or the establishment of a universal key pool among IoT device manufacturers [130, 141]. On the other hand, rule-based filtering approaches incur significant delays in detecting attacks and can not detect unknown attacks [75, 108].

Applying ML is becoming an increasingly interesting approach for both authentication [7, 11] and IoT malware detection [3, 27, 177] to mitigate such dynamic attack landscape. In our works, we have leveraged several ML techniques such as classification for context-based proofs of co-presence [7, 11] or Federated Learning FL for IoT Intrusion Detection Systems (IDSs) [3]. However, ML itself is also vulnerable to critical security and privacy attacks like backdoor attacks [12, 23, 33, 54, 65, 111, 125, 145, 153]. Therefore, to provide a complete secured system, we need to not only apply ML for security applications to increase defense effectiveness but also consider the security of the used ML algorithms by design.

Table 1.1: Summary of research results. Publications to be presented in this dissertation are marked with *

Context-based Authentication for IoT			Secure Federated Learning (FL) for IoT IDS	
Device Pairing	Contact Tracing	Proof of Presence	FL-based IoT IDS	Secure FL
ConXPair2* DAC'18[1]	**TraceCorona*** TECT'22[2]	DoubleEcho PerCom'19[11]	**DÏoT*** ICDCS'19[3]	**FLAME*** USENIXSec'22[4]
OmniShare IC'18[9]	MindtheGap TrustC.'20[16]	ConXPop ACCS'14[7]	AuDI JASC'19[10]	**DeepSight*** NDSS'22[5]
ConXPair CCS'14[15]	PDCT MTD'20[13]		PFLIoT DISS'20[12]	SAFELearn DLS'21[14]
Other publications: ContainerSecurity-S&P'24[6], CodeProvisioning- FC'15[8]				

1.1 DISSERTATION GOALS AND CONTRIBUTIONS

We aim to provide comprehensive solutions to tackle these critical security challenges in IoT and federated learning FL. We focus on FL because it is an emerging distributed learning paradigm and used to build our IoT intrusion detection system [3]. In particular, this dissertation presents our collaborative works to tackle the challenges in IoT device paring, FL-based IoT intrusion detection, and backdoor-resilient FL. In response to the COVID-19 Pandemic, we leveraged our research on context-based authentication to the usecase of DCT applications to identify infection chains as both usecases aim to achieve the same technical goal - verifying the co-presence of IoT devices.

Table 1.1 summarizes our works and highlights the publications presented in this dissertation. We start with IoT device pairing, which is fundamentally important for securing IoT communication and protecting the privacy of IoT data. We introduce a novel longitudinal context-based zero-interaction pairing approach for IoT [1, Appendix A]. Further, inspired by our context-based authentication concept, we design a secure and effective DCT system, TraceCorona, [2, Appendix B]. Furthermore, we propose a novel federated self-learning-based anomaly detection system to tackle the challenge posed by IoT malware [3, Appendix C]. Finally, we introduce a resilient FL system to protect FL against security attacks (e.g., backdoor attacks) and privacy attacks (e.g., inference attacks) [4, 5, Appedices D and E]. In the following, we will elaborate on these works and our contributions in detail.

1.2 CONTEXT-BASED PAIRING FOR IOT

Implementing secure authentication for IoT device pairing faces significant challenges due to the heterogeneity of IoT devices, the variety of application scenarios, and the often cumbersome requirements for user involvement. Traditional methods for device pairing can be divided into two categories: Human-In-The-Loop [38, 94, 102, 211, 213] and Pre-Shared Security Associations (PSSA) [42, 49, 52, 98, 135, 138].

The first pairing approach requires physical interaction between users and devices. This includes user actions such as comparing verification codes, entering passwords, scanning barcodes or QR codes, or simultaneously shaking two devices to create matching patterns. These steps are crucial for mitigating potential MITM attacks during the initial secure key establishment phase [52]. However, this approach has two significant limitations: (1) it may not be feasible for IoT devices lacking user interfaces, such as screens for displaying verification codes or cameras for scanning QR codes, and (2) it burdens users, especially in settings with many devices, making the authentication process tedious, error-prone, and not scalable. The second pairing approach, PSSA, is also impractical in many IoT settings. This is because establishing a universal key pool or a Public Key Infrastructure (PKI) [52] is infeasible due to the vast array of IoT device manufacturers and the heterogeneity of devices [130, 141]. Further, manufacturer-specific PSSA solutions also fall short in typical application scenarios as they cannot differentiate devices in separate trust domains, such as those in neighboring smart homes [1, 15, 130, 141]. This complexity highlights the need for innovative pairing strategies that address the limitations of current methods, ensuring secure, user-friendly authentication in the increasingly interconnected IoT landscape. Context-based pairing is a potential approach to address this problem since it can operate without user involvement, following the so-called Zero-interaction pairing (ZIP) paradigms [104, 130, 141, 142]. This approach assumes that co-present devices, e.g., in the same room, can be considered to be in the same trusted domain and share similar context information such as ambient noise or light. Therefore, such context information can be used to verify the co-presence status of the devices without user intervention. However, existing approaches (1) often rely on a one-shot fingerprint and fall short in providing sufficient entropy, (2) demand exact time synchronization, and (3) fail to assure long-term trusted domain. Thus, these limitations underscore the need for advancements in zero-interaction security mechanisms, as we discussed in detail in [1, 15].

ConXPair2. To address the challenges of context-based device pairing, we introduce a novel zero-interaction pairing method for IoT devices [1, Appendix A] based on our initial scheme[15]. Unlike existing context-based pairing approaches that capture a snapshot of context information [130, 141], ConXPair pairs devices by recognizing their consistent proximity over time. The pairing process utilizes context fingerprints, derived from changes in ambient light and noise over long periods. Our approach does not require precise time synchronization and is robust against MITM and replay attacks. Specifically, we propose a resilient context-based entropy extraction approach for ambient noise and light and validate it with real-world data. Further, to tackle the primary challenge of the existing longitudinal context fingerprinting approaches that often generate low entropy fingerprints due to the infrequent changes in context, we design an advanced fingerprinting extraction approach based on our *peak detection and alignment* strategy that can generate high-entropy context fingerprints [1]. Furthermore, we propose a

new key evolution scheme that automatically establishes pairing keys, ensuring devices only pair when in prolonged close proximity.

Security analysis of context-based pairing. Recent works have introduced context-based pairing systems that utilize error-correcting codes to generate shared secrets from observed context information [15, 130]. However, there is a notable absence of a comprehensive empirical assessment of their security within real-world settings and data. Hence, we provide a systematic analysis of security aspects influenced by these context-based authentication schemes and examine their impact in typical IoT settings. In particular, we propose and empirically evaluate a framework to measure the security of a context-based scheme utilizing min-entropy for measuring the 'worst-case' entropy of a context fingerprint in the most favorable outcome for the adversary [1].

1.3 DIGITAL CONTACT TRACING

The global waves of infection from the SARS-CoV-2 coronavirus have emphasized the crucial role of efficient contact tracing in identifying and isolating infection chains. However, traditional contact tracing relying on manual work is labor intensive and relies on the infected people to recall past contacts, which is often incomplete or inaccurate. For example, people cannot reliably identify contacts in public places such as on buses or at sport events. In contrast, digital contact tracing DCT can address such limitations since it utilizes contact tracing apps deployed on smartphones or wearable devices to identify nearby devices automatically via the Global Positioning System (GPS) or short-range wireless technologies like Bluetooth Low Energy (BLE). Thus, DCT can capture all possible known and unknown contacts precisely. As the COVID-19 pandemic swept across continents, many nations quickly adopted DCT smartphone apps as a complementary approach to traditional manual contact tracing methods, aiming to enhance their capacity to break infection chains and halt the virus's spread. According to the tracking of MIT Technology Review, as of May 07, 2020, 50 countries and 33 states in the USA were deploying DCT apps, just a few months from the global outbreak of the virus [107]. Given such quick deployment of DCT apps in the race against time and the virus's spread, it is important to critically review the advantages and drawbacks of prominent DCT systems behind the apps. Several works have highlighted critical privacy, security, and ethical issues that could lead to mass surveillance using DCT apps or large-scale fake exposure claims [28, 48, 74, 78, 143, 148, 149, 188, 195, 205, 206].

To tackle such challenges, we systematically analyze existing DCT approaches, point out their deficiencies, and propose a novel approach to address these deficiencies [2, Appendix B]. In particular, we classify state-of-the-art DCT systems by their design principles and evaluate their performance based on four requirements: effectiveness, security, privacy, and ethical aspects. Specifically, we delve into the limitations of the widely used contact tracing platform co-developed by Google

and Apple named Google and Apple Exposure Notification API (GAEN) [159] that has been adopted by more than 30 countries, mostly from Europe [150, 189, 200, 202]. Our study shows that GAEN is susceptible to large-scale security and privacy attacks [2, 16].

TraceCorona. Further, we propose TraceCorona, a novel user-driven privacy-preserving contact tracing system based on Diffie-Hellman key exchange [2]. Unlike most current methods that rely on exchanging pseudonyms with devices in proximity [181, 182, 193], our method utilizes advanced cryptographic techniques to establish and verify encounters between two users. Hence, TraceCorona not only offers better security and privacy guarantees compared to state-of-the-art approaches but also enhances the system's overall efficacy and transparency. In addition, we developed and rolled out a beta version of the TraceCorona app for Android smartphones [20]. Over 2,000 users have used the app without significant functional issues, demonstrating that designing and deploying an effective DCT system is possible without compromising security and privacy requirements.

1.4 FEDERATED SELF-LEARNING INTRUSION DETECTION FOR IOT

The increasing cyber threat on IoT devices caused by IoT malware raises significant concerns. Numerous attacks on IoT systems have resulted in severe consequences, such as the large-scale disruption of cloud services [71, 84, 108, 127, 173] or making devices unusable [160, 167, 176, 178]. Unfortunately, existing protection methods are ineffective in capturing the ever-increasing attack landscape on IoT devices. The most prevalent approach is to release patches [75] after identifying a vulnerability. However, many IoT devices lack appropriate automatic update functions. Moreover, there can be a significant delay between when a vulnerability is identified and the time that the manufacturer releases and rolls out patches for the vulnerable devices. Another strategy involves using Intrusion Detection System (IDS) based on recognized attack patterns, i.e., signature-based IDS [44]. This method falls short as it cannot identify new attacks until IDS providers update the attack signatures. Thus, this approach is ineffective against previously unknown attacks (zero-day attacks) which are typical in IoT settings because of the dynamicity of the threat landscape. For instance, Pa Pa et al. point out that 83% IoT malware samples captured by their honey pot are new to VirusTotal [108]. A promising approach for detecting unknown attacks is anomaly detection [86, 110, 116]. This approach learns normal device behaviors and identifies deviations from these behaviors (i.e., abnormal behaviors). However, given the heterogeneity of IoT devices, learning all normal behaviors of devices is challenging. Consequently, anomaly-based systems often introduce many false alarms (detecting normal behaviors as abnormal), making them impractical [105, 174]. For instance, anomaly-based IDS systems developed by Aqil *et al.* [174] and Nobakht *et al.* [105] report the False Positive Rates (FPRs) of 9.1% and 5.8%, respectively.

DÏoT. To address these challenges, we propose DÏoT, an FL-based anomaly detection system that employs natural language processing techniques and advanced neural network models to detect attacks on IoT devices. DÏoT effectively identifies abnormal network behaviors potentially caused by cyberattacks on IoT devices with a negligible number of false alarms. Unlike conventional IDSs that create a generic model for the whole network, DÏoT offers a unique detection model for each IoT device type to enhance detection accuracy. Further, we provide an automatic approach to identify device types, i.e., the whole process of DÏoT operates autonomously without human intervention [10]. Inspired by the application of Deep Learning (DL) in natural language processing, DÏoT transforms network packets into symbolic representations. This allows DÏoT to utilize the word prediction model in language processing to learn network packet sequence patterns that are similar to learning word sequence patterns. This new network modeling technique enables DÏoT to precisely and accurately detect irregular packet sequence patterns generated by attacks. Furthermore, we leverage federated learning FL that allows participants to train detection models on their local potentially sensitive data and then send only their model updates to a central aggregation server (aggregator) where the updates are integrated into global device-type models. To the best of our knowledge, DÏoT is the first IoT IDS utilizing FL. This technique ensures the detection model benefits from diverse participant data without the need for sharing such potentially sensitive data with a central server or any other party. Our evaluation demonstrates that DÏoT surpasses existing approaches as it can accurately and quickly detect attacks with very few false alarms (Appendix C).

1.5 MITIGATING BACKDOOR ATTACKS ON FEDERATED LEARNING

Federated learning (FL) is an emerging paradigm for distributed machine learning ML, where many participants (clients) collaboratively train an ML model without the need to share their data with any other parties. In each FL training iteration, participants train local models using their own data and send model updates to an aggregator, that aggregates all local model updates to a global model. The new aggregated global model is then sent back to the participants for the next training iteration. This process is repeated until the model converges or achieves a certain accuracy level. FL offers several benefits: (1) enhanced participants' data privacy as their private data are always kept locally and not shared to any other party and, (2) improved training efficiency as the model can learn from many participants' data, and (3) scalability as the training task is distributed among many participants and executed in parallel. Therefore, many FL applications have been proposed in various fields such as natural language processing [101, 175], image classification [101], medical applications [46, 76, 82, 124], and IoT [3, 113, 120, 177]. Our federated self-learning-based IoT intrusion detection system, DÏoT, exemplifies the advantages of FL as it

provides an effective and privacy-preserving distributed deep learning approach for highly dynamic and heterogeneous IoT applications. Despite such benefits, FL is vulnerable to backdoor attacks targeting the security of the FL model [12, 23, 54, 96, 145, 153] and model inference attacks targeting the privacy of participant data [33, 65, 111, 125, 131]. In a backdoor attack, the adversary manipulates the global model to provide attacker-chosen outputs (predictions) for specific inputs, known as triggers. For instance, in image classification applications like traffic sign recognition for advanced driving systems, an adversary can manipulate the model to output an 80 km/h speed limit for a traffic sign showing 30 km/h [132]. Such an attack may cause severe accidents if a car is in self-driving mode or if a driver relies on the traffic sign recognition system. In addition to current backdoor attacks on typical FL applications like image classification and word prediction, these attacks also affect critical security applications like FL-based IoT intrusion detection systems (IDS) [12, 68, 95]. In this scenario, the adversary aims to fool the system into falsely recognizing IoT malware traffic as normal by injecting malicious traffic data into benign data during the training phase. It is worth noting that these attacks apply only to known malware traffic, not to future malware, as the adversary has to choose specific malware traffic patterns as backdoors for training. In model inference attacks, the adversary (known as an honest-but-curious aggregator) aims to learn information about participants' local data through the analysis of their local model updates. Unfortunately, existing backdoor defenses are not effective at mitigating state-of-the-art attacks. Most existing approaches use clustering techniques to identify and remove poisoned model updates [26, 132]. However, these approaches require specific assumptions about attacks and data distributions, which will fail if these assumptions do not hold or the adversary adapts its attack strategies [23, 96, 145].

FLAME. To address these challenges, we proposed FLAME [4] to effectively eliminate backdoors and mitigate inference attacks on FL. FLAME utilizes our adaptive noising approach to dynamically estimate the necessary amount of noise added to the aggregated model to neutralize poisoned updates. This concept is based on existing works showing that adding noise to the model weights can mitigate the impact of the outlier samples including backdoors [47]. That means, adding noise can removal of poisoned model updates, regardless of the type of backdoor attacks. However, introducing a large amount of noise to eliminate poisoned updates can degrade the benign performance of the model [23, 54, 145, 153]. To tackle this issue, we propose (1) an adaptive noising approach that calculates the amount of required noise for every training iteration to ensure backdoor removal (see Section 5, Appendix D) and (2) novel dynamic clustering and adaptive clipping techniques as complementary components. These supportive components minimize the amount of noise required to remove backdoors, ensuring that the noise does not significantly impact the model's benign performance. The dynamic clustering component identifies and removes poisoned models with high attack impact by clustering and identifying the models showing large deviations as outliers. The clip-

ping component reduces the impact of attacks by ensuring that all model weights are clipped to a max value as a clipping bound. Thus, this process mitigates the effects of poisoned updates, which often have weights of large magnitudes. While existing approaches apply a fixed clipping bound [23, 133], our approach estimates the bound in every training iteration and ensures that the bound is within the value distributions of benign updates. Further, to enhance the accuracy of *FLAME*'s clustering in non-independent and identically distributed (IID) data, we introduced DeepSight [5], a new deep model filtering approach. DeepSight analyzes the internal structure and output layer of models to identify and eliminate potentially poisoned models. In addition, we propose *Private FLAME* framework to protect the privacy of the participants' data. Private FLAME prevents the aggregator from directly accessing the local model updates in plain text, thereby preventing it from analyzing the updates for inference attacks to learn information about the data used in training. To achieve this, we have designed several efficient Secure Two-Party Computation (STPC) protocols for the clustering and clipping components. For example, we introduce approximate secure HDBSCAN to avoid expensive operations in STPC when applying the construction of the minimal spanning tree in HDBSCAN. As a result, the private FLAME only introduce 3x more overhead on the runtime compared to standard FLAME (cf. Section 8, D).

1.6 IMPACT: STARTUP PROJECT TO BRING RESEARCH IDEA TO PRACTICE

Our research on federated self-learning intrusion detection, DÏoT, has generated many follow-up studies in both academia and the industry sector. At the time of writing, the DÏoT publication has received about 800 citations. We thank major technology vendors, including Cisco and Intel who assisted us in formulating real-world settings and usage scenarios of DÏoT. Further, we are fortunate to have received 0.8 million Euros from the PioneerFund [1] and the Federal Ministry of Education and Research (BMBF) [2] for further technical and business development of DÏoT. These funding programs will help in bringing DÏoT to real-world application through the formation of a startup company.

1.7 SUMMARY OF MY CONTRIBUTIONS

Of my 16 peer-reviewed publications, five – where I either took the lead or was one of the main authors – were chosen to form this dissertation (see Table 1.1). These publications would not have been possible without the substantial inputs and invaluable support from my co-authors. In the following, I will detail my specific contributions to each publication.

1 https://www.informatik.tu-darmstadt.de/fb20/aktuelles_fb20/fb20_neuigkeiten/neuigkeiten_fb20_details_241728.de.jsp

2 https://www.forschung-it-sicherheit-kommunikationssysteme.de/projekte/diot

ConXPair 2 [1, Appendix A]:

> *Markus Miettinen, Thien Duc Nguyen, Ahmad-Reza Sadeghi, and N. Asokan. "Revisiting Context-Based Authentication in IoT." In: Proceedings of the 55th Annual Design Automation Conference (DAC'18). DOI: 10.1145/3195970.3196106. CORE Rank A.*

Markus Miettinen was the lead author. He led the design of the evaluation framework for context-based authentication schemes and crafted a significant portion of the manuscript. My contribution involved co-designing the evaluation framework. Further, I proposed an advanced fingerprinting approach based on *peak detection and alignment* that extracts high-entropy context fingerprints. This addresses a primary challenge of the existing longitudinal context fingerprinting approaches, where the majority of the bits possess low entropy due to the infrequent changes in context. Furthermore, I took on the responsibility for data collection, implementation, and evaluation. It is worth noting that this paring scheme is based on our previous scheme ConXPair [15] where I co-designed and was in charge of the implementation of the ambient noise-based fingerprinting approach, the fuzzy commitment scheme based on Reed-Solomon codes and the key derivation scheme (in collaboration with Majid Sobhani).

TraceCorona [2, Appendix B]:

> *Thien Duc Nguyen, Markus Miettinen, Alexandra Dmitrienko, Ahmad-Reza Sadeghi, and Ivan Visconti. "Digital Contact Tracing Solutions: Promises, Pitfalls and Challenges." In: IEEE Transactions on Emerging Topics in Computing (2022): DOI: 10.1109/TETC.2022.3216473.*

I was the lead author and proposed TraceCorona, a decentralized contact tracing system that leverages asymmetric cryptography. This system not only offers robust security and privacy guarantees but also enhances effectiveness compared to state-of-the-art approaches. I also led the technical design, implementation, beta-deployment and evaluation of the TraceCorona App. Further, my responsibilities extended to systematizing related work, pinpointing the limitations of existing methods, and writing a major part of the manuscript.

DÏoT [3, Appendix C]:

> *Thien Duc Nguyen, Samuel Marchal, Markus Miettinen, Hossein Fereidooni, N. Asokan, and Ahmad-Reza Sadeghi. "DÏoT: A Federated Self-learning Anomaly Detection System for IoT." In: 2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS'19). DOI: 10.1109/ICDCS.201900080. CORE Rank A.*

As the lead author, I drove the design of DÏoT. I proposed a novel anomaly detection method based on language models, employing the recurrent neural network to estimate the occurrence probability of each network packet in sequences in collaboration with the co-authors. I was

responsible for the main implementation tasks such as packet symbol generation, occurrence probability estimation, anomaly detection, data collection, and evaluation. Markus Miettinen and I drafted the major part of the manuscript, which was then edited by all co-authors.

FLAME [4, Appendix D]:

> *Thien Duc Nguyen, Phillip Rieger, Huili Chen, Hossein Yalame, Helen Möllering, Hossein Fereidooni, Samuel Marchal, Markus Miettinen, Azalia Mirhoseini, Shaza Zeitouni, Farinaz Koushanfar, Ahmad-Reza Sadeghi and Thomas Schneider. "FLAME: Taming Backdoors in Federated Learning." In: 31st USENIX Security Symposium (USENIX Security 22). ISBN: 978-1-939133-31-1. CORE Rank A*.*

As the lead author, I led the design of FLAME and proposed the high-level design of Private FLAME. I proposed a comprehensive defense concept that prevents adversaries from simultaneously achieving attack impact and stealthiness. Together with Phillip Rieger, we developed the dynamic clustering, clipping, and noising techniques. I outlined the requirements and crafted a plan for the evaluation. Furthermore, I took on the responsibility of drafting the manuscript.

DeepSight [5, Appendix E]:

> *Phillip Rieger, Thien Duc Nguyen, Markus Miettinen, and Ahmad-Reza Sadeghi and. "DeepSight: Mitigating Backdoor Attacks in Federated Learning Through Deep Model Inspection." In: Network and Distributed System Security Symposium (NDSS'22). CORE Rank A*.*

Phillip Rieger was the lead author of this publication. I collaborated with him on the design of DeepSight as an extension of FLAME and edited the manuscript.

1.8 DISSERTATION OUTLINE

The dissertation includes six chapters. The first four chapters summarize our contributions and discuss relevant studies and the final chapter concludes the dissertation and outlines future work.

Chapter 2: Context-based Pairing for IoT. In this chapter, we present ConXPair, our novel context-based zero-interaction pairing scheme and a framework to evaluate the security of a context-based scheme utilizing min-entropy.

Chapter 3: Digital Contact Tracing. This chapter summarizes our contributions in response to the COVID-19 pandemic as proposing novel DCT approach, TraceCorona, and systematizing existing DCT systems . This is based on our experiences with various works in context-based authentication such as context-based pairing [1, 15] and proof-of-presence [7, 11]. We highlight TraceCorona, an advanced DCT scheme to enhance security, privacy, effectiveness, and ethical aspects of existing DCT systems.

Chapter 4: Federated Self-learning Intrusion Detection for IoT. In this chapter, we discuss DÏoT, our novel FL-based anomaly detection that detects attacks on IoT devices caused by IoT malware.
Chapter 5: Taming Backdoors on Federated Learning. In this chapter, we discuss FLAME and DeepSight, our comprehensive approach to identifying and eliminating poisoned updates caused by backdoor attacks in FL.
Chapter 6: Conclusion and Future Work. We conclude this dissertation and outline future research directions on the security and privacy of IoT devices and federated learning.

2 CONTEXT-BASED PAIRING FOR IOT

As mentioned in Chapter 1 (Section 1.2), securing IoT device pairing is challenging due to device diversity, varied application scenarios, and complex user involvement requirements. Traditional pairing methods like Human-In-The-Loop pairing require user participation, such as entering passwords or scanning QR codes, for mitigating MITM attacks [38, 94, 102, 103, 211, 213]. However, these methods may not be suitable for devices without user interface capabilities and can burden users in multi-device environments, making the process tedious and error-prone. Other methods like Pre-Shared Security Associations (PSSA) approaches are impractical due to the challenge of establishing a universal key pool or Public Key Infrastructure (PKI) across heterogeneous IoT devices and manufacturers, failing to distinguish devices in different trust domains [42, 49, 52, 98, 135, 138]. The limitations of these traditional methods underscore the need for new, user-friendly authentication strategies in the IoT ecosystem. Context-based, Zero-Interaction Pairing (ZIP) emerges as a promising solution, leveraging shared context information to verify device co-presence without user input [104, 130, 141, 142]. However, current context-based solutions lack sufficient entropy and long-term reliability, highlighting the need for further research in secure, zero-human intervention authentication methods.

2.1 OUR CONTRIBUTIONS

To tackle such challenges of context-based pairing, we introduce ConXPair2, a key evolution scheme utilizing longitudinal context modalities such as ambient noise and luminosity. This section provides an overview of the key contributions from our research as detailed in the following publication:

[1] Markus Miettinen, Thien Duc Nguyen, Ahmad-Reza Sadeghi, and N. Asokan. “Revisiting Context-Based Authentication in IoT.” In: Proceedings of the 55th Annual Design Automation Conference (DAC’18). DOI: 10.1145/3195970.3196106. CORE Rank A. Included in Appendix A.

Robust Context-Based Shared Entropy Extraction ConXPair2 [1] is an enhanced iteration of our previous work, ConXPair [15]. It incorporates a novel fingerprint extraction method to generate high-entropy bits. Unlike conventional approaches that typically capture a single snapshot of context information [130, 141, 142], ConXPair continuously monitors dynamic contextual elements, such as ambient noise and luminosity, to assess the proximity status of devices to be paired. It extracts context fingerprints over an extended period, ensuring more comprehensive data collection. However, the original ConXPair faced a critical limitation: its fingerprint extraction method yielded low-entropy bits. The

generated fingerprints contained disproportionately more "zero" bits compared to "one" bits, primarily due to the infrequent variations in context. This issue is a common drawback of existing approaches [130, 141, 142], which rely on extracting fingerprints directly from context information. When the context changes infrequently, mostly "zero" bits are produced, limiting the entropy of the fingerprint. ConXPair2 addresses this limitation by adopting a fundamentally different approach called peak detection and alignment. Instead of depending solely on context-derived fingerprints, ConXPair2 first generates a fully random fingerprint (serving as a random secret key) and then uses context information to encode it. In this method, "one" bits are encoded at peak timestamps, while "zero" bits are encoded at non-peak timestamps. This ensures that the fingerprint is inherently random and retains high entropy regardless of the variability in context. By leveraging this novel encoding strategy, ConXPair2 guarantees the generation of high-entropy, randomized fingerprints, overcoming the limitations of its predecessor and other existing methods [15, 130, 141, 142].

Systematic Analysis. Existing context-based pairing solutions often use error-correcting codes to create shared secrets. However, a systematic analysis and empirical evaluation of their security in real-world applications is lacking. To address this gap, we systematically analyze how these context-based authentication methods affect security in typical IoT deployments [1]. Firstly, we propose a unified model of using context as a shared secret in authentication applications to address the challenges of establishing secure communication without user interaction. Secondly, we provide a security analysis focusing on entropy loss and privacy amplification to understand the influence of these factors on the security of context-based pairing schemes. Thirdly, we conduct an empirical evaluation by leveraging real-world data to validate the effectiveness and applicability of context-based authentication methods in practical IoT scenarios.

2.2 RELATED WORK

Several approaches have been proposed to ensure secure device pairing. These approaches can be categorized into three categories: (1) Human-In-The-Loop pairing, (2) Pre-Shared Security Associations (PSSA), and (3) Context-based pairing.

Human-In-The-Loop pairing. This approach relies on users to physically interact with the devices, for example, by comparing verification codes, entering passwords, scanning Bar/QR codes, pressing buttons on IoT devices for pairing, or shaking two devices simultaneously to generate similar acceleration patterns [38, 94, 102, 103, 211, 213]. However, this approach has two main drawbacks: (1) it is not suitable for IoT devices that may not have, e.g., a screen to show a verification code or a camera to scan a QR code, and (2) it burdens users in settings with numerous devices, making authentication tedious and often prone to errors.

Pre-Shared Security Associations (PSSA). Eschenauer et al. [49] introduce a key distribution system for Digital Sensor Networks (DSN) that ensures neighboring nodes can establish a shared key. This basic pre-distribution scheme is later extended by Chan et al. [42] to enhance the system to a q-composite scheme, multi-path reinforcement, and random pairwise key pre-distribution. Later, Liu et al. [98] introduce two new key predistribution schemes based on the random subset assignment and hypercube approaches. Further, Traynor et al. [138] propose an unbalanced probabilistic key distribution scheme and a hybrid scheme that is applied if key distribution centers (KDC) are available. However, these key pre-distribution-based schemes have two main drawbacks. Firstly, there are billions of IoT devices from thousands of manufacturers [53], leading to practical deployment issues since it is unlikely that all device vendors will establish mutual security associations needed for pre-keying devices. Secondly, even if all devices have the same pre-shared key, this is not enough to establish separated secured keys for different trust zones, e.g., to prevent IoT devices from one home from being paired with the devices from neighbors' homes. In contrast to these approaches, our scheme is not based on key pre-distribution but employs ambient context information to gradually establish a secure key between devices sharing the same context, i.e., potentially located in the same trust zone.

Context-based pairing. To address the limitations of Human-In-The-Loop and PSSA approaches, several context-based approaches have been proposed. Varshavsky et al. [142] introduce an immediate proximity verification scheme using WiFi signal strength fluctuation patterns to tackle the trust zone separation problem. This scheme ensures that only the devices at very close distances (roughly one meter or less) are paired. However, this method has two main limitations: (1) it is not suitable for general IoT settings where distances between the devices are usually more than one meter and (2) it is vulnerable to MITM attacks as the authors have discussed in their publication [142]. Further, Schürmann and Sigg [130] use audio signals to generate shared secrets between co-located devices. Unfortunately, this approach requires precise time synchronization and sound sample alignment which can be challenging if the devices are not very close to each other. Truong et al. [141] propose zero-interaction authentication using contextual proofs. However, they focus on co-location verification in settings with pre-established trust. In contrast, our approach can manage short-term adversarial presence without compromising pairing authenticity. Further, our approach addresses the unique challenge of pairing devices without any preceding security associations and assumptions.

Recent related work. Recent works on context-based authentication fall into three categories: (1) exploring new application scenarios and new context modalities [61, 83, 157], (2) utilizing active context-based pairing, and (3) expanding fusion modality techniques [69]. In the first line of research, Fomichev et al. [61], extended context-based approaches for intra-car device pairing scenarios where the devices inside a car should be paired but not to ones in other cars. Instead of using typical context modalities like ambient noise or light, the au-

thors utilize data generated by smartphone sensors like the accelerator, gyroscope, and barometer to capture the typical *car-moving context*, such as road turns, bumps, and speed changes. Yang et al., [157] also consider intra-car device pairing scenarios but use only GPS as a context modality. Their evaluation shows that two devices in the same car can establish a 128-bit key in 1.32 minutes, sharing comparable performance to the Fomichev et al. [61] approach that uses a different set of context modality sensors (accelerator, gyroscope, and barometer). Secondly, instead of passively measuring context information, some approaches actively inject context information to increase context fingerprint entropy and shorten context measurement time [11, 60]. For example, Fomichev et al., [60] leverage actuators, e.g., smart speakers, lights, and humidifiers, to inject audio, light, and CO_2 into the environment so that other devices with corresponding sensors can capture and extract context fingerprints. However, this approach is intrusive, i.e., users will be annoyed if a speaker makes a random noise or a light bulb starts blinking. All the above-mentioned approaches assume that devices are equipped with the same sensing modalities, e.g., a microphone if ambient noise is used to extract fingerprints. The third line of research tackles this problem by focusing on the timing in which an event like *door opening* can be captured by different sensors like geophones, microphones, and light sensors [57, 69]. Thus, IoT devices with different types of sensors can still capture the same event simultaneously to extract timing-based event fingerprints.

3 DIGITAL CONTACT TRACING

As mentioned in Section 1.3 (Chapter 1), existing DCT apps raise significant concerns about security, privacy, effectiveness, and ethical aspects. We aim to address these problems by providing an extensive analysis of DCT systems and introducing a new scheme that fulfills the critical requirements of an effective and secure DCT. This chapter will highlight our contributions and summarize related work.

3.1 OUR CONTRIBUTIONS

In this section, we summarize the contributions of this dissertation aiming to analyze and tackle the limitations of existing DCT systems, as detailed in the following publications:

[2] Thien Duc Nguyen, Markus Miettinen, Alexandra Dmitrienko, Ahmad-Reza Sadeghi, and Ivan Visconti. "Digital Contact Tracing Solutions: Promises, Pitfalls and Challenges." In: IEEE Transactions on Emerging Topics in Computing (2022).
DOI: 10.1109/TETC.2022.3216473. Included in Appendix B.

Real-world empirical analysis of Google and Apple Exposure Notification API (GAEN). We started our studies with an empirical analysis of GAEN [159], a jointly developed DCT platform by Apple and Google that has been widely adopted, especially in European countries [150, 189, 200, 202]. GAEN is a BLE-based proximity detection system and runs in the background of iOS and Android smartphones. It allows third parties (eventually only state governments) to build their DCT applications using GAEN APIs. However, the core functions, such as generating, broadcasting, collecting, and matching device ephemeral IDs, so-called Rolling Proximity Identifiers (RPI), are done by the GAEN platform itself. We implemented and deployed a real-world setting of GAEN and critical attacks against it in three cities in Germany [16]. Our empirical study demonstrates that even such a high-profile system is vulnerable to large-scale security and privacy attacks, including *profiling attacks* (Section III [16]) and *relay-based wormhole attacks* (Section IV [16]). In a profiling attack, an adversary can track the movements of COVID-19-infected users by collecting RPIs and comparing those with the published RPIs of infected users. This movement tracking can also be exploited further to profile users' daily routes and use this to de-anonymize users [80, 112, 198]. In a relay-based wormhole attack, an adversary can inject massive incorrect exposure contacts, i.e., generate a large number of false notifications of contacts with infected users. Hence, the attack severely reduces the reliability of the system and introduces unnecessary pressure on the health system to conduct COVID-19 tests to a large number of false alarms.

Systematization of DCT systems. We conducted a comprehensive examination of state-of-the-art DCT systems, e.g., [35, 140, 159, 182, 193, 196], classifying them by their design principles and technologies. Firstly, we analyze requirements for DCT, in which we identify four critical aspects, including effectiveness, security, privacy, and ethics, that need to be assessed thoroughly when designing, implementing, and deploying a DCT system (Section III, Appendix B). We then provide a systematization of existing DCT systems and point out their deficiency in addressing the four critical requirements. Specifically, we delve into the limitations of widely used DCT systems, e.g., GAEN [159], DP-3T [140], BlueTrace [182], PACT [196], and PEPPPT [193] (Section V, Appendix B). Our study indicates significant security and privacy gaps in such systems, which are vulnerable to extensive large-scale threats [16, 28, 48, 74, 91, 143, 148, 149, 188, 195, 205, 206, 210].

TraceCorona. To address these challenges, we propose TraceCorona, a novel contact tracing approach that fulfills the requirements better compared to state-of-the-art approaches (Section IV, Appendix B). TraceCorona is a decentralized contact tracing approach utilizing public-key protocols such as the Diffie-Hellman (DH) key exchange protocol to establish secret keys, so-called encounter tokens for contacts between users. Our system utilizes BLE to exchange short-lived public keys after monitoring the sustained co-presence of users for a certain time interval, e.g., 15 minutes. TraceCorona requires verification of every encounter to elevate the system's overall efficacy and resilience. In contrast to existing adopted DCT systems relying on broadcasting and receiving pseudonymous proximity identifiers [35, 140, 159, 182, 193, 196], our bidirectional communication method based on a key exchange protocol establishes a unique, verifiable token for each encounter between two users, thus providing a robust defense against profiling and relay attacks compared to unilateral identifier broadcasting. Further, we provide an in-depth analysis to demonstrate the advantages of TraceCorona with regard to all critical requirements in comparison to existing systems (Section V, Appendix B).

Real-world deployment of TraceCorona. We developed a system and rolled out a beta version of the TraceCorona app for Android phone users. Encouragingly, our app has been used by more than 2,000 users over a month without significant functional issues. The success of our real-world deployment demonstrates that it is possible to design and deploy a DCT system without compromising critical requirements.

3.2 RELATED WORK

Overall, DCT approaches are categorized as centralized and decentralized based on where the detection of potential exposure is performed (Section II.B, Appendix B). In centralized approaches, the ephemeral IDs are generated by a central server and sent to clients (mobile devices). The server then collects the ephemeral IDs of infected users and performs ephemeral ID matching to find potential contacts with infected users. In contrast, in decentralized approaches, the clients per-

form both ephemeral ID generating and matching. Thus, decentralized approaches limit the ability of the server to collect massive amounts of sensitive information about users.

Centralized Contact Tracing. There are several centralized contract tracing systems [24, 73, 77, 179, 182–185, 187, 190–194, 197, 199, 201, 203, 207, 208] (see [17, Section A] for the details). Many of those systems are based on widely adopted and deployed schemes, for example, BlueTrace [182] is a BLE-based DCT framework used by several countries such as Singapore [204], Australia [186], and France [203]. Some other systems, like the AarogyaSetu app used in India [179], are considered invasive of privacy because they gather sensitive personal data, including GPS locations and user phone numbers. There have been proposals to enhance the security and privacy of centralized methods. For example, Hoepman et al. suggest two protocols to reduce the risk of location tracking and replay attacks [73]. Castelluccia et al. propose a 'hybrid solution' called Desire, which blends centralized and decentralized techniques [29], in which the clients generate Diffie-Hellman keys instead of temporary IDs, and infected users anonymously upload encounter tokens derived from these keys, using privacy-enhancing networks like Tor [170]. Despite its hybrid, Desire is categorized as centralized since the server still receives all encounter tokens, matches them, and detects contacts with infected users.

Decentralized Contact Tracing. There are several decentralized contact tracing approaches, and many of them are also widely deployed, especially in European countries and the USA, e.g., DP3T [140], MIT-PACT [196], and the Google/Apple Exposure Notification API GAEN [159]. These approaches share basic structure and protocols as they allow the clients to generate and match ephemeral IDs and notify users of potential COVID-19 exposures [17, Section IV.A]. Even though these approaches provide better user privacy guarantees than centralized approaches, these still face critical security, privacy, effectiveness, and ethical problems, as discussed in Section 3.1.

DH-based Decentralized Contact Tracing. PRONTO-C2 [21] and CleverParrot [30] aim to solve the problem of exceeded message length when using BLE advertising messages to send and receive Elliptic-curve Diffie-Hellman (ECDH) public keys. PRONTO-C2 utilizes blockchain technology to store and share the keys on the bulletin board. Hence, only the keys' location references, not the keys, are directly transmitted over BLE. CleverParrot condenses the public key size to 224 bits (28 bytes) based on the elliptic curve P-224 that aligns with the Bluetooth message length in Apple's *Find My Device Protocol* [161]. However, Android and iOS predominantly support 128-bit BLE advertising messages as a standard. Thus, without modifications to the BLE framework by Google and Apple, CleverParrot's practical application seems limited. As highlighted in Section IV-B in Appendix B, TraceCorona addresses the BLE advertising message length limitation by employing BLE Connection that establishes a data transfer channel between two Bluetooth devices to transmit public keys without imposing to communication constraints and a need of blockchain-based bulletin board. Another line of work is to combine DH with Private Set Intersection (PSI) Cardinality

(PSI-CA), Epione [139] uses Function Secret Sharing methods [25] to prevent other users from accessing the encounter tokens shared by infected users. In this approach, the clients and the server collaboratively identify matching encounter tokens so that users can determine the number of interactions they have had with infected users without downloading encounter tokens.

4

FEDERATED SELF-LEARNING INTRUSION DETECTION FOR IOT

As mentioned in Section 1.4 (Chapter 1), large-scale attacks on IoT devices are increasingly emerging. However, existing defense mechanisms are not effective. We aim to tackle this problem by proposing a new anomaly detection approach specifically targeting attacks against IoT systems. This chapter will highlight our contributions and summarize related work.

4.1 OUR CONTRIBUTIONS

In this section, we summarize the contributions of this dissertation aimed at detecting attacks on IoT devices, as detailed in the following publication:

[3] Thien Duc Nguyen, Samuel Marchal, Markus Miettinen, Hossein Fereidooni, N. Asokan, and Ahmad-Reza Sadeghi. "DÏoT: A Federated Self-learning Anomaly Detection System for IoT." In: 2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS'19). DOI: 10.1109/ICDCS.201900080. CORE Rank A. Included in Appendix C.

Autonomous device-type-specific anomaly detection. Traditional anomaly detection-based IDS approaches use a generic detection model for the whole network. However, this method is not effective due to the heterogeneity of IoT devices as there are thousands of IoT device types and IoT vendors, i.e., it is challenging to build a universal model that can learn such diverse device behavior patterns effectively. However, each specific device type often operates only a limited number of particular functionalities, exposing relatively predictable behavior patterns. Therefore, rather than relying on a singular, extensive detection model, DÏoT designates a specific model to each device type. By doing so, the model can profile all possible legitimate behaviors of each device precisely, thus, effectively identifying any deviation from benign behavior and reducing false alarms. However, this approach also introduces a challenge as the system needs to identify device types before training or applying detection models. This is a challenging task due to the heterogeneity and dynamic landscape of IoT devices. We address this problem by introducing AuDI, a novel autonomous device type identification approach [10]. The idea is based on identifying the unique behavior of IoT devices caused by so-called heartbeat messages that devices use to communicate with their servers or apps for status updates and notifications. We, therefore, group the devices to device types based on their periodic communication patterns. In particular, we propose 33 features to profile periodic behavior and leverage

an unsupervised clustering technique, the k-nearest neighbors algorithm (kNN), to cluster the devices to different device types. Devices that share closely similar feature values are grouped to the same device type without a need for data labeling or human intervention, enabling the whole process of DÏoT to operate autonomously.

Network traffic profiling based on natural language modeling. One of DÏoT's key objectives is to design a profiling algorithm tailored for IoT device communication that requires minimal training data and computing power. To achieve this, we utilize a language model-based technique, integrating packet-level features and the Gated Recurrent Unit (GRU) model [36], a lightweight Recurrent Neural Network (RNN) algorithm. In particular, DÏoT models network packet sequences as symbolic sequences akin to word sequences in natural languages. It then estimates the occurrence probability of each packet based on the sequence of preceding packets. Our intuition is that malicious packets will have significantly lower occurrence probabilities compared to benign packets, as packet sequences containing such packets did not appear during model training. We then introduce an anomaly detection strategy that computes the occurrence probability for each packet and assesses whether a given packet is normal or abnormal. Further, we validate the anomaly of a traffic snippet by calculating its anomaly score based on all occurrence probabilities of the packets in the snippet. This approach boosts the detection accuracy since an alarm is made based on combining several packet-level granularity assessments. It is worth noting that while our periodic communication profiling approach can help to distinguish device types, it cannot be applied for anomaly detection since neither normal device operations nor attack activities are purely periodic in nature.

Federated learning (FL)-based IoT IDS. While deep learning requires huge amounts of data for model training, a typical IoT device generates only little network traffic. Furthermore, IoT data frequently reflect sensitive user information, such as information about the users' health and user activities [92, 146, 180, 214]. Therefore, an IoT defense system should not allow third parties to gather and store potentially sensitive IoT data. Our solution utilizes FL [101] to enable numerous clients (e.g., Security Gateways) and an aggregator (IoT Security Service) to collaboratively train *global* device-type-specific models. Each of the global models is aggregated from the collective local models trained by the clients that hold data corresponding to the device type. This federated scheme allows DÏoT to train efficient detection models by maximizing available client data while eliminating the need to transfer data to the centralized server or any other party, thus better preserving user privacy.

4.2 RELATED WORK

IDS for IoT can be categorized into signature-based and anomaly-based approaches depending on the detection techniques used. In this sec-

tion, we discuss both approaches and the most recent work on this topic.

Signature-based IoT IDS. This technique aims to learn and detect attack traffic patterns called attack signatures. Several approaches have been proposed for identifying and mitigating intrusions in IoT and sensor networks [81, 116, 119], and industrial management systems [79, 90]. SVELTE is designed to detect intrusions in IoT networks against known attacks, tailoring traditional detection methods for IoT-centric protocols like 6LoWPAN [119]. Similarly, Doshi et al. suggested a method based on identifying attack signatures to spot recognized DDoS attacks by examining network traffic intensity characteristics [44]. On the other hand, DÏoT aims to dynamically identify even unknown attacks by detecting any deviation from normal device behavior.

Anomaly-detection-based IoT IDS. This technique aims to learn the benign traffic patterns and consider any deviation from them as anomalies. Several anomaly-detection-based IDS have been proposed [86, 110, 122, 129]. Common methods are to analyze network flow features such as number of packets or network load transferred per time window to identify potential threats [89, 110, 116]. Some studies consider network communication as a sequence of states [90, 122]. For example, Sekar et al. [122] construct finite state machines based on communication protocols at network layers three and four. The state machines assess packets to find discrepancies in the protocol. However, this approach can only handle short packet sequences. In our approach, we utilize GRU to assess longer sequences, increasing model capacity to detect subtle changes in network traffic patterns. Additionally, while most methods offer a broad view of the network status, our technique focuses on detailed features and semantics of packet sequences making it harder to be manipulated.

Context-based anomaly detection. Recently, there has been a growing number of research on context-based anomaly detection for IoT with a focus on smart home settings [22, 45, 64, 114, 121, 126, 136]. Tang et al. propose an ensemble model to detect *anomalous events* in smart homes based on multiple data sources, e.g., binary sensor data, device status, and numerical sensor data (like temperature) [136]. Their approach requires a combination of multiple supervised learning models, including Decision Tree, Gaussian Naive Bayes, and Logistic Regression to deal with such diverse data types. Also, in this line of work, Dai et al. introduce HomeGuardian to detect abnormal smart home events based on using a Neural Network model trained on hybrid-context data: temporal context and environmental context. However, both approaches from Tang et al. and Dai et al. require both legitimate and attack data for training. Sikder et al. introduce 6thSense that monitors changes in sensor data during different user tasks and generates a contextual model to differentiate between benign and malicious sensor behaviors [121]. 6thSense employs three ML detection models, including Markov Chain, Naive Bayes, and Logistic Model Tree to identify malicious activities involving sensors. However, 6thSense focuses only on smart devices like smartphones that have multiple sensors. The authors later extended 6thSense to Aegis, a security framework for Smart

Home Systems, focusing on comprehensive, context-aware monitoring of user activities and sensor-device interactions [126]. Aegis employs a Markov Chain-based machine learning model to distinguish between normal and malicious behaviors by understanding the complex interplay of smart home components and user activities.

HAWatcher utilizes semantic information from app descriptions and source code to match devices with correlated attributes, generating correlation rules [64]. While this structure enables the enforcement of strict policies, the requirement for semantic information limits its applicability when such information is unavailable, e.g., lacking semantic details about involved sensors and apps [114].

Very recently, Rieger et al. designed a Deep Neural Network-based system, Argus, that detects abnormal events in smart homes. While existing approaches focus on certain types of data, Argus works with various data from heterogeneous IoT devices and diverse manufacturers. However, Argus also shares the critical limitation of context-based approaches as it will raise high false alarms if the context is changed due to new legitimate activities. For example, if a home has a guest, that would generate event chains that the system has not seen before and consequently result in false alarms. Solving such problems is still an open challenge [114].

Further, several anomaly detection approaches are designed for specific Smart Home Automation platforms like Samsung Smarthings [22, 39, 43, 81, 137]. For example, Amraoui et al., utilize One-class SVM to train a detection model on device-triggered commands provided by SmartApps [22]. However, this approach does not consider sensor values or physical channels, limiting their ability to detect the attacks that are based on such changes. For example, if this automation rule is applied- "The heating is turned on if the temperature is below 18 Celsius degree", the adversary can turn on heating systems by manipulating temperature sensors. Jia et al. introduce a context-based system to spot critical actions on IoT platforms, mainly to address security lapses in specific IoT platforms, such as Samsung SmartThings [81]. Unlike these systems, DÏoT is not limited to a single IoT platform, i.e., it is a versatile across-platform approach.

5 TAMING BACKDOORS ON FEDERATED LEARNING

FL is an emerging distributed learning paradigm offering a number of benefits such as data privacy, training efficiency, and scalability. However, FL is susceptible to both security and privacy threats such as backdoor attacks and inference attacks that circumvent existing defenses [23, 54, 96, 145, 153, 155] as discussed in Section 1.5 (Chapter 1). We tackle these problems by proposing a robust and secure FL framework that is resilient against both poisoning and inference attacks. This chapter will highlight our contributions and summarize related work.

5.1 OUR CONTRIBUTIONS

This section summarizes the contributions of this dissertation aimed at mitigating backdoor and inference attacks on FL, as detailed in the following publications:

[4] Thien Duc Nguyen, Phillip Rieger, Huili Chen, Hossein Yalame, Helen Möllering, Hossein Fereidooni, Samuel Marchal, Markus Miettinen, Azalia Mirhoseini, Shaza Zeitouni, Farinaz Koushanfar, Ahmad-Reza Sadeghi and Thomas Schneider. “FLAME: Taming Backdoors in Federated Learning.” In: 31st USENIX Security Symposium (USENIX Security 22). ISBN: 978-1-939133-31-1. CORE Rank A*.

[5] Phillip Rieger, Thien Duc Nguyen, Markus Miettinen, and Ahmad-Reza Sadeghi and. “DeepSight: Mitigating Backdoor Attacks in Federated Learning Through Deep Model Inspection.” In: Network and Distributed System Security Symposium (NDSS’22). CORE Rank A*.

Backdoor characterization. As discussed in Section 1.5, in a backdoor attack in FL, the adversary aims to manipulate the global model so that it provides adversary-chosen outputs for specific inputs (backdoors). Typical defenses rely on analyzing model updates to distinguish poisoned and benign updates. However, one of the main limitations of existing backdoor defenses is that they rely on specific assumptions about attack strategies, thus, these defenses fail if such assumptions do not hold [23, 54, 96, 145]. To overcome such limitations, we identify fundamental characteristics of backdoor attacks and develop countermeasures based on carefully considering them to ensure that our defense is effective for all types of backdoors. Specifically, we identify three types of backdoors: large angular deviation, large magnitude, and stealthy (see Section 3, Appendix D). We then propose a mitigation framework, FLAME, to effectively mitigate all of these types of backdoors as summarized in the following.

FLAME: Backdoor Resilient Framework. The core idea of FLAME is to introduce a new method to estimate the amount of noise that should be added to the aggregated model to ensure that poisoned model updates are eliminated, regardless of attack type, i.e., FLAME is able to mitigate all types of backdoor attacks. However, using noise alone can lead to deterioration of the benign performance of the model due to the large amount of required noise [23, 54, 153]. We address this problem by introducing new dynamic clustering and adaptive clipping techniques as complementary components that help to minimize the amount of required noise to remove backdoors while preserving the benign performance of the model. FLAME is a fusion of three defense components: Clustering, clipping, and noising to ensure that backdoor updates are either filtered out or averaged out.

The Dynamic Clustering component employs Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), a Density-Based Spatial Clustering approach, with a parameter tuning that forms a large cluster consisting of benign models, while potential poisoned models with significant deviations are considered outliers. Our clustering approach overcomes several limitations of existing defenses since it can handle dynamic attack scenarios such as multiple backdoor injections and reduce the false positive rate.

The Adaptive Clipping component limits the impact of model updates by scaling down updates that have large magnitudes. This ensures all model updates have L_2-norm (Euclidean distances of local models to the global model) below a clipping bound. However, selecting a clipping bound value that effectively removes backdoored updates while maintaining the benign performance of the model is challenging. This is because (1) selecting a low clipping bound can effectively remove the backdoor but has a negative effect on model performance and vice versa and (2) the magnitudes of the model updates vary in each training iteration. To address these challenges, FLAME dynamically updates the clipping bound based on the median value of the L_2-norms for every training iteration. Since we assume the majority of clients are benign, the clipping bound is always in the range of the L_2-norms of benign models.

The Adaptive Noising component adds Gaussian noise directly to global model weights to reduce the influence of outlier samples, including backdoor samples. Existing works have shown that the more noise is introduced during training, the less impact poisoned samples have, enhancing the model's robustness against backdoors, but also the more negative effect on model performance [23, 47, 133]. Therefore, the challenging goal here is to introduce minimal noise to counteract backdoors without compromising the model's performance. To tackle this, we carefully analyze the effectiveness of noise level on model updates, model performance, and backdoor accuracy on various training iterations and datasets. We then introduce a new noise level estimation approach that is updated dynamically for each training round to ensure backdoor contributions are effectively eliminated, as shown in Lines 13-14 of Alg. 1 and discussed in Section 5 in Appendix D.

DeepSight: Deep Model Inspection. To improve the clustering accuracy of FLAME on non-IID data, we propose DeepSight, a new deep model filtering approach that analyzes the internal structure and the output layer of the neural networks to identify potential poisoned models [5, Appendix E]. In contrast to FLAME, which only measures the coarse-grained differences between models based on the cosine distances of the weights, DeepSight analyzes the internal weight distribution among the neurons and outputs. This is based on our key observation that a backdoor training task affects (activates) certain neurons more than others depending on the targeted inputs and outputs. To capture this phenomenon, we introduce two novel metrics: Division Differences (DDifs), which aim to measure the distribution of model outputs (prediction scores), and Normalized Update Energies (NEUPs), which estimate how frequently each label is used for training that reflects the frequent use of backdoor samples in training by malicious clients.

Private FLAME. To protect the privacy of local model updates against inference attacks, we propose Private FLAME based on STPC techniques that prevents a dishonest aggregator from accessing local model updates. In particular, we carefully design efficient STPC protocols for FLAME's clustering and clipping components including various functions such as cosine and Euclidean distance calculations, HDBSCAN clustering, and clipping as presented in Section 8 in Appendix D.

5.2 RELATED WORK

In general, the defenses against backdoors can be categorized into five categories: (1) backdoored model identification, (2) robust aggregation, (3) update smoothing, (4) model evaluation, and (5) ensemble FL.

Backdoored model identification [56, 62, 63, 87, 100, 109, 115, 132, 147]. These defenses are based on the hypothesis that backdoored models are different from benign ones due to the embedding of backdoor objectives in backdoor training. The defenses typically use ML-based clustering techniques such as k-means [132] to cluster local models based on pairwise Euclidean or cosine distances of the local models or between the models and the global model. These approaches separate models into two groups. The big group with the majority of local models are considered benign while the small group or outlier models are then considered malicious [132].

Robust aggregation [26, 50, 51, 70, 85, 123, 158]. Instead of attempting to identify backdoored models, robust aggregation approaches aim to select potential benign updates to be included in the global model and ignore other updates. For example, Krum [26] selects the model that has the smallest sum of Euclidean distances to all other models as the global model, while Median [158] uses the median values of model updates for each parameter as the value for the parameter in the global model. However, these approaches are only effective for specific data distributions and attack strategies. For instance, Auror [132], Krum [26] , Median [158] work under the assumption that benign data are

IID. Further, [23] shows that their attack can bypass such defenses by carefully constraining and scaling the poisoned updates to be within the benign update's distribution. On the other hand, FoolsGold [62] assumes that benign data are non-IID while poisoned data is IID. With this assumption, FoolsGold considers models that are very similar to others as potential backdoored models. In contrast, FLAME is not reliant on such specific assumptions and can thwart all three types of attacks discussed in Section 5.1.

Update smoothing [47, 93, 133, 134]. Clipping and noising, a typical approach to ensuring Differential Privacy (DP) [47, 133], can also be applied to averaging out backdoor updates. However, directly applying DP to defend against backdoor comes with negative impacts the model's accuracy. FLAME tackles this problem by (1) filtering potentially backdoored models that have high attack impact and (2) using adaptive clipping bounds and noise levels to eliminate the backdoor while maintaining the model's accuracy.

Model evaluation [31, 209]. Solutions like FLTrust [31] excel against a variety of threats, including backdoors. However, they require the aggregators to have access to clean baseline datasets. Another approach, Baffle [209], requires clients to use their data to test the aggregated model's performance and pinpoint backdoors. This strategy has inherent limitations as only attackers know the backdoor triggers, making it uncertain if benign clients will possess the trigger data. Additionally, in the non-IID setting, Baffle falls short, as distinguishing performance drops caused by backdoors or by data scarcity becomes challenging.

Ensemble FL [32, 37]. In these approaches, clients are randomly divided into several groups, and each client also participates in multiple groups. The core idea is to train multiple global models concurrently, with each group working on a different model. These models are then evaluated using a clean dataset, and the best-performing model is selected based on a majority vote. However, this method has three critical drawbacks: (1) the performance of each model might be negatively affected since only a portion of clients contributes to each global model, (2) it requires significantly higher computing and communication resources because clients have to train multiple models in parallel compared to one model as in typical FL settings, and (3) it requires having a root dataset for testing, similar to the **model evaluation** approaches.

Revisiting Attacks Claiming to Bypass FLAME. Since our FLAME paper presentation at the USENIX Security Conference in 2022, it has drawn significant attention, evidenced by more than 200 citations on Google Scholar. We reviewed the follow-up papers and identified two attacks claiming to bypass FLAME [96, 155]. However, our investigation into these attacks revealed significant methodological flaws and a misunderstanding of FLAME's fundamentals, particularly its Adaptive Clipping and Noising features, which are crucial for deterring backdoor attacks. We have discussed with the authors of these works which led to corrections by Xu et al. [155]. Further, our empirical studies using the exact methods and source code from the 3DFed [96] demonstrated FLAME's effectiveness in countering these proposed attacks. This highlights the necessity of a comprehensive understanding of our defense

mechanisms when developing offensive strategies. The details of our investigation can be found in Section 10 in the extended version of the FLAME paper [18].

6 CONCLUSION AND OUTLOOK

In this chapter, we summarize the the dissertation's contributions and outline future research directions.

6.1 CONCLUSION

This dissertation summarizes our contributions to the development of context-based authentication and FL-based intrusion detection solutions for securing IoT. In Chapter 2, we introduce ConXPair 2, an innovative context-based zero-interaction mechanism for IoT device pairing [1, Appendix A]. In contrast to the traditional methods that capture a snapshot of context information that require tight time synchronization and pose insufficient fingerprint entropy, ConXPair 2 continually monitors context changes to assess device proximity, extract a context fingerprint, and evolve secured paring keys over time. This process employs our novel context fingerprint extraction based on peak detection and alignment, generating high-entropy context fingerprints. Chapter 3 analyzes existing Digital Contact Tracing (DCT) systems and discusses TraceCorona, our security and privacy-centric contact tracing system for identifying potential contacts with Covid-19 infected users [2, Appendix B]. The security, privacy, and effectiveness of TraceCorona are strengthened by utilizing Diffie-Hellman (DH) key exchange protocol and BLE-based distance estimation to generate and verify unique encounter tokens between users. Our deployed beta version of the TraceCorona app has been successfully used by many users showing its effectiveness, security, and privacy advantages.

In Chapter 4, we present DÏoT, an advanced IoT anomaly detection system utilizing a novel, semi-unsupervised deep learning approach [3, Appendix C]. DÏoT assigns a specific detection model to each device type, enhancing model accuracy while requiring less training time. Moreover, DÏoT uses deep learning techniques to analyze network packet sequences based on learning word sequences in natural language processing to precisely assess anomalous traffic at packet-level granularity. Furthermore, DÏoT leverages FL to allow many participants to contribute to training a global detection model without sharing sensitive data with any other parties. Our evaluation shows DÏoT's effectiveness with a high detection rate and negligible false alarms. Finally, chapter 5 introduces FLAME and DeepSight, two methods designed to mitigate backdoor and inference attacks in FL systems [4, 5, Appendices D and E]. FLAME employs an adaptive noising technique to neutralize poisoned model updates. Further, we introduce a dynamic clustering and an adaptive clipping approach to remove model updates with high attack impact, thus reducing the required noise added to maintain benign performance. In addition, we propose DeepSight to enhance FLAME's

effectiveness in non-IID data settings by using deep model filtering to identify and eliminate potentially poisoned models.

6.2 FUTURE DIRECTIONS

Context-based pairing for IoT. As discussed in 2, context-based pairing offers many advantages compared to other pairing approaches such as Human-In-The-Loop pairing or pre-shared key (Pre-Shared Key (PSK)). Hence, many context-based pairing approaches have been proposed recently (see Section 2.2). Despite such active efforts and its potential, context-based pairing has not yet been realized in practice. The main reasons for this are (1) the heterogeneity of devices in terms of sensing, computing capabilities, and deployment scenarios, and (2) low fingerprint entropy and high noise in the context. One line of future research should explore new context modalities and how to effectively combine them so that even devices with different context sensing capabilities could still establish a secure key. A broader line of research would focus on large-scale deployment to address the heterogeneity of IoT devices. On the one hand, this research should aim to tailor the pairing scheme for each deployment scenario and device type, a so-called subgroup pairing. On the other hand, the new approach should still enable the establishment of a secure key between the subgroups.

Multi-layer anomaly detection for IoT IDS. Although DÏoT focuses on network traffic data, our concept can utilize data from other layers to enhance accuracy and coverage. Therefore, one line of future research should investigate multi-layer anomaly detection, for instance, by combining the data from the physical, network, and application layers. For example, recent research on the application layer, known as context-based anomaly detection, shows high potential (see Section 4.2). Hence, this approach can be integrated into DÏoT to cover attacks that cannot be captured by analyzing network traffic alone.

Understand and unlearn backdoors in FL. Although researches on backdoor attacks and defenses have been extremely active recently, most of these works resemble a hide-and-seek game. On the one hand, attackers apply different optimization algorithms to tune poisoned models to be similar to benign models. On the other hand, most defenses aim to explore various distance metrics and clustering algorithms to distinguish between poisoned and benign model updates (see Section 5.2). Moreover, existing defenses cause model deterioration or slow down model training by removing entire backdoor models or adding noise.A new line of research should focus on understanding backdoors and propose unlearning mechanisms [156] to make models forget the backdoor while avoiding damage to model integrity.

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Part II

PUBLICATIONS PART OF THIS CUMULATIVE DISSERTATION

A

REVISITING CONTEXT-BASED AUTHENTICATION IN IOT

Revisiting Context-Based Authentication in IoT

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ABSTRACT

The emergence of IoT poses new challenges towards solutions for authenticating numerous very heterogeneous IoT devices to their respective trust domains. Using passwords or pre-defined keys have drawbacks that limit their use in IoT scenarios. Recent works propose to use contextual information about ambient physical properties of devices' surroundings as a shared secret to mutually authenticate devices that are co-located, e.g., the same room. In this paper, we analyze these context-based authentication solutions with regard to their security and requirements on context quality. We quantify their achievable security based on empirical real-world data from context measurements in typical IoT environments.

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1 INTRODUCTION

The emergence of the Internet of Things (IoT) is rapidly and drastically increasing the number of connected devices. Hence, there is an increasing need for reliable and usable solutions for provisioning security associations among devices belonging to the same trust domain (e.g., Smart Home, Smart Office, etc.). At the same time, state-of-the-art techniques can't provide adequate authentication solutions in such scenarios. Firstly, device pairing protocols like, e.g., Bluetooth pairing tend to quickly encounter usability limitations in settings with many devices, as it is tedious (and error-prone) to use a relatively laborious authentication process for every device separately. Secondly, solutions based on pre-shared keys or certificates can't be applied in practice due to the huge number of IoT device manufacturers that would need to set up a common key pool or PKI. Manufacturer-specific pre-shared keys also do not address the problem adequately, since it is not possible to use them to distinguish between devices belonging to different trust domains (e.g., Smart Home devices of different neighbors).

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As a solution for IoT device pairing scenarios, several previous works [7, 8, 10, 11] proposed to use common contextual features observed by co-located devices as a shared secret to enable them to authenticate their co-presence in the same contextual environment, e.g., in the same physical space like a room. The underlying assumption is that the ability to observe common contextual features like audio is spatially and temporally limited, either by mutual distance or environmental perimeters like walls. This can be utilized to distinguish between the devices to be paired and other devices. The related pairing can be either a one-time user-initiated process, or, performed implicitly by utilizing the sustained co-presence of devices in mutual proximity as a means to identify devices belonging to the same trust domain.

Goals and Contributions. In this paper, we revisit the schemes that have been proposed for context-based device pairing. We analyze their applicability to IoT scenarios and the security assurance that they provide. Concretely, we provide following contributions:

- A unified model of the use of context as a shared secret in authentication applications (Sect. 3),
- A security analysis of proposed schemes taking the entropy loss incurred by used error-correction schemes and privacy amplification into account (Sect. 4), and,
- An empirical evaluation of the security of context-based pairing based on real-world context data from environments relevant to IoT (Sect. 5).

2 CONTEXT-BASED PAIRING SCHEMES

2.1 System Model

Context-based pairing can be applied in situations in which two IoT devices A and B do not have a prior security association and want to establish one because they belong to the same *trust domain* $\mathcal{D}$. A trust domain denotes a set of devices that are intended to be able to communicate with one another and form collaborative (trusted) ensembles. Typically, devices owned by the same person or organization form such a trust domain. We also assume that there is *a priori* no key management infrastructure for authenticating the membership of devices A and B in the same trust domain $\mathcal{D}$.

In all context-based pairing approaches [8–11], A and B utilize measurements of physical features of their ambient surroundings observed with their on-board sensors for deriving a *context fingerprint* w. This fingerprint is subsequently used to establish a shared secret between the devices. These approaches are either based on demonstrative identification via proximity or implicit context-based authentication as we describe in the following.

2.2 Demonstrative Identification via Proximity

In these scenarios, pairing is a one-time operation where the user *demonstratively identifies* [1] devices to be paired by placing them close to each other. Usability considerations dictate that pairing completes within a few seconds as it is unacceptable for users to maintain A and B in close proximity for longer periods. This approach is amenable to mobile devices like smartphones that are relatively easy to place in any desired constellation. It requires active involvement of the user to explicitly initiate pairing and make sure that no other adversarial devices are within pairing distance d of either device A or B. Pairing can thus not be automated, as otherwise devices might pair with any devices sufficiently close to them. Especially in mobile scenarios, e.g., in crowded public transport systems this would lead user's devices to potentially establish pairings with devices of complete strangers just happening to stand nearby the user.

ProxiMate by Mathur *et al.* [8] is a scheme that uses fluctuations in a radio signal that A and B jointly observe to extract random secret bits to be used as a shared secret. Its security is based on the fact that these fluctuations are correlated between A and B only if they are located within half the wavelength λ of the used RF frequency of each other. Beyond this distance, no correlation exists.

The scheme by Schürmann and Sigg [10] extracts entropy from ambient audio and bases its security on the assumption that only if A and B are located close to each other they can observe similar audio environment. They extract context fingerprints by observing significant changes in the sound energy levels at different frequency bands in order to extract a maximum amount of entropy. In their approach, both A and B extract context fingerprints w and w', respectively, based on their context observations. A uses its fingerprint w to 'hide' a randomly selected secret s in a *fuzzy vault* [5] based on a Reed-Solomon error-correcting code. The check-in function of the fuzzy vault provides error-correcting information P, which A transmits to B. Using P and a fingerprint w' sufficiently similar to w, i.e., within Hamming distance $dist(w, w') \leq t$, B is able to retrieve secret s from the fuzzy vault. In a similar fashion, also the scheme by Mathur *et al.* uses an error-correcting Golay code to enable B to correct deviations between w' and w and subsequently use the corrected fingerprint as the shared secret between A and B.

2.3 Implicit Context-Based Authentication

A scheme utilizing implicit context-based authentication was first introduced by Miettinen *et al.* [9]. It allows establishing security associations between devices that are *permanently* located in the same context. The underlying assumption is that all such devices belong to the same trust domain $\mathcal{D}$. In this approach A and B repeatedly monitor their context and iteratively execute a pairing protocol, which will succeed if the context observations of A and B are similar enough, e.g., if A and B are located in the same room, or fail otherwise. After a sufficient number of successful pairing iterations, A and B will accept the established pairing as authentic.

A challenge for implicit context-based authentication are devices not belonging to trust domain $\mathcal{D}$ that might be temporarily present in the context C (e.g., a visitor's smartphone). Therefore the implicit scheme requires *sustained* presence from devices by repeating authentication iterations over a prolonged period of time longer than the reasonable assumed duration of a visiting device's visit. This does, of course, not preclude A or B from granting *guest-level* access to the counterpart already after one or a few successful authentication iterations. However, full access to trust domain $\mathcal{D}$ would be granted only after a sufficient number of successful iterations.

3 ADVERSARY MODEL AND SECURITY GOALS

We consider the following adversary model. Given two legitimate IoT devices A and B belonging to the domain $\mathcal{D}$, the adversary $\mathcal{E}$ is a device that is not in the same proximate context C as A and B. Depending on the pairing scheme, *proximate context* may either denote close proximity in terms of physical distance d, or, the physical space that encloses both devices and is separated from the outside space by an enclosure like the walls of a room. In particular, we assume the adversary $\mathcal{E}$ to have following properties:

- It is equipped with the same contextual sensors as legitimate devices A and B.
- It can wirelessly communicate with both A and B in the same way as A and B with each other.

Impersonation. In an impersonation attack, adversary $\mathcal{E}$ that does not belong to the same trust domain $\mathcal{D}$ as A attempts to convince device A that it is a legitimate device $B \in \mathcal{D}$ and establish a successful pairing with it. This can happen if $\mathcal{E}$ can fabricate context observations that are similar enough to those of A that it will lead to successful authentication.

Man-in-the-Middle. If $\mathcal{E}$ can successfully execute the impersonation attack simultaneously with both A and B, it will gain the ability to perform man-in-the-middle attacks against A and B, i.e., completely controlling the communications between them.

In the schemes presented above, the context measurements of A and B are used to derive a shared secret s to be used either as an *authentication token*, or, directly as a *cryptographic key*. Depending on its use, s has to fulfill following requirements.

Use as Authentication Token. It is necessary that s has sufficient entropy to resist an on-line guessing attack by $\mathcal{E}$. A should implement strict rate-limiting for the number of permissible authentication attempts for each set of context observations, since re-trying does not help if the used context data do not change. It is therefore sufficient for s to have a min-entropy of approximately 20 bits, i.e., $\widetilde{\mathbf{H}}_\infty(S) \geq 20$, where S denotes the probability distribution from which s is drawn. This achieves a comparable resilience against guessing attacks as in the PIN-based Bluetooth pairing protocol, which can be considered a widely accepted industry standard for device pairing applications.

Use as Cryptographic Key. In schemes where the shared secret s is used directly as a cryptographic key, the requirements are much stricter. Not only has the min-entropy $\widetilde{\mathbf{H}}_\infty(S)$ to be sufficient to withstand off-line known-plaintext attacks, but, also the probability distribution S from which s is drawn, needs to be sufficiently indistinguishable from the uniform distribution in order for s to be considered a good cryptographic key.

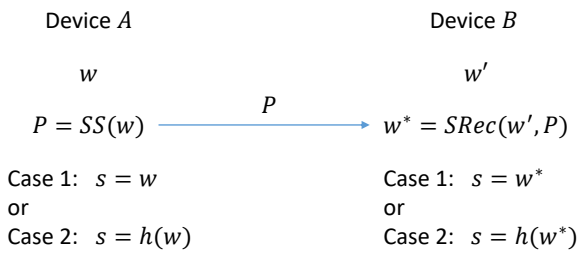


Figure 1: The context-based authentication approach for using context fingerprint w as an authentication token (Case 1) or for deriving a cryptographic key (Case 2).

4 SECURITY OF PAIRING SCHEMES

Recent context-based pairing schemes proposed in literature [8–10] use error-correcting codes to derive the shared secret s from context observations. None of these works, however, provide a quantitative empirical evaluation of their security under practical real-world requirements. In the following, we analyze the factors influencing security that these context-based pairing schemes can provide and evaluate their effectiveness in a real-world setting that is typical for IoT environments.

4.1 Context-Based Authentication

Since context observations in practice always are influenced by random errors arising from, e.g., context sensors' hardware or random fluctuations in the monitored context parameter, the observations of devices A and B will be similar but not identical. To compensate for these deviations, error-correcting codes like Golay or Reed-Solomon are used to perform *information reconciliation* [3] to 'correct' the context fingerprints of A and B to be identical.

The process of context-based authentication is shown in Fig. 1. First, device A derives a *context fingerprint* w, a quantization of its context observations. How this quantization is done is specific to each scheme and depends on the used context modality. In the subsequent discussion, we will simply refer to this process as *context fingerprinting*. Subsequently, A derives error-correcting information P from its fingerprint with the help of an appropriate error-correcting code (ECC), and sends it to B. Using this information B can adjust any deviations in its own context fingerprint w' in comparison to w, as long as the Hamming distance of its fingerprint w' to A's fingerprint w is within the error-correcting capability t of the used ECC, i.e., $dist(w, w') \leq t$. The resulting adjusted fingerprint $w^* = w$ can then either directly be used as the authentication token s or utilized further for deriving the cryptographic key s.

For deriving a cryptographic key s from the context fingerprints, A and B need to employ *privacy amplification*, as the error-correcting information P may provide partial information about the fingerprint w to adversary $\mathcal{E}$. The privacy amplification step will take fingerprint w about which $\mathcal{E}$ has partial information and output a secret s of which $\mathcal{E}$ has virtually no information. In addition, privacy amplification is used to make sure that the distribution S from which s is drawn is arbitrarily indistinguishable from the uniform distribution.

4.2 Entropy Loss

The shared secret s is derived from the context fingerprint w. Therefore its secrecy is dependent on the entropy of w from the point of view of adversary $\mathcal{E}$. This is measured in terms of its min-entropy $\widetilde{\mathbf{H}}_\infty(W|P)$, where W is the probability distribution of the fingerprints w and P denotes the error-correcting information. Min-entropy is a measure of the 'worst-case' entropy, i.e., it measures the entropy of values of w that are easiest to guess for $\mathcal{E}$. It is therefore a good measure for the security of the scheme, since it considers the most favorable outcome for $\mathcal{E}$.

Information reconciliation. When device A reveals the error-correcting information P for its fingerprint w this inevitably leaks some information about w. The extent of this entropy loss depends on the used error-correcting scheme. In the Schürmann and Sigg [10] scheme this is realized through a *fuzzy vault* [5] that utilizes *fuzzy commitments* [6]. Fuzzy commitments are equivalent to a *secure sketch* [4] utilizing the so-called code-offset construction, in which P is obtained by adding fingerprint w to the codeword $C(s)$ of secret s, i.e., $P = w \oplus C(s)$. We therefore analyze the entropy loss incurred by the error-correction with the help of secure sketches, as these can be generalized also to other schemes utilizing ECCs.

A secure sketch as introduced by Dodis *et al.* [4] is a pair of efficient algorithms $SS(\cdot)$ and $SRec(\cdot,\cdot)$ such that the secure sketching operation $SS(w) = P$ provides error-correcting information P that can be used to reconstruct w using the operation $SRec(w', P) = w$ given a value w' that is sufficiently similar to w, i.e., $dist(w, w') \leq t$. For secure sketches based on $[n, k, 2t+1]$ ECCs it can be shown [4] that the entropy loss incurred by revealing the error-correcting information P is bounded by $(n-k)$, where n denotes the length, k the dimension and t the error-correcting capability of the ECC. The selection of the code is dependent on the amount of error-correction t that is required. In general, an ECC with higher error-correction capability will also incur a higher entropy loss.

Privacy Amplification. If the reconciled context fingerprint w is used to derive a cryptographic key, privacy amplification is needed to obtain a secret s over which $\mathcal{E}$ does not have even partial information. This is not considered in the Schürmann and Sigg scheme. Mathur *et al.* discuss privacy amplification, but do not take the entropy loss caused by it into account. To this end, a universal hash function $h(\cdot)$ can be used on the fingerprint w to generate a close-to-uniformly distributed secret, of which the adversary $\mathcal{E}$ does not have any information. According to the generalized Leftover Hash Lemma (LHL) [2], the privacy amplification will incur $\log \epsilon^{-1}$ bits of entropy loss, where ϵ is a security parameter determining how indistinguishable the output is from the uniform distribution.

5 EVALUATION

To evaluate the feasibility of context-based authentication for IoT devices in a real-world setting that is applicable to typical smart home appliances like smart light bulbs, smart power plugs, IP cameras, etc., we performed two longitudinal experiments in domestic and office environments, representing typical deployment environments for IoT devices. In both experiments, data collection was performed continuously over a time period of 30 days in order to capture typical variations in contextual activity caused by daily and

weekly differences in routines. In our evaluation we focus on the audio modality, as it is readily available and the required sensors relatively inexpensive to integrate in devices.

We focus on two measures of fitness: the *false accept rate* (FAR) and the *false reject rate* (FRR). FAR measures the rate at which fingerprints of adversary $\mathcal{E}$ will be falsely accepted by A as genuine, enabling thus an impersonation attack. FRR in contrast, measures the rate at which fingerprints of a genuine device B will be falsely be rejected by A. As FAR is a measure of the security of the scheme and FRR for its usability in practice, a good context-authentication scheme will seek to minimize both of these measures.

5.1 Data Collection

For data collection we used recent models of Android smartphones for which we had developed a data collection app recording the ambient sound energy level in the context every 100 ms. In each experiment we considered two different settings: one with two and another with three co-located devices marking IoT devices in the same trust domain $\mathcal{D}$, and one adversary device $\mathcal{E}$. In total the dataset covered therefore 12 distinct devices over a period of 30 days, covering more than 8000 hours of context measurements.

To model the positioning of typical IoT devices, data collection devices were installed in a room of the target environment at a distance of 2-3 meters from each other and adversary devices were placed in adjacent rooms. However, due to practical constraints in the experimental set-up in the Home environment, the contextual isolation of the adversary device $\mathcal{E}$ was not as good as in the office environment, as the adjacent room was connected by a light-weight door that had to be opened from time to time. This allowed us, however, to analyze what impact the quality of the contextual separation has on the security of the context-based pairing.

5.2 Context Quantization

We utilize a fingerprint quantization scheme based on detecting prominent peaks in the audio measurements and using *list-encoding* to generate context fingerprints w. List-encoding is an efficient way of transforming continuous measurements into binary fingerprints as, e.g., Mathur *et al.* [8] have shown. In contrast to their scheme, which used minima and maxima of observed RF-measurements to encode "1" and "0" bits of the fingerprint, respectively, we slightly modified their scheme, as the audio signal doesn't contain clear minima. In our scheme A detects significant peaks in the audio measurements and uses these to encode "1" bits of its context fingerprint w. To encode "0" bits, A will randomly pick a roughly equal amount of non-peak observations at a minimum distance of 500 ms from any observed peaks and use these to encode zero bits. For the resulting fingerprint w, A will then derive the error-correcting information P and sends it along with the timestamps ts_i of the observations used to encode the fingerprint bits to B, which uses the timestamps ts_i to decode its fingerprint w' based on its own context measurements. It will decode each ts_i corresponding to a peak within a distance of 500 ms as a "1" bit and as a "0" bit if it does not correspond to a peak within this time window.

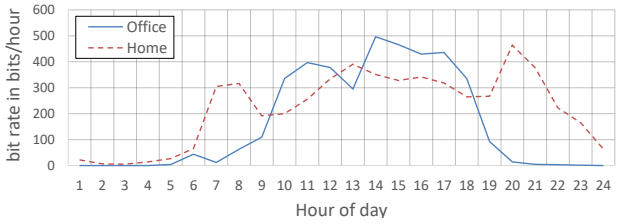


Figure 2: Bitrate of fingerprint extraction during different times of day

5.3 Contextual Activity

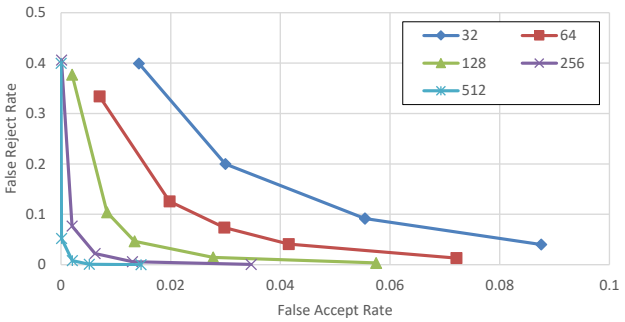
As fingerprint extraction is dependent on observed contextual activity, the amount of fingerprint bits that can be obtained from the context typically varies depending on the hour of day. The average hourly bitrate during different times of the day for the evaluation data is shown in Fig. 2. We focus our analysis therefore on the active hours of the day, i.e., on the hours between 6.a.m. to 9 p.m. in the Home environment and between 9 a.m. and 6 p.m. in the Office environment. During these times the average bit rate was 309 in the Home and 368 bits per hour in the Office environment.

5.4 Similarity of Fingerprints

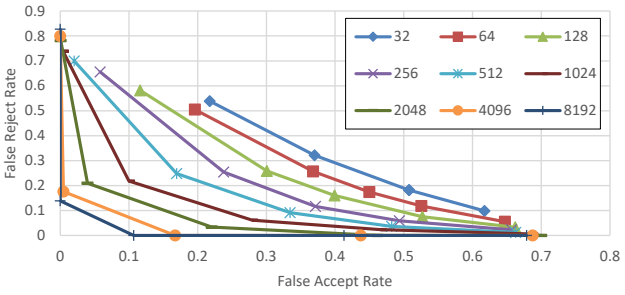
In the Home environment, average similarity of fingerprints extracted during the active hours of the day is constantly over 92%, the average being 93.2%. For the Office environment, during the active office hours on weekdays, even higher similarity can be reached, being constantly at least 94%, the average being 95.2%. Fingerprint similarity for adversary devices is in both scenarios consistently lower than 90%, 86.1% in the Home and 67.9% in the Office scenario on average, showing the impact that the lower quality of contextual separation in the Home experiment has. In both environments, an ECC with error-correcting capability of ca. 10% is sufficient to allow co-located devices to successfully pair, while adversarial devices would not be able to do so.

However, the above figures apply only to the *average* case. Our evaluation revealed that another factor, which earlier works [8, 10] have not explicitly taken into account has to be considered, namely the inherent variation in the similarity of context fingerprints. Our data show that from time to time the fingerprint of adversary $\mathcal{E}$ is in fact sufficiently similar to the fingerprint of A, thus enabling $\mathcal{E}$ to falsely authenticate with A. Two factors affect the probability of this happening: 1) higher error-correcting capability t increases the probability that $\mathcal{E}$'s fingerprint will be accepted, while 2) longer fingerprints average out short-term fluctuations in fingerprint similarity, thus reducing $\mathcal{E}$'s success probability. Figure 3 shows the impact of these factors on the FAR and FRR values.

Due to the better contextual separation in the Office experiment, the FAR/FRR values (Fig. 3a) are clearly lower than in the Home experiment (Fig. 3b). For short fingerprint lengths, the FAR is relatively high, e.g., ranging from 1.4% to 8.6% for 32-bit fingerprints. Increasing the fingerprint length effectively reduces FAR,

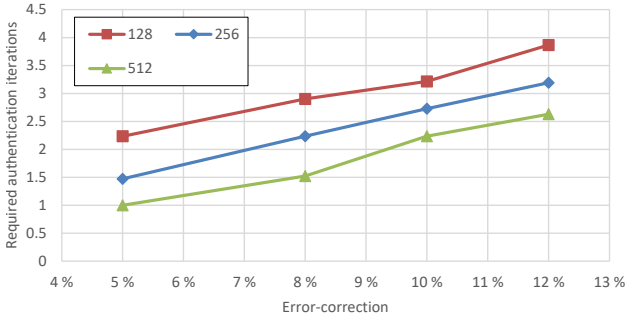


(a) Office

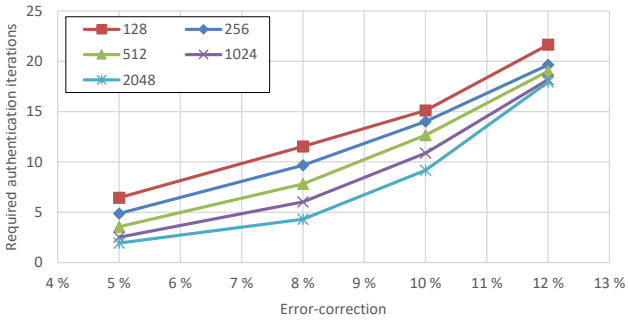


(b) Home (with insufficient contextual separation)

Figure 3: FAR vs. FRR for error-correction levels 5%, 8%, 10%, 12% and 15% for different fingerprint lengths.



(a) Office



(b) Home (with insufficient contextual separation)

Figure 4: Required number of authentication iterations to reach FAR of 2^{-20} for different fingerprint lengths.

so that close-to-optimal performance can be achieved with a 512-bit fingerprint length with a FAR of 0.2% and FRR of 0.8% at an error-correction level of 10%.

The values for the Home experiment in Fig. 3b show how crucial contextual separation is for the security of the scheme. For short fingerprint lengths, $\mathcal{E}$ has a relatively high success probability of 21.8% to 61.7%. In this experiment, even using extremely long fingerprints of 8192 bits would bring down the FAR to only 10.7%.

From Fig. 3 we can, however, see that even under favorable conditions, the adversary has a non-negligible chance of succeeding. This means that in order to further decrease the FAR for increased security, one needs to adopt the approach proposed by Miettinen *et al.* (Sect. 2.3), where the authentication is iteratively repeated, in order to increase the confidence in the counterpart's authenticity. The number of authentication iterations required is dependent on the FAR of the used ECC. Figure 4 shows the amount or required iterations for reaching a FAR of 2^{-20} (comparable security to Bluetooth pairing) for the different ECCs in the examined environments. We can see that, e.g., at the 10% error-correction level, $3-4$ iterations in the Office environment would be required, while $10-16$ repetitions would be needed in the Home environment.

5.5 Entropy Analysis

As discussed in Sect. 4.2, an $[n, k, 2t+1]$-code will incur an $(n-k)$-bit entropy loss during the information reconciliation stage. The higher the required error-correcting capability is, the larger also the entropy loss. From this point of view, Reed-Solomon (RS) codes provide an optimal trade-off between error-correction capability and entropy loss, as for each symbol of error-correction capability, the code will incur an entropy loss of two symbols, i.e., in practice an error-correction capability of t bits will incur $2t$ bits of entropy loss. This assumes an approach used, e.g., by Schürmann and Sigg [10], where fingerprint bits are encoded with the help of symbols of the RS-code. Our evaluation shows that an error-correction capability of ca. 10% is required to enable A and B to perform successful pairing with low FRR. The fingerprint w would therefore need to have initially at least 25 bits of min-entropy to retain a leftover entropy of 20 bits after the information reconciliation step with 20% of entropy loss. As discussed in Sect. 3, this would be sufficient for using the fingerprint as an authentication token.

For deriving a cryptographically strong secret of 128 bits, also the entropy loss incurred by privacy amplification needs to be taken into account. As discussed in Sect. 4.2, this amounts to $\log \epsilon^{-1}$ bits, where ϵ is a parameter defining the desired indistinguishability of S, the distribution of the secrets s, from the uniform distribution. For, e.g., $\epsilon = 2^{-20}$ this would result in additional 20 bits of entropy loss associated with the privacy amplification step. To retain a min-entropy of 128 bits after information reconciliation and privacy amplification, the min-entropy of the context fingerprint would therefore need to be at least $\frac{128+20}{80\%} = 185$ bits, if a Reed-Solomon error-correcting code with 10% error-correction capability is used.

5.6 Duration of Pairing

The best strategy for adversary $\mathcal{E}$ to guess A's fingerprint is to use its own fingerprint, as on average 86.1% of fingerprint bits in the Home environment and 67.9% of the fingerprint bits in the Office environment will be identical with A's fingerprint bits. Therefore, the amount of entropy of each fingerprint bit from $\mathcal{E}$'s point of view is only 0.24 bits in the Home and 0.32 bits in the Office environment. Obtaining sufficient min-entropy, i.e. 25 bits, for an authentication token will therefore require $\lceil \frac{25}{0.24} \rceil = 105$ fingerprint bits in the Home and $\lceil \frac{25}{0.32} \rceil = 79$ fingerprint bits in the Office environment, on average. At average bit generation rates of 309 and 368 bits per hour, the required time for acquiring sufficient bits would therefore be 20.4 min in the Home and 12.9 min in the Office environment.

Similarly, for obtaining the required 185 bits of min-entropy for a cryptographic secret would require $\lceil \frac{185}{0.24} \rceil = 771$ fingerprint bits in the Home and $\lceil \frac{185}{0.32} \rceil = 579$ fingerprint bits in the Office environment. The respective required times to harvest this entropy would accordingly be 149.7 minutes in the Home and 94.4 minutes in the Office environment.

5.7 Summary

Our evaluation shows that using context measurements for establishing a shared secret is possible, given sufficient time to harvest entropy from the ambient environment. However, for any contexts where a complete contextual separation from the outside environment can't be guaranteed, the authentication process has to be repeated a sufficient number of times to bring down the false accept rate to an acceptable level (cf. Fig. 4). Therefore, an approach along the lines of [9], in which initially only basic level access is granted and additional privileges only added as more successful authentication iterations are completed should be followed in applying context-based pairing in real-world environments.

6 RELATED WORK

Earlier proposals for context-based pairing have focused on using RF-signals. AMIGO by Varshavsky *et al.* [11] aimed at authenticating the co-presence of devices by comparing the received signal strength indicators (RSSI) of WiFi data packets. This approach was subsequently extended by Kalamandeen *et al.*'s Ensemble [7], which not only observed incoming packets, but utilized also transmissions by an ensemble of trusted wearable devices to verify proximity of devices. However, subsequent work showed that RSSI values can potentially be inferred or influenced by a remote adversary, if it knows the positions of A and B. Mathur *et al.* [8] therefore introduced the ProxiMate system (cf. Sect. 2.2), which relies on physical properties of the RF-field for secrecy. These approaches are, however, only applicable for demonstrative identification via proximity, as the devices have to be very close to one another (e.g., 15 - 35 cm) to authenticate. Their applicability for large-scale authentication of numerous IoT devices, e.g., in a Smart Home environment, is questionable, as the user needs to separately point out each and every of the (potentially numerous) devices.

The scheme of Schürmann and Sigg [10] uses audio in the proximate context to transfer a random secret s selected by A to B to be used as a shared key (cf. Sect. 2.2). However, they don't consider that the secrecy of s depends only on the min-entropy of the used w, over which $\mathcal{E}$ obtains partial information due to the released error-correcting information P, making privacy amplification necessary. They also don't quantitatively analyze the entropy loss associated with the use of ECCs.

Our approach builds on the scheme of Miettinen *et al.* [9] (Sect. 2.3) that proposes an implicit context-based authentication scheme based on audio and luminosity. In this scheme, an initial strong *unauthenticated* shared secret is established between A and B, which is subsequently iteratively evolved by repeated context-based authentication steps in order to gradually establish confidence in the authenticity of the counterpart. Our evaluation shows that this indeed is necessary, unless complete contextual isolation of the target context from adversary $\mathcal{E}$ can be guaranteed.

7 CONCLUSION

Context-based pairing for authentication of IoT devices can provide significant usability benefits as compared to traditional solutions like, e.g. Bluetooth pairing. Applying it in practice, however, has caveats that have not been sufficiently considered in earlier proposals [8–11]. Firstly, one has to consider and quantify the entropy losses related to the applied error-correction and privacy amplification in order to estimate a sufficient amount of entropy to be harvested from the environment. In addition, our evaluation shows that one also has to have a good understanding about the performance of the fingerprinting approach as well as the level of contextual separation that the target environment provides. Therefore, before deployment of context-based pairing solutions, sufficient understanding about the target contexts should be acquired in order to make informed decisions about relevant parameters like error-correction level, used fingerprint lengths and number of required authentication iterations, so that the used approach can in fact provide sufficient security in a real-world setting.

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DIGITAL CONTACT TRACING SOLUTIONS: PROMISES, PITFALLS AND CHALLENGES

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Digital Contact Tracing Solutions: Promises, Pitfalls and Challenges

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***Abstract*—The COVID-19 pandemic has caused many countries to deploy novel digital contact tracing (DCT) systems to boost the efficiency of manual tracing of infection chains. In this paper, we systematically analyze DCT solutions and categorize them based on their design approaches and architectures. We analyze them with regard to effectiveness, security, privacy and ethical aspects and compare prominent solutions based on these requirements. In particular, we discuss shortcomings of the Google and Apple Exposure Notification API (GAEN) that is currently widely adopted all over the world. We find that the security and privacy of GAEN has considerable deficiencies as it can be compromised by severe large-scale attacks.**

We also discuss other proposed approaches for contact tracing, including our proposal TRACECORONA, that are based on Diffie-Hellman (DH) key exchange and aim at tackling shortcomings of existing solutions. Our extensive analysis shows that TRACECORONA fulfills the above security requirements better than deployed state-of-the-art approaches. We have implemented TRACECORONA and its beta test version has been used by more than 2000 users without any major functional problems[1], demonstrating that there are no technical reasons requiring to make compromises with regard to the requirements of DCT approaches.

***Index Terms*—digital contact tracing, privacy, security**

I. INTRODUCTION

The pandemic caused by the SARS-CoV-2 corona virus has still the world in its grip since it was officially announced by the World Health Organization (WTO) on March 11, 2020. At the time of writing, we have been witnessing the surge of several infection waves all around the world. Reliable and efficient contact tracing for containing the spread of infections has therefore become more important than ever. In many countries, digital contact tracing apps on smartphones have already been rolled out to support manual contact tracing with the hope of significantly improving its effectiveness in breaking infection chains and preventing the virus from spreading further. In this paper, we focus on analyzing how theoretical results of epidemiologists (e.g., [1]) are taken into account in current proposals for identifying at-risk contacts in the presence of technological errors, data pollution attacks and privacy and ethics regulations. Initially we analyze deployed solutions, as many countries are currently actively employing them and millions of users are affected by such systems. Regardless of the potential usefulness of digital contact tracing or a lack thereof, contact tracing apps have become a reality in many countries. At the time of writing, 49 countries around the world (including, e.g., most European countries, Australia, China, Singapore) and 27 states in the USA have deployed contact tracing apps[2]. Many of these systems in use today were designed, implemented and rolled out in great haste with the goal of containing the spread of the pandemic as quickly as possible. It is therefore ever more important to take a step back and try to obtain a critical view of the benefits and disadvantages of individual approaches.

In this context, *effectiveness*, *security*, *privacy* and *ethics* are key aspects that need to be considered thoroughly: (i) the system should be *effective*, i.e., able to provide acceptable detection accuracy (high true positive and low false positive rate), (ii) it should be *secure* so that malicious adversaries cannot manipulate the system to trigger false alarms, (iii) it should protect *privacy* to increase users' trust in the DCT system, and (iv) it should consider ethical aspects as it should be transparent and based on voluntary use. Ensuring all above properties is necessary to achieve high adoption rates to then significantly contain the spread of the virus. Otherwise, users will not be willing to use contact tracing apps, negatively impacting their adoption rate that would be crucial for their effectiveness in practice (ideally higher than 60%) [2].

While the first countries (predominantly in Asia) that deployed tracing apps adopted centralized approaches, and extensively collected sensitive user information (e.g., names, addresses, mobile phone numbers, location), a widespread and heated debate on user privacy broke out in Europe and the USA[3]. In this turmoil of evolving contact tracing approaches, Google and Apple established an unprecedented collaboration and provided their special application programming interface for decentralized contact tracing called *Exposure Notification*

[1]https://tracecorona.net/download-tracecorona/

[2]MIT Covid Tracing Tracker, https://tinyurl.com/3ey44r5c

[3]In the course of this debate about 300 security and privacy researchers from 26 countries signed an open letter criticizing the specific privacy risks of some centralized contact tracing approaches, advocating privacy-preserving solutions whenever better privacy can be obtained without penalizing effectiveness (https://drive.google.com/file/d/1OQg2dxPu-x-RZzETlpV3lFa259Nrpk1J/view). This signed letter has been often abused claiming that centralized systems are bad and decentralized systems do what is needed to detect at-risk contacts, and moreover they do it protecting privacy.

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API (GAEN) [3] which they rapidly integrated into their mobile operating systems. Google and Apple give in each country access to this interface only to one organization that is authorized by the local government. GAEN runs an almost complete contact tracing solution as a part of the underlying mobile operating systems, so that the role of national organizations is reduced to developing a user interface to GAEN through a smartphone app and providing the backend server infrastructure required for acquiring and distributing information about at-risk contacts. Further, although Apple and Google initially promised not to get directly involved in contact tracing by developing their own backend server and app, later they did so by providing the GAEN Express solution that is used in several US states, e.g., Maryland and Utah[4]. Unfortunately, it is known that existing rolled out Digital Contact Tracing (DCT) systems exhibit a number of important security and privacy risks [4], [5], [6], [7].

In order to tackle the shortcomings of existing approaches, we introduce a novel user-controlled privacy-preserving contact tracing system called TRACECORONA. It leverages a robust privacy architecture based on Diffie-Hellman key exchange to provide a level of security and anonymity unparalleled by any of the other systems proposed so far. It also improves the effectiveness and accuracy of the overall system and its resilience to misuse through the ability to *verify* all critical encounters.

In particular, we provide following contributions:

- We introduce a categorization of the requirements on DCT systems in four dimensions, namely: effectiveness, privacy, security and ethical considerations (Sect. III).
- We propose a novel distributed contact tracing system based on Diffie-Hellman (DH) key exchange, TRACECORONA, providing strong security and privacy guarantees (cf. Sect. IV). In contrast to almost all existing approaches that are based on exchanging pseudonymous proximity identifiers, our approach leverages advanced cryptographic algorithms to establish and verify encounter tokens that are unique to each encounter between two users. Futher, we propose various use cases and deployments of TRACECORONA including a hybrid approach (cf. Sect. IV-D). We implemented, deployed, and published TRACECORONA for beta user test (cf. Sect. IV-E).
- We analyze TRACECORONA in comparison to prominent schemes w.r.t these aforementioned requirements (cf. Sect. V). Our analysis shows that DH-based systems provide better security and privacy guarantees than GAEN while maintaining comparable effectiveness.

In summary, we provide a comprehensive set of requirements to evaluate DCT systems. We show that current approaches do not fulfill such requirements at large, e.g., have number of security, privacy and effectiveness issues. Hence, we propose TRACECORONA, a novel approach that address the deficiencies of existing DCT systems. In the following, we will present those requirements of DCT systems as well as TRACECORONA in details. Further, we have published a full version of this paper as a technical report that includes a systematization and extensive analysis of existing DCT schemes as well as the extended application scenarios of TRACECORONA [8].

[4]MD COVID Alert, https://tinyurl.com/yeymtrm2

TABLE I: Notations.

User (U)	A Person that uses a DCT App
User App (App)	A DCT app installed on users' devices
Tracing Service Provider (SP)	Providing a system (e.g., servers and apps) for identifying at-risk contacts
Health Authority (HA)	Authenticating the user infection status
Infected user	A user that has tested positive for COVID-19
Affected user	A user that has encountered an infected user
Indirect contacts	A user that has encountered an affected user

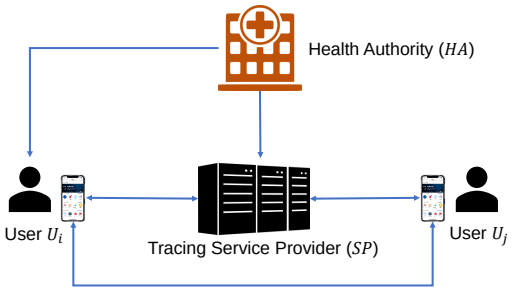

Fig. 1: System model of Digital Contract Tracing (DCT).

II. DIGITAL CONTACT TRACING

In this section, we present the system model, architectures and technologies of DCT systems.

A. System Model

Figure 1 shows the typical system model of contact tracing schemes. There are three types of entities: Users U (e.g., U_i and U_j) of the tracing system (app), a contact tracing Service Provider (SP), as well as a health authority (HA). In the following, we discuss these roles in more detail.

1) Users: A user U_i uses a dedicated *contact tracing app* installed on its device (typically a smartphone) to collect information required to determine contacts with other users of the system. Different technologies can be used for this purpose, e.g., directly through exchange of specific information over a proximity communication protocol like Bluetooth LE, or, indirectly with the help of a trace of location information obtained from a positioning system like GPS, by determining simultaneous co-presence of the users at the same location at the same time. We will discuss various technologies in Sect. II-C. Users' contact tracing apps collect and store this information about contacts of users locally on users' mobile devices. In case a user U_i is tested positive with a disease (like COVID-19), the user is expected to use the contact tracing app to warn other users of the system by uploading the collected information about his/her contacts to the contact tracing service provider SP.

2) Tracing Service Provider: The Tracing Service Provider SP is responsible for collecting and distributing information necessary for identifying contacts with infected users and/or notifying other users of such contacts. In *centralized* systems,

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the *SP* determines contacts between infected users and other users and issues notifications to them, whereas in *decentralized* systems, the determination of possible contacts is performed by the users' contact tracing apps.

3) Health Authority: The Health Authority *HA* is responsible for identifying infected users (e.g., through administered medical tests) and authenticating their infection status towards *SP*. This is necessary to prevent malicious users $\mathcal{A}^u$ from pretending to be infected and thereby triggering false alarms with users they have had contacts with. To do this, *HA* will issue a user-specific unique authenticator, e.g., a transaction authentication number (TAN) (a form of single use one-time password (OTP)) to an infected user U_i, who can subsequently present this authenticator when uploading their information to *SP*. By verifying the authenticator with *HA*, the *SP* can verify the infection status of the user U_i.

B. Centralized vs. Decentralized Architectures

In general, contact tracing approaches can be divided into two main design architectures, *centralized* and *decentralized*, based on whether the identification of encounters between users is performed by the tracing service provider *SP* or by the tracing apps of users *U*. Both approaches are based on individual users' tracing apps recording temporary identifiers (*TempID*s) of other devices they encounter. In the case a user U_i is infected, he uses his tracing app to upload identifiers to *SP*. In centralized systems, the recorded identifiers of *other* apps will be uploaded, whereas in decentralized systems, the *TempID*s used by the tracing app *itself* in the recent past will be uploaded. The main difference between these schemes is the fact that in the centralized system the service provider *SP* generates all *TempID*s centrally and is therefore able to link the infected user with the (pseudonymous) identities of other users, whereas in the decentralized approach, the *TempID*s are generated individually by each tracing app. The determination of contacts can therefore only be performed by the actual tracing apps involved in an encounter. The tracing app conducts this by downloading the *TempID*s of infected users, e.g., U_i from *SP* and comparing these to the *TempID*s the tracing app has encountered in the past. This approach therefore effectively limits the exposure of sensitive information about encounters to *SP*.

In contrast to common belief, however, this difference does not directly guarantee "privacy by design" for decentralized systems and susceptibility to "mass surveillance" in centralized systems. The actual evaluation of these models highly depends on the underlying architectural decisions and on the various threat models considered.

Due to space constraints, we refer the reader to Sect. IV of our technical report [8] for a systematization and discussion of state-of-the-art contact tracing schemes.

C. Technologies to Determine Encounters

In general, there are two types of technologies to determine encounters: (1) location-based technologies such as GPS and QR-codes used for venue check-ins and (2) peer-to-peer proximity detection-based technologies like Bluetooth, Ultra-wideband (UWB), and ultrasound. Currently, Bluetooth is the most dominant technology deployed in contact tracing. Therefore, in the following, we focus on Bluetooth technology and refer the reader to Sect. II.B of [8] for the detailed discussion of other technologies.

Bluetooth Low Energy (BLE). BLE can be used for sensing the proximity between individual users' devices, e.g., [3], [9]. Indeed, many recent approaches for contact tracing on smartphones use Bluetooth proximity detection. The participating smartphones beacon out information like temporary identifiers (*TempID*s) that can be sensed by other devices. In addition, also related metadata like the signal strength of the beacon may be recorded. Using the signal strength information, some approaches seek to provide estimates about the distance of the encounter. However, it has been shown that signal strength can provide only a very rough estimate about the actual distance of devices, as it is influenced by other factors like device orientation and surrounding structures [10]. Nevertheless, since BLE is widely available on most recent smartphone versions, it seems the most viable alternative for implementing proximity detection on smartphones that are widely used by the population in many countries.

Compared to GPS and QR-code based approaches, BLE would seem to reveal the least amount of information about the users because *HA* and *SP* do not collect physical locations as well as actual encounter times. Thus, only anonymized random strings are shared among the apps using BLE. However, BLE-based approaches still have several security, privacy, effectiveness, and ethical problems. For example, they are susceptible to fake exposure injection attacks, e.g., relay attacks, or user profiling, e.g., movement tracking and user identification. We will elaborate all of these problems in detail in Sect. V.

III. Requirements for DCT Systems

As mentioned above, digital contact tracing (DCT) schemes need to collect information about infected individuals. Although many countries have deployed contact tracing apps, the effectiveness of DCT is so far still unclear. Moreover, DCT poses a number of privacy and security challenges on the underlying scheme design, since it collects and processes sensitive information which is related to users' health and users' contacts to some extent. In this section, we systematically consider the requirements for DCT based on four pillars: effectiveness, privacy, security, and ethical aspects. These requirements are broken down and listed in Tab. II. Next, we will discuss each of them in detail.

A. Effectiveness

In the following, we discuss three sub-requirements for the effectiveness of a DCT system, namely, *Accuracy*, *Superspreader*, and *Accountability*.

1) Accuracy (R-Ef1): For accurately estimating the risk of contagion it is necessary to estimate the duration of each contact (in minutes) along with a good estimate of the distance between the users involved in the encounter. The duration of contacts ideally could be detected by continuously scanning

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for the presence of BLE devices in proximity to verify the continued presence of other devices. This aggressive approach will, however, lead to significant energy consumption draining the smartphone battery quickly. In practice, one needs therefore to pause the scanning for several seconds before the next scan to preserve energy. Computing a good estimate of the distance between devices is even more challenging since there are multiple factors (e.g., positioning of the antenna in the smartphone, obstacles in between smartphones, and their orientations) that introduce significant errors to distance estimates. Indeed, experiments performed by Leith and Farrel [10] showed that GAEN is quite imprecise in estimating the distance of devices of potential at-risk exposures.

2) Superspreaders (R-Ef2): The mere capability of detecting at-risk exposures was initially considered sufficient by many endorsers of decentralized systems like, e.g., the team around the influential DP-3T [11] contact tracing approach, which also had a considerable influence on the GAEN design adopted by Google and Apple. However, along the way, more epidemiological insights about the behavior of SARS-CoV-2 have been discovered. Among them is the fact that a very relevant aspect for understanding the spread of the virus is the important role of so-called *superspreaders*. Indeed, Reichert et al. [12] showed that while there is a large percentage of infected individuals that do not transmit the virus at all, there is a small fraction of infected individuals that instead are very contagious and cause numerous further infections. A DCT system aiming at effectively defeating SARS-CoV-2 should therefore also take into account the importance of superspreaders and provide mechanisms allowing to detect them and their potential contacts.

Contagious asymptomatic infected individuals (CAIIs). Particularly problematic are so-called asymptomatic infected individuals, i.e., persons that are infected and contagious, but asymptomatic and thus may unwillingly spread the disease. Such individuals have a very low chance of being tested positive since they do not show any symptoms of being sick and therefore will not likely seek to be tested. Even if they want to be tested, in many countries, they will not be prioritized in testing. Hence, they can have an active role in spreading the virus. However, as such individuals are unlikely to be tested and receive a positive diagnosis from *HA* (which is a prerequisite for uploading information about contacts to the service provider *SP*), it is unlikely that such persons will ever be able to use the DCT system to warn other users about possible at-risk contacts with them.

3) Accountability (R-Ef3): Implementing, deploying, and operating a DCT system can be very costly and requires a majority of the population to participate in its operation. Therefore, the system should provide adequate and valid information about its effectiveness in a privacy-preserving way. For example, the system should be able to provide basic statistics about the number of active users, infected users, users notified about potential at-risk exposures, as well as false positive rates, etc. At a minimum, the system should be able to demonstrate clear benefits in comparison to a purely random selection of users to be quarantined in specific at-risk groups (e.g., where the infection rate is higher) [10]. Although some GAEN-based apps do provide reports on some measures related to the system's effectiveness, such measures can be biased, unreliable or misleading [13], [14] as we will discuss in Sect. V.

B. Privacy

The main privacy concerns relate to the abuse of a DCT in order to *identify* users, *track* users, or *extract the social graph* of users. Information that is emitted to the user's surroundings by contact tracing apps and shared with other involved parties should not introduce such privacy risks as elaborated next.

1) Identifying users (R-P1): DCT systems aim at identifying encounters, not users. Therefore, the systems should not leak any information that can be used to establish the true identity of any individual user.

2) Tracking users (R-P2): DCT apps work by continuously beaconing pseudonymous identifiers into their surroundings. These identifiers should not be linkable, i.e., it should not be possible to trace the movements of any user over time, as this may potentially enable to deduce facts about the user's behaviour and lead to an identification of the user.

3) Extracting the social graph (R-P3): In general, contacts (especially long encounters), are often related to social relationships (i.e., users that decide to be close to each other). When handling contact information, a DCT system should make sure that one cannot abuse information collected by it to generate a relevant part of the social graph of any user, since this may enable to draw conclusions about social relationships between users and thus potentially identify them.

Note: Obviously, there exists in some cases inherent information leakage due to specific circumstances, e.g., in situations in which the adversary is in the proximity only to one specific person. If the adversary later receives an at-risk notification, it will be trivial for the adversary to conclude that this one person is indeed the infected person. Therefore, when considering the above three privacy requirements, we will always focus on *large-scale attacks* and will in particular focus on identifying attacks affecting potentially many users.

C. Security

The effectiveness of a DCT system is severely impacted if a system is not resilient to large-scale data pollution attacks. Such attacks can generate, for instance, false at-risk notifications (false positives) therefore jeopardizing the correctness of the contact tracing system. Indeed, massive false at-risk notifications could result in spreading panic among the general population. Moreover, this could also cause unnecessary strain on the health system through unnecessary testing and negative impact on the society due to unnecessary self-quarantining.

1) Fake exposure claims (R-S1): The system should prevent a malicious or dishonest user $\mathcal{A}^u$ that aims to circumvent the DCT system to claim that he or she has encountered an infected user. There can be different motivations for this attack: (i) $\mathcal{A}^u$ aims to harm the reliability of the system by manipulating encounter checking results, (ii) $\mathcal{A}^u$ uses the fake exposure status as an excuse to stay at home instead of going to work or participating in an event, and (iii) $\mathcal{A}^u$ intentionally

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shares wrong encounter information to epidemiologists, thus sabotaging their analysis of the epidemiological situation.

2) Fake exposure injection - Relay/replay attacks (R-S2): This attack aims to inject fake contacts on a large scale resulting in many false exposure notifications. Here, a fake contact indicates the state that the DCT system incorrectly determines that two users were in "close contact" at a specific time although they were not. It affects the main goal of DCT system as to identify contacts that potentially cause high exposure risks. Relay attacks are a typical example of fake exposure injection attacks. In a relay attack, the adversary captures the temporary IDs of a user U_i and broadcasts them in other locations (e.g., other cities). As a result, the system incorrectly identifies the users in the other locations who captured those temporary IDs to have encountered U_i.

D. Ethics

1) Transparency and voluntary participation (R-Et1): The whole process (design, development, deployment, and operation) of a contact tracing system must be transparent to users and the systems must be removed immediately when the pandemic is over to avoid misuse. Further, users should be free to decide whether they want to participate in the system or not, and be free to withdraw their participation anytime they wish. Otherwise, users will not trust, and thus will not be willing to use DCT apps. This will affect the crucial need of a high adoption rate of DCT.

2) Independence (R-Et2): The contact tracing process (design, development, deployment and operation) in a particular region should be independent of any parties with potential vested interests. Procedural controls of the contact tracing system should underlie a transparent public scrutiny and be solely under the control of democratically-elected governments. In particular, giant technology corporations (e.g., Mobile OS vendors) should not be allowed to use their technological or market dominance to control or drive DCT systems since they might be biased in it for the sake of their own subjective benefits, e.g., using DCT data for business purposes could undermine the de-facto ability of legitimate governments to oversee the use of data collected for contact tracing purposes.

TABLE II: List of requirements for digital contact tracing.

	Requirement	Description
	Effectiveness	
R-Ef1	Accuracy	Specifying distance and duration of encounters
R-Ef2	Superspreader	Identifying superspreaders and their contacts
R-Ef3	Accountability	Providing statistics to evaluate the actual effectiveness
	Privacy	
R-P1	Identifying users	Users should always remain anonymous
R-P2	Tracing users	Users should not be tracked
R-P3	Extracting social graph	Making sure that no social graph can be extracted
	Security	
R-S1	Fake exposure claim	Preventing malicious users to lie about their exposure status
R-S2	Fake exposure injection	Preventing relay/replay attacks
	Ethics	
R-Et1	Transparency and voluntary use	The system must be transparent and based on voluntary use
R-Et2	Independence	Ones should not be allowed to use their technological or market dominance to control DCT systems in their favour

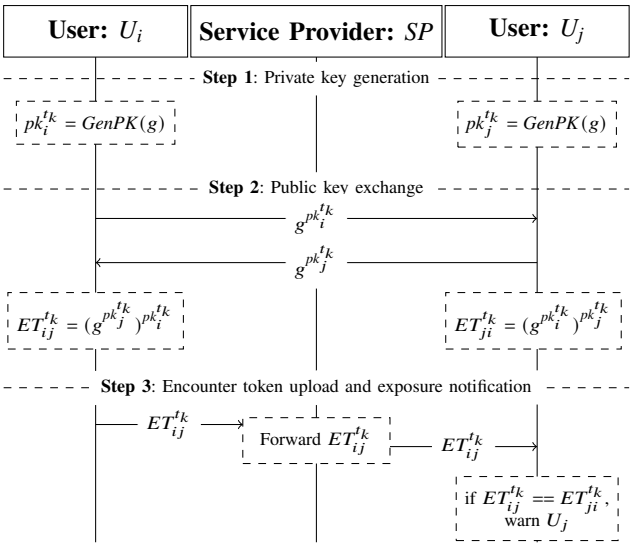

Fig. 2: Generic framework of DH-based Approaches.

IV. Proposed Approach - TraceCORONA

In this section, we first provide a generic framework for Diffie-Hellman (DH)-based schemes. We then present our novel scheme, TraceCORONA, a fully fledged example of a DH-based approach and highlight its benefits compared to the prominent approaches analyzed in Sect. V.

A. Generic framework of DH-based approaches.

The core idea of decentralized approaches based on asymmetric key cryptography like Diffie-Hellman is that two users establish a *unique and secret* Encounter Token (ET) using a key exchange protocol when they are in proximity by exchanging short-lived random public keys via BLE. In this paper, we use Diffie-Hellman as a key exchange protocol. Figure 2 shows an overview of the use of DH-based encounter tokens in a contact tracing scheme. In **Step 1**, users U_i and U_j generate their own private keys $pk_i^{t_k}$ and $pk_j^{t_k}$ respectively for each time interval t_k that is changing every T (e.g., 15) minutes. These private keys are used to derive corresponding public keys $pubk_i^{t_k} = g^{pk_i^{t_k}}$ and $pubk_j^{t_k} = g^{pk_j^{t_k}}$. In **Step 2**, the public keys are exchanged via BLE when two devices are in vicinity. For encounters surpassing a specified minimal duration, e.g., 5 minutes, an ET will be calculated, e.g., U_i calculates $ET_{ij}^{t_k}$ from U_i's private key $pk_i^{t_k}$ and U_j's public key $pubk_j^{t_k}$ as follows: $ET_{ij}^{t_k} = (g^{pk_j^{t_k}})^{pk_i^{t_k}}$. Since U_i and U_j never share their private keys, only they can know their secret encounter token $ET_{ij}^{t_k}$. It is worth noting that the DH key generation and encounter token calculation processes do not

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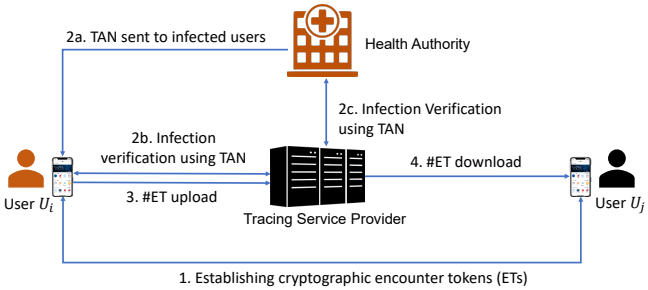

Fig. 3: TRACECORONA system overview.

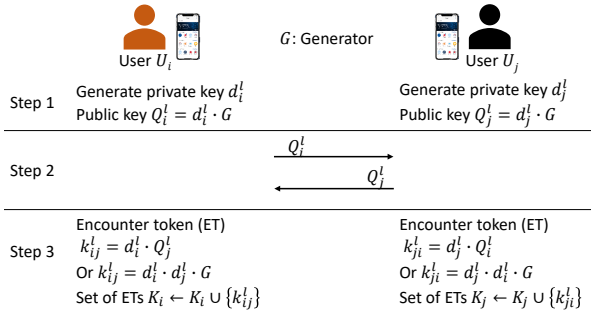

Fig. 4: Elliptic-curve Diffie–Hellman (ECDH)-based encounter token establishment.

need to happen on-line. For saving battery, it can be deferred to the next time when the smartphone is being charged. In **Step 3**, when a user (e.g., U_i) is tested positive for COVID-19, U_i sends its encounter token $ET_{ij}^{t_k}$ to the *SP* which will forward $ET_{ij}^{t_k}$ to other users. Once U_j receives $ET_{ij}^{t_k}$, it will compare $ET_{ij}^{t_k}$ to the ETs it has calculated. If $ET_{ij}^{t_k}$ is equal to $ET_{ji}^{t_k}$, U_j is notified that it has encountered an infected user.

Although we use the well-known DH-based approach for illustrative purposes, any other two-party key-exchange protocols where parties send only one short message to each other are applicable. Thus, existing proposals like CleverParrot [15], PRONTO-C2 [16], and Epione [17] use Elliptic-curve DH (ECDH). Further, these approaches provide several modifications and optimizations to improve the effectiveness, security and privacy of the system (cf. Sect. VI-A).

B. Limitations of DH-based approaches

Our proposed approach TRACECORONA seeks to address three technical limitations of DH-based approaches as follows:

- **Size restriction of BLE beacon message.** Since public keys are in general too big for BLE beacon messages, existing solutions apply workarounds, e.g., PRONTO-C2 needs to handle a bulletin board, or CleverParrot has to reduce the key size and requires operating systems to enable special BLE advertising messages.
- **Sharing encounter tokens ETs.** Uploading ETs directly may raise privacy risk. Hence, we aim to keep ETs always secret.
- **No time window restriction.** Existing approaches do not limit limit time window that would open opportunity for two-way relay attacks.

In the following, we will present TRACECORONA and discuss how we address those limitations in detail.

C. TRACECORONA Design

1) System Overview: Our design follows the system model (cf. Fig. 1) and the generic framework for DH-based schemes shown in Fig. 2. An overview of the basic usage scenario of TRACECORONA is shown in Fig. 3. For a discussion on complementary application scenarios like wearable devices and private contact tracing please refer to Appendix C of [8].

The functionality of TRACECORONA can be divided into four phases: (1) Encounter token establishment, (2) infection verification, (3) token information upload, and (4) token information download and contact verification. Next, we will describe each of these phases in detail.

2) Encounter Token Establishment: TRACECORONA App uses BLE as a proximity communication protocol to advertise a random ephemeral identifier to other devices in the environment and to scan for the identifiers of other apps. Once an ephemeral identifier of another app has been observed for a minimum duration (e.g., 5 minutes), a connection over BLE to the other app is opened and an Encounter Token (ET) is established using the Elliptic Curve Diffie-Hellman (ECDH) key exchange protocol. Figure 4 shows the token establishment protocol in detail for two users U_i and U_j. Following typical ECDH notation, let Q denote the public key, d the private key and G the generator. Let T denote the period of a rolling key time frame and l be the index of the time frame $f^l = [l*T, (l+1)*T]$. Let K_i and K_j be the sets of ETs of users U_i and U_j, respectively. Let k_{ij}^l be an ET established between two user Apps U_i and U_j at time point t_{ij}^l, i.e., a timestamp falling in time frame f^l. The process of establishing an ET is then as follows:

1) **Step 1:** For every time frame f^l, users U_i and U_j generate a ECDH keypair including private keys d_i^l and d_j^l, and public keys $Q_i^l = d_i^l * G$ and $Q_j^l = d_j^l * G$, respectively, where G is the generator defining the used cyclic subgroup of the elliptic curve.
2) **Step 2:** U_i and U_j exchange their public keys Q_i^l and Q_j^l via Bluetooth LE.
3) **Step 3:** Each user calculates the encounter token based on its private key and the received public key. In particular, U_i calculates $k_{ij}^l = d_i^l * Q_j^l$ while U_j calculates $k_{ji}^l = d_j^l * Q_i^l$. Obviously, $k_{ij}^l = k_{ij}^l = d_i^l * d_j^l * G$. Each user then adds the encounter token into its encounter token set: $K_i \leftarrow K_i \cup \{k_{ij}^l\}$ for U_i and $K_j \leftarrow K_j \cup \{k_{ji}^l\}$ for U_j. After k_{ij}^l is established, U_i and U_j continue exchanging their ephemeral identifiers periodically to monitor the duration D_{ij}^l of the encounter and the strength of the Bluetooth signals S_{ij}^l (which roughly correlate with how far or near two users are from each other). In summary, the data recording the start of the encounter t_{ij}^l, the duration of the encounter $D_{k_{ij}^l}$ and the strength of the Bluetooth signal S_{ij}^l, are stored as metadata associated with token k_{ij}^l.

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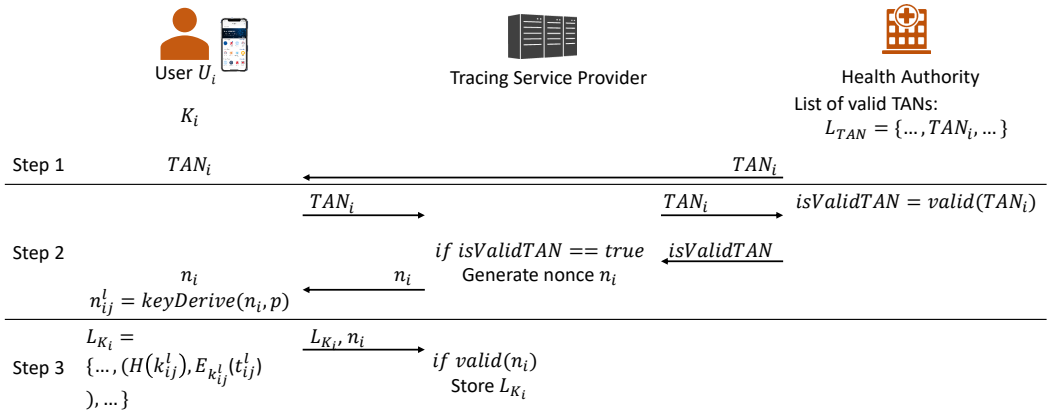
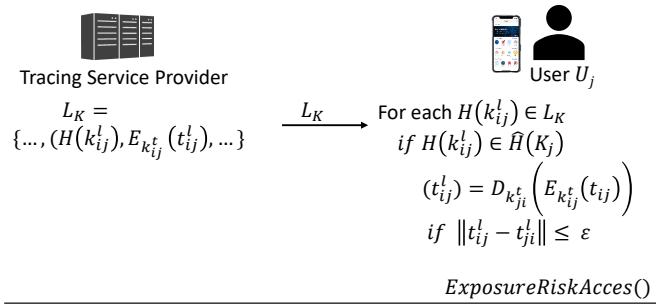


Fig. 5: Infection verification and encounter token upload.



L_K : The set of shuffled hashes and metadata of all encounter tokens of the infected users from the last update.

Fig. 6: Encounter Token Download and Exposure notification.

It is worth noting that in order to preserve battery lifetime, **Step 1** and **Step 3** can be done offline, i.e., when the smartphones are being charged (e.g., during the night).

3) Infection Verification and Encounter Token Upload: Since the main goal of the system is to notify users who have encountered infected users (tested positive for COVID-19), the system needs to make sure that only infected users can use the system to release their encounter tokens K. In our system, the Health Authority *HA* issues for each infected user a unique authentication code, a so-called Transaction Authentication Number (*TAN*). If an infected user wants to share their encounter tokens, it can use this *TAN* to prove its infection status by uploading the *TAN* along with their encounter token information.

Fig. 5 illustrates the infection verification and encounter token uploading phases. **In Step 1** and **Step 2** *HA* sends a TAN_i to infected user U_i. This can be done by using any appropriate out-of-band channel: in person, via SMS, via regular mail or via e-mail. TAN_i can also be sent along with the test results. The infected user can input their *TAN* directly by typing the number in or use their smartphone's camera to scan a QR code containing the *TAN*. **Step 3** shows how U_i can upload its encounter token information. Timestamp t_{ij}^l is encrypted using AES encryption using the encounter token k_{ij}^l as the key (or a key derivation function can be used to derive a key from k_{ij}^l). Let $m_{ij}^l = E_{k_{ij}^l}(t_{ij}^l)$ denote the encryption of t_{ij}^l. U_i sends TAN_i and a list L_{K_i} consisting of the m_{ij}^l along with corresponding hashes $h_{ij}^l = H(k_{ij}^l)$ of the encounter tokens k_{ij}^l to server *SP*. We have thus $L_{K_i} = \{\ldots, (m_{ij}^l, h_{ij}^l), \ldots\}$. *SP* forwards TAN_i to *HA* to verify whether TAN_i is valid or not. If TAN_i is valid, it will extract and store each element (m_{ij}^l, h_{ij}^l) of L_{K_i} separately.

It is worth noting that TRACECORONA provides both usability and privacy benefits by enabling infected users to remove specific unnecessary or sensitive encounter tokens that, e.g., (1) had only a short duration, thus being not essential for contracting the disease, or, (2) happened at a time or place that users do not want to disclose even anonymously, e.g., at a sensitive event or meeting.

4) Encounter Token Download: All TRACECORONA Apps download regularly, e.g., every night, encounter token information from server *SP* to identify potential exposure risks. Figure 6 shows the encounter download protocol. Let $L_k = \{\ldots, (H(k_{ij}^l), E_{k_{ij}^l}(t_{ij}^l)), \ldots\}$ be the list of the hashes and metadata of all encounter tokens of all infected users since the last update. To avoid linking entries related to a particular infected user together based on their position in the list, all entries in L_k are shuffled before sending them to users. Once a user U_j receives L_k, it compares the received token hashes to its own token hashes to discover matching encounters. If a matching encounter hash, e.g., $H(k_{ij}^l)$ is identified, U_j decrypts the matching encounter token metadata using the associated encounter token k_{ij}^l as the key: $t_{ij}^l = D_{k_{ji}^l}(E_{k_{ij}^l}(n_i||t_{ij}^l))$. U_j then checks the validity of encounter token w.r.t. to encounter time t_{ij}^l to make sure that k_{ij}^l and k_{ji}^l were established during the same time frame. This will limit the time-window available for a relay attack as we will discuss in Sect. V-C. Assuming that the clocks of the two devices are deviating by at most ϵ seconds, if $|t_{ij}^l - t_{ji}^l| \leq \epsilon$, k_{ij}^l and k_{ji}^l are considered to have been derived at the same time, i.e., the matching of k_{ij}^l and k_{ji}^l is valid. The system then uses metadata information, e.g., the time of the encounter t_{ij}^l, the duration of the encounter $D_{k_{ij}^l}$ and the signal strength S_{ij}^l to assess the risk of this exposure.

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TABLE III: Useful information for epidemiological analysis and evaluation and optimization of a DCT system.

Number of active users
Number of infected users
Number of encounters of infected users
Number of affected users
Number of encounters of affected users
True positive rate
Importance of notification [5]
Distribution of risk score
The correlation between risk score and true positive rate

D. Hybrid Approach

In the following, we will present a hybrid approach that provides a trade-off between the effectiveness and the privacy requirements of centralized and decentralized architectures, i.e., maximizes effectiveness of the app while preserving privacy of the users. As discussed in Sect. III-A3, the accountability requirement (R-Ef3) refers to the possibility to evaluate the effectiveness of a DCT scheme. Therefore, we focus on this requirement by specifying what kind of data are needed to satisfy it and how they can be submitted to the health authority *HA* and the tracing service provider *SP*.

1) Useful data: To fulfill the requirement R-Ef3 (Accountability), the App needs to send authentic, but anonymized data in a privacy-preserving way to *SP*. Table III shows potentially useful types of data that can help to evaluate and optimize the DCT system. Such types of data can also be helpful to epidemiologists and decision makers to understand the virus spreading patterns and, e.g, deploy effective policies to limit the pandemic.

2) Sharing Epidemiological Information with Health Authorities: As discussed in the previous section, a direct contact U_j can prove it exposure status with an infected user (U_i) based on the possession of the secret value of the encounter token ET_{ij}. TRACECORONA utilizes this to authenticate the correctness of exposure information that users may voluntarily want to share with health care research institutions, thereby preventing malicious users from corrupting the data by providing faked exposure information to the researchers. This helps in improving the accuracy and correctness of the epidemiological modelling used as as basis for political decision making in the crisis situation.

3) Sharing Epidemiological Information via Healthcare Professionals: Since healthcare professionals like doctors collect information about their patients that come for a COVID-19 test or for consultation for their symptoms, doctors can act as a source of reliable information for epidemiological analysis in a properly anonymized form. For example, the healthcare professional could provide for each patient following anonymous information to help in assessing the epidemiological situation as well as the effectiveness of the contact tracing system: whether the user was notified by the contact tracing app and what the possible risk score was, whether the user knew about a potential exposure status even before being notified by the app, possible symptoms, and the test result. These kind of data provided to the epidemiological analysis do as such not reveal any information about the true identity of individual patients, but they do provide crucial information necessary to evaluate the effectiveness of the contact tracing app.

[5]Exposure notification from a DCT is less important if users already knew their exposure status before being notified by a DCT app, e.g., the affected users who live in the same household to an infected users are expected to be informed immediately when the test result is available.

E. Implementation and Beta Test

We prototyped TRACECORONA for the Android smartphone platform and tested it in a public beta test. We have not implemented TRACECORONA on iOS because it does not allow apps to use Bluetooth communication in the background [18]. We use the native Android BLE APIs to implement the Encounter Token Establishment protocol. Further, our cryptographic functions, e.g., ECDH are based on the Bouncy Castle library. For the server acting as *SP*, the code is written in Java and run on Ubuntu Server operating system. In principle, our app can run on any Android smartphone that supports Bluetooth LE, i.e., Android 5.0 and later.

Alpha testing. We internally tested the app with 25 devices covering various models and manufacturers. The results show that our app works without any problems and consumes 5 to 8% battery for a whole day (24 hours) of contact tracing without further optimizations.

Beta test. We published the TRACECORONA app on our website and interestingly the app has drawn a lot of attention[6]. Indeed, more than 2000 users have downloaded and tested the app. We have received many positive feedbacks on the app features and performance, except received criticism that the app does not work on very old devices that do not support Bluetooth LE. However, this is a technical limitation that is out of our control.

Implementation on wearable devices. To demonstrate the possibility of deploying TRACECORONA even on on wearable devices like wristbands a MCU developer board that costs about US $20 (For a full description please refer to Appendix C of our full technical report [8]), we have implemented our design on Adafruit HUZZAH32 (ESP32).

V. SECURITY AND PRIVACY ANALYSIS OF TRACECORONA

In this section, we will analyze DH-based approaches in general and TRACECORONA in particular in comparison to GAEN and BlueTrace with regard to requirements laid out in Sect. III. Due to space constraints, we refer the reader to Sect. V of our full technical report [8] for detailed discussion on the shortcomings of state-of-the-art contact tracing schemes including BlueTrace [9] and GAEN [3].

A. Effectiveness

Accuracy. As discussed in Sect. III-A1, measuring the distance between smartphones using BLE is not very reliable due to its the inherent technical limitations. Hence, we note that all approaches based on BLE-proximity sensing share the same challenge of not being able to reliably estimate the distance between devices involved in a contact. Therefore, none of

[6]https://tracecorona.net/download-tracecorona/

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BLE-based approaches can entirely fulfill the Accuracy requirement R-Ef1. One potential solution to increase distance measuring accuracy could be using BLE in combination with other sensors like ultra-wideband (UWB) (cf. Sect. II-C of [8] for the details).

Superspreader. Although the Tracing Service Provider *SP* only receives anonymous encounter tokens that are not sufficient to detect Superspreaders and CAII users, the contact tracing App itself can be used to warn its user in case the App identifies a large number of contacts with other infected users, since this can be an indication that actually the user itself is a Superspreader or CAII who has been the source of contagion for those infections. As a result, the user could seek immediate testing, but also immediately upload their encounter tokens to warn others. Further, the App can prove the user's status as a suspected Superspreader or CAII to *SP* by uploading the secret encounter tokens it has in common with infected users. By verifying these against the published hashes of encounter tokens of infected users the *SP* can verify that the user is indeed a person with many contacts with infected people and therefore a possible Superspreader. The *SP* can then tag the encounter tokens of the user accordingly, so that exposure notifications related these tokens can additionally be marked as being related to a 'possible superspreader' contact. Hence, requirement R-Ef2 related to the ability to identify Superspreaders can be successfully addressed.

B. Privacy

In DH-based systems, the public keys change every 15 minutes. This means that an eavesdropper adversary $\mathcal{A}^e$ cannot link public keys of a user, i.e., $\mathcal{A}^e$ can only track the movement of a user for less than 15 minutes, which is not enough to build informative movement profiles of the user.

Surveillance. Like other decentralized BLE systems, this attack fails against DH-based systems since the matching of contacts is done exclusively by the Apps. A malicious service provider $\mathcal{A}^s$ does not benefit from learning the ETs of infected users since the uploaded encounter tokens do not reveal any information about the counterparts of those encounters.

Mass Surveillance. In TRACECORONA, even if a malicious service provider $\mathcal{A}^s$ colludes with an eavesdropper $\mathcal{A}^e$, the adversaries only get to know the hashes of encounter tokens of infected users and possible locations where $\mathcal{A}^e$ has collected them. However, as discussed in Sect. IV-B, since $\mathcal{A}^e$ can obtain ETs only through direct interaction with the monitored users and ETs are created only if encounters last for a specific time (e.g., 5 minutes), $\mathcal{A}^e$ is much more limited in its ability to obtain ETs associated with other users. In particular, $\mathcal{A}^e$ will be unable to establish *any* ETs with users that are just shortly passing by an eavesdropping station, so that the adversary's ability to track the movements of infected users is very limited. It is to be noted that this is a significant difference existing approaches (cf. Sect V of [8]), since in these approaches the ability of the eavesdropping adversary $\mathcal{A}^e$ is in this sense unlimited and it can effectively sense the presence *all* users passing by its eavesdropping stations, even based on *one single observation* of the user.

In the case of malicious service provider $\mathcal{A}^s$ (i.e., the service provider *SP* is dishonest), $\mathcal{A}^s$ could link encounter tokens ETs of a specific infected user since the tokens would be submitted in one transaction when they are uploaded to the service provider *SP*. One solution to prevent this threat is to apply appropriate anonymization (privacy) techniques, e.g., blind signatures with an anonymous postbox service [19] or private set intersection [17] to the upload process of encounter tokens. We discuss such advanced privacy techniques in details in Appendix B of [8]. In particular, these techniques minimize the risks that neither malicious service provider $\mathcal{A}^s$, health authority HA nor any party can link individual encounter tokens of infected users, thereby limiting the trackability of individual users to relatively short time frames of, e.g., 15 minutes. Therefore, by applying such techniques, TRACECORONA can effectively address the requirements regarding providing protections against identifying (R-P1) and tracking (R-P2) users and extracting their social graphs (R-P3).

C. Security

Next, we will explain how DH-based systems can mitigate current attacks, hence, fulfill the security requirements.

Fake exposure claim. DH-based systems can mitigate fake exposure claims (requirement R-S1). As mentioned in Sect. IV, infected users only share the hashes of encounter tokens meaning that the values of the encounter tokens themselves are always kept secret, so that only users actually participating in the encounter obtain the corresponding encounter token. Therefore, by proving possession of the (secret) encounter token, a user can prove that a contact with the counterpart has in fact taken place. The only way a dishonest user $\mathcal{A}^u$ can make fake exposure claims is to obtain access to the phones of users having matching encounter tokens and extracting them. However, this attack requires compromising individual devices one-by-one and hence cannot be easily scaled.

Relay/Replay Attacks. These attacks aim to inject false exposure notifications *on a large scale*. Unfortunately, widely adopted approaches like BlueTrace and GAEN are vulnerable to various relay attacks [5], [13], [7], [20], [21]. For example, Baumgärtner et al. [5] have demonstrated a real-world relay attack on GAEN in two cities (Frankfurt and Marbug) in Germany. They show that the adversary can capture and relay $tempID$s among those cities. They estimate that the attack can inject about 76 $tempID$s from infected users to a mobile device within 15 minutes. Principally, all proximity-based approaches are vulnerable to such attacks. However, DH-based systems provide two effective mitigation techniques that reduce the window of opportunity for attackers: (i) *two-way communication* is required for establishing contact tokens, prohibiting massive abuse by just copying and broadcasting beacon information, and (ii) using *limited time windows* for validating the timestamp of an encounter.

Two-way communication. In contrast to existing approaches [3], [11], [22], [23], [9] that are vulnerable to *one-way* relay attacks (cf. Sect. V [8]), DH-based schemes utilize a *handshake* protocol requiring *two-way* communication to establish an encounter token. This means $\mathcal{A}^w$ cannot simply capture

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the beaconed information in one place and broadcast it in many other places like it would be possible in other schemes. $\mathcal{A}^w$ has to capture and relay messages at both places at the same time. This not only limits the time window of the attack but also imposes a restriction on the scale of the attack since a mobile device cannot communicate with too many other devices at the same time due to the limited number of channels and bandwidth that Bluetooth LE provides. Based on our estimation, an average smartphone can only handle 8 Bluetooth LE connections simultaneously in a reliable manner. Therefore, in theory $\mathcal{A}^w$ can relay the handshake of one device to at most 8 other remote devices, while this number is not limited in other approaches.

Limited time window. In DH-based schemes, two users U_i and U_j in proximity of each other establish a unique secret encounter token ET_{ij}. An infected user U_i can use ET_{ij} to encrypt any meta-data that only U_j can decrypt. Leveraging this property, in a DH-based scheme, e.g., TRACECORONA, the exact timestamp of an encounter can be encrypted and added to encounter token metadata so that user Apps checking encounter tokens can also check the exact encounter time. Therefore, only matching encounters that took place within a time window of at most ϵ seconds are considered as valid encounters, thereby limiting the window of opportunity for relay attacks. Other decentralized schemes like [3], [11], [23] cannot impose such limitations on the timestamps of ephemeral IDs, because the involved tracing apps can not mutually verify the actual time point of when contacts take place due to the fact that only one-way communication is used. Due to this, the GAEN API [24] allows a two-hour time window for synchronizing *RPI*, i.e., $\mathcal{A}^w$ can have up to two hours to conduct relay attacks. In DH-based schemes, this ϵ could be limited to seconds when assuming that smartphones used for contact tracing apps can sync their clocks via an Internet connection or during the exchange of the public keys. Note that all contact tracing apps need a frequent Internet connection for uploading and downloading encounter information.

Therefore, the combination of these two advantages, requirement of two-way communication and small time window help DH-based schemes such as TRACECORONA to significantly reduce the impact of relay attacks on the system.

D. Ethics

Like BlueTrace, DH-based systems like TRACECORONA can be implemented with complete access to the source code, guaranteeing transparency. It is a standalone app that does not depend on any built-in contact tracing APIs running deep inside the mobile operating systems such as Android or iOS, thus satisfying requirements with regard to transparency and (R-Et1) and independence (R-Et2). This is in stark contrast to proprietary and closed GAEN systems strictly enforced by Google and Apple. Especially in Apple's iOS systems independent contact tracing applications that continuously need to use BLE in the background are blocked by the operating system so that effective BLE sensing as required by contact tracing apps is in practice not possible. Instead, Apple forces all contact tracing approaches to rely on their closed and proprietary GAEN API whose functionality can not be independently examined nor verified. It is therefore highly debatable, whether this approach is ethical, as Apple in fact forces users into using their GAEN solution, having to involuntarily accept all possible related deficiencies, or, refrain from using contact tracing solutions at all. One solution to make DCT systems independent from mobile OS vendors w.r.t BLE and GAEN APIs is to use third-party wearable devices as discussed in detail in Appendix C of [8].

E. Summary of Benefits of DH-based Approaches and Comparison to Other Approaches

We summarize key differences and security and privacy advantages of DH-based systems in comparison to existing approaches in Tab. IV. As can be seen in the table, GAEN does not fulfill the requirements. The DH-based systems provide better security and privacy protection than all other discussed solutions. For example, DH-based approaches are resilient to fake exposure claim attacks and wormhole adversary (i.e., narrowing the attack window time and requiring more communication effort as the adversary would have to operate real-time two-way communication relays). Moreover, comparing to the most widely spread contact tracing framework by Apple and Google, which is vulnerable to profiling attacks as the adversary can track the movements of infected users, DH-based systems guarantee a better protection. Interesting but not surprisingly, BlueTrace is the best w.r.t to fulfilling effectiveness requirements since it can potentially detect Superspreader and CAII and provide useful data to epidemiologists while this could be challenging to other approaches. In terms of ethics, GAEN again is on the lower end because it received many criticisms due to their coercion and the lack of transparency. More importantly, our hybrid approach inherits the advantages of DH-based approaches in terms of security and ethical aspects, while being on par with centralized approaches with regard to effectiveness.

VI. RELATED WORK

A. DH-based approaches

PRONTO-C2 [16]. The main problem of DH-based approach is that the size of the public key might exceed the space limit of BLE advertising messages. The minimum requirement for a standardized ECDH key is 256 bits (or 384 bits to provide security against a powerful adversary) while in a typical BLE advertising message there is space for 128 bits only. PRONTO-C2 stores the public keys on a bulletin board that can be maintained by the *SP* or can be decentralized, and implemented with a blockchain. Hence, instead of broadcasting the public keys via BLE, the devices only beacon the references (i.e., addresses) of the keys in the bulletin. When a user is infected, a cryptographic hash of encounter tokens is uploaded to the bulletin board. As discussed in Sect. IV-B, TRACECORONA solves this problem by utilizing BLE connections to transfer public keys without any data restrictions.

CleverParrot [15]. To deal with the issue of fitting a DH public key in a BLE advertising message, CleverParrot proposes using a minimum key size of 224 bits (28 bytes) based on the

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TABLE IV: The advantages of DH-based approaches in comparison to state-of-the-art approaches. (*) on the user side. (**) Possibly only infected users. (***) prevent one-way and limit real-time two-way attacks. +/- means achieve/not achieve corresponding requirements.

	Centralized	Decentralized		
	BlueTrace/ PEPP-PT/ TousAntiCovid	GAEN/ DP3T-1	DP3T-2/ MIT-PACT/ UW-PACT	TraceCORONA/ Pronto-C2/ CleverParrot
User identifier	Phone number /App ID	Random keys	Random keys	Random keys
Life-time of initial keys	Long-lived	Daily	Short-Lived	Short-lived
Superspreader	+	-*	-*	+*
CAII	+	-*	-*	+*
Identifying users	-	-**	+	+
Tracking users	-	-**	+	+
Extracting social graph	-	-**	+	+
Fake exposure claim	-	-	-	+
Relay attack	-	-	-	+***
Transparency	+	-	+	+
Independency	+	-	+	+

elliptic curve P-224. They choose this key size since it is the same as the one use in Apple's Find My protocol. However, it is worth noting that is a special function in iOS. In fact, both Android and iOS support only 128-bit BLE advertising messages. Therefore, CleverParrot cannot be implemented in practice unless Google and Apple change their BLE platform or they have to adopt and treat CleverParrot as a special function like Apple's Find My.

DH with Private Set Intersection Cardinality (PSI-CA). Epione [17] leverages Function Secret Sharing (FSS) techniques [25] to prevent other users from learning information about the encounter tokens uploaded by infected users. In particular, this approach enables clients (user Apps) in collaboration with the servers *SP* to learn matching encounter tokens, i.e., U_j can know how many encounters with infected users it has without downloading these encounters.

B. Survey on existing DCT schemes, apps and challenges

There are a number of works that survey existing DCT schemes, apps and challenges. Those works can be categorized into two groups: (i) discussing technical specifications, operations and issues of the rolled out apps [26], [27] and (ii) studying certain aspects of some DCT schemes [28], [20]. Sun et al. [26] focus on investigating the security and privacy issues of DCT apps on Android. Wen et al. [27] vet privacy issues of 41 country apps that have rolled our worldwide, in which they focus on analysis of documentation but also binary code to figure out what data an app collects and discuss the potential privacy risks. Unlike those works that focus on the apps, Vaudenay et al. [20] focus on investigating the security and privacy issues of several schemes along with their architectures. The most relevent to our work is the study provided by Ahmed et al. [28]. They discuss 8 different potential attacks on 12 country apps divided in three groups: centralized, decentralized and hybrid architectures. However, those works do not provide an abstraction that groups evaluation requirements of similar schemes as we do in our work.

While existing works point out a number of privacy problems of GAEN [20], [14], [29], [5], Ahmed et al. claim that GAEN protects privacy of users and criticize that existing attacks are unrealistic [30]. However, they do not provide arguments and evidence for their claim, i.e., it is not clear how GAEN can defend against such attacks. In fact, their main experiments only confirm the principal design requirements of GAEN like Randomness of Bluetooth addresses or RPI intervals that are also included in existing attack models [5], [11], [16], [13]. Unfortunately, the paper also gives some misleading information. For example, it states that: "in normal operation, the TEK downloaded are not readily available to the user and the exposure assessment is done away from the user." However, the uploaded TEK keys of infected users are in fact by design public information that is accessible to any moderately sophisticated adversary[7]. For a summary on existing works analyzing DCT, please refer to Tab. VIII of our full technical report [8].

VII. Conclusion

In this work, we propose TraceCORONA that addresses security and privacy challenges of existing contact tracing approaches while providing comparable effectiveness. In contrast to state-of-the-art approaches that are based on exchanging ephemeral IDs, TraceCORONA allows users to anonymously establish encounter-specific tokens using short-range wireless communication like Bluetooth. We systematically and extensively analyze the security and privacy of TraceCORONA in comparison to existing approaches in Sect. V to show that TraceCORONA is resilient to various attacks and thus provides better security and privacy guarantees than other approaches. We have implemented TraceCORONA and published a beta test version of TraceCORONA that has been downloaded and used by more than 2000 users without any major functional problems demonstrating that TraceCORONA is practical. In future work, we will explore approaches to improve the accuracy of distance measuring using ultra-wideband and privacy-enhancing techniques like

[7]An archive collecting *TEK*s of the German DCT App: https://ctt.pfstr.de/

blind signatures to prevent malicious service providers from linking encounter tokens of users.

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C

DÏOT: A FEDERATED SELF-LEARNING ANOMALY DETECTION SYSTEM FOR IOT

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DÏoT: A Federated Self-learning Anomaly Detection System for IoT

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***Abstract*—IoT devices are increasingly deployed in daily life. Many of these devices are, however, vulnerable due to insecure design, implementation, and configuration. As a result, many networks *already* have vulnerable IoT devices that are easy to compromise. This has led to a new category of malware specifically targeting IoT devices. However, existing intrusion detection techniques are not effective in detecting compromised IoT devices given the massive scale of the problem in terms of the number of different types of devices and manufacturers involved.**

In this paper, we present DÏoT, an autonomous self-learning distributed system for detecting compromised IoT devices. DÏoT builds effectively on device-type-specific communication profiles without human intervention nor labeled data that are subsequently used to detect anomalous deviations in devices' communication behavior, potentially caused by malicious adversaries. DÏoT utilizes a federated learning approach for aggregating behavior profiles efficiently. To the best of our knowledge, it is the first system to employ a federated learning approach to anomaly-detection-based intrusion detection. Consequently, DÏoT can cope with emerging new and unknown attacks. We systematically and extensively evaluated more than 30 off-the-shelf IoT devices over a long term and show that DÏoT is highly effective ($95.6\,\%$ detection rate) and fast ($\approx 257\,\mathrm{ms}$) at detecting devices compromised by, for instance, the infamous Mirai malware. DÏoT reported *no false alarms* when evaluated in a real-world smart home deployment setting.

***Index Terms*—Internet of Things; IoT security; IoT malware; anomaly detection; federated deep learning; self-learning**

I. Introduction

Many new device manufacturers are entering the IoT device market, bringing out products at an ever-increasing pace. This "rush-to-market" mentality of some manufacturers has led to poor product design practices in which security considerations often remain merely an afterthought. Consequently, many devices are released with inherent security vulnerabilities that can be exploited, which has led to an entirely new category of malware explicitly targeting IoT devices [1]–[4].

The preferred way to cope with vulnerabilities are security patches for the affected devices [5]. However, many devices lack appropriate facilities for automated updates or there may be significant delays until device manufacturers provide them, mandating the use of reactive security measures like intrusion detection systems (IDS) for detecting possible device compromise [6]–[9]. Signature-based IDSs look for specific communication patterns, so-called *attack signatures*, associated with known attacks. Such systems are, however, unable to detect novel attacks until the IDS vendor releases attack signatures for them [6].

To detect previously unknown attacks *anomaly detection* needs to be used which works by profiling the normal behavior of devices and detecting attacks as deviations from this normal behavior profile [7]–[9]. However, this approach often suffers from a high false alarm rate, making it unusable in practice. This problem is exacerbated in the IoT setting: First, there are hundreds of very heterogeneous devices on the market, which making it challenging to train a precise detection model covering all behaviors of various IoT devices. Second, IoT devices do typically not (notwithstanding a few exceptions) generate a lot of network traffic, as their communications are limited to, e.g., status updates about sensor readings or (relatively) infrequent interactions related to user commands. This scarcity of communications makes it challenging to train comprehensive models that can accurately cover the full behavior of IoT devices.

An effective anomaly detection model needs to capture *all* benign patterns of behavior to be able to differentiate them from malicious actions. The ever-increasing number of literally thousands of types of IoT devices (ranging from temperature sensors and smart light bulbs to big appliances like washing machines) and the typical scarcity of their communications, makes an all-encompassing behavior model 1) tedious to learn and update, and 2) too broad to be effective at detecting subtle anomalies without generating many false alarms.

Goals and Contributions. To tackle the above challenges we present DÏoT, a system for detecting compromised IoT devices. It uses a novel *device-type-specific* anomaly detection approach to achieve accurate detection of attacks while generating almost no false alarms. Major IoT device vendors, including Cisco, assisted us formulating real-world settings for our solution and usage scenarios.

We make the following contributions:

- DÏoT, a self-learning distributed system for security monitoring of IoT devices (Sect. II) based on *device-type-specific detection models* for detecting anomalous device behavior:
  - It utilizes a novel anomaly detection approach based on representing network packets as symbols in a language allowing to use a language analysis technique to effectively detect anomalies (Sect. III).

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  - It is the first system to apply a *federated* learning approach for aggregating anomaly-detection profiles for intrusion detection (Sect. IV).
- Systematic and extensive experimental analysis using more than 30 off-the-shelf IoT devices, showing that DÏoT is fast (detection in $\approx 257\,\mathrm{ms}$) and effective ($95.6\,\%$ true positive rate, *zero false alarms*, i.e., $0\,\%$ false positive rate) (Sect. VI).
- An *Attack* dataset of network traffic generated by real off-the-shelf consumer IoT devices infected with real IoT malware (Mirai [1]) using which we evaluate the effectiveness of DÏoT (Sect. V-A).

We will make our datasets as well as the DÏoT implementation available for research use.

II. System Model

Our system model is shown in Fig. 1. We consider a typical SOHO (Small Office/Home Office) network, where IoT devices connect to the Internet via an access gateway.

A. System Architecture

The DÏoT system consists of *Security Gateway* and *IoT Security Service*. The role of *Security Gateway* is to monitor devices and perform anomaly detection in order to identify compromised devices in the network. It is supported by *IoT Security Service*, which can be, e.g., a service provider like Microsoft, Amazon or Google that aggregates device-type-specific anomaly detection models trained by all *Security Gateway*s in the system.

1) Security Gateway: acts as the local access gateway to the Internet to which IoT devices connect over WiFi or Ethernet. It hosts the *Anomaly Detection* component. When a new device is added to the network, *Security Gateway* identifies its type as outlined in Sect. II-C. The *Anomaly Detection* component monitors the communications of identified IoT devices and detects abnormal communication behavior that is potentially caused by malware (Sect. III) based on anomaly detection models it trains locally and which are aggregated by the *IoT Security Service* to a global detection model.

2) IoT Security Service: supports *Security Gateway* by maintaining a repository of device-type-specific *anomaly detection models*. When a new device is added to the local network, *Security Gateway* identifies its *device type* and retrieves the corresponding anomaly detection model for this type from *IoT Security Service*. *IoT Security Service* also aggregates updates to device-type-specific anomaly detection models provided by the *Security Gateway*s in the system.

B. Adversary Model and Assumptions

Adversary. The adversary is IoT malware performing attacks against, or launching attacks from, vulnerable devices in the SOHO network. Hereby we consider all actions undertaken by the malware that it performs to discover, infect and exploit vulnerable devices as discussed in detail in Sect. V-A3.

Defense goals. The primary goal of DÏoT is to detect attacks on IoT devices in order to take appropriate countermeasures, e.g., by preventing targeted devices from being compromised or isolating compromised devices from the rest of the network. We aim to detect attacks at the earliest stage possible, preferably even *before* a device can be successfully infected.

In addition, we make following assumptions:

- **A1 - No malicious manufacturers.** IoT devices may be vulnerable but are not compromised when first released by a manufacturer. Adversaries must first find a vulnerability and a way to exploit it, which takes some time during which non-compromised devices generate only legitimate communications, leaving sufficient time (cf. Sect. VI-C) to learn benign models of device behavior.
- **A2 - Security Gateway is not compromised.** Since *Security Gateway* is the device enforcing security in the SOHO network, we assume that it is not compromised. Like firewall devices or antivirus software, if *Security Gateway* is compromised the SOHO network stops being protected by it. Several approaches can be used to protect it. For instance, if *Security Gateway* supports a suitable trusted execution environment, like Intel SGX [10] or trusted platform module, its integrity can be remotely verified using *remote attestation* techniques [11].
- **A3 - Automated identification of IoT devices.** A technique for automatically identifying and labeling IoT devices in the local SOHO network must be available. This technique should be implementable in the *Security Gateway* to identify IoT devices connected to it.

C. Device-Type Identification

As DÏoT uses device-type specific anomaly detection models, it requires the possibility to identify the *type of devices* in the network. Several solutions have been designed to automatically identify and label unknown IoT devices in a network [12]–[14]. Alternatively, manufacturer-provided explicit device-type specifications like MUD [15] or manual labeling of IoT devices could be used. For DÏoT, we selected an existing approach - AuDI [14] that autonomously identifies the *type* of individual IoT devices in a local network. This approach is accurate and fast (requiring only 30 minutes to identify device type at the accuracy of $98.2\,\%$). This approach considers *abstract device types* representing families of similar devices from the same device manufacturer with similar hardware and software configurations, resulting in highly identical communication behavior. It can be trained *without the need to manually label* communication traces of pre-defined real-world device types since it works by clustering device fingerprints so that each cluster can be automatically labeled with an abstract label, e.g., $type\#k$ which represents a specific IoT device type. It justifies our assumption A3 as mentioned above.

Using this approach we can reliably map devices to a corresponding *device type* for which DÏoT can build a device-type-specific model of normal behavior that can be used to effectively detect anomalous deviations. This allows DÏoT to be trained and operated autonomously, *without the need for human intervention at any stage*.

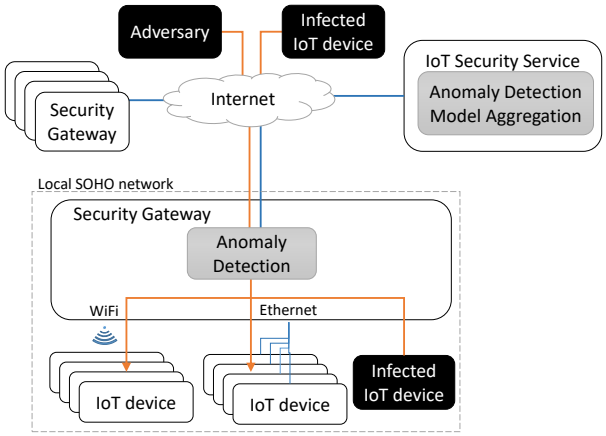


Fig. 1: DÏoT system model

D. Challenges

Anomaly detection techniques face challenges in the IoT application scenario:

- **C1- Dynamic threat landscape.** New IoT devices are released on a daily basis. A significant fraction of them have security vulnerabilities. Exploits targeting vulnerable devices are also being developed by adversaries at a similarly high pace. This makes the threats against IoT devices highly dynamic and ever-increasing.
- **C2- Resource limitations.** IoT devices have limited capabilities w.r.t. available memory, computing resources and energy often making it infeasible to perform on-device detection.
- **C3- IoT device heterogeneity and false alarms.** Behaviors of different IoT devices are very heterogeneous, so that anomaly detection techniques easily raise false alarms. However, to be useful in practice, anomaly detection systems must minimize false alarms.
- **C4- Scarcity of communications.** In contrast to high-end devices, IoT devices generate only little traffic, often triggered by infrequent user interactions.

E. Design Choices

1) Gateway monitoring: As on-device monitoring is rarely feasible due to challenge C2, we perform monitoring of IoT device communications on *Security Gateway*.

2) Device-type-specific anomaly detection: Since different IoT devices can have very heterogeneous behaviors (challenge C3), we model each device type's behavior with a dedicated model. Consequently, each model needs to cover only the behavior of a specific device type. As IoT devices are typically single-use appliances with only a few different functions, their behavior patterns are relatively static and limited, allowing the model to accurately capture all possible legitimate behaviors of a device type. Thus, the model is less prone to trigger false alarms (details in Sect. VI-D), thereby effectively addressing challenge C3.

3) Federated learning approach: Anomaly detection models are learned using a *federated learning approach* where *Security Gateway*s use locally collected data to train local models which *IoT Security Service* aggregates into a global model (details in Sect. IV). This aggregation maximizes the usage of limited information obtained from scarce communications at each gateway (challenge C4) and helps to improve the accuracy of anomaly detection models by utilizing all available data for learning.

4) Autonomous self-learning: Anomaly detection models are trained using data autonomously labeled with the device-type that generated it. Device types are also learned and assigned in an autonomous manner. The whole process does therefore not require any human intervention, which allows DÏoT to respond quickly and autonomously to new threats, addressing challenge C1. It is worth noting that DÏoT starts operating with no anomaly detection model. It learns and improves these models as *Security Gateway*s aggregate more data.

5) Modeling techniques requiring little data: As discussed in detail in Sect. III, we select features and machine learning algorithms (GRU) that can be efficiently trained even with few training data. This design choice addresses challenge C4.

III. Device-Type-Specific Anomaly Detection

Our anomaly detection approach is based on evaluating the communication patterns of a device to determine whether it is consistent with the learned benign communication patterns of that particular device type. The detection process is shown in Fig. 2. In **Step 1** the communication between the *Security Gateway* and the IoT device is captured as a sequence of packets $pkt_1, pkt_2, \ldots$. Each packet pkt_i is then in **Step 2** mapped to a corresponding symbol s_i characterizing the type of the packet using a mapping that is based on distinct characteristics $c_1, c_2, \ldots, c_7$ derived from each packet's header information as discussed in Sect. III-A. The mapped sequence of symbols $s_1, s_2, \ldots$ is then in **Step 3** input into a pre-trained model using Gated Recurrent Units (GRUs) [16], [17]. The GRU model will calculate a probability estimate p_i for each symbol s_i based on the sequence of k preceding symbols $s_{i-k}, s_{i-k+1}, \ldots, s_{i-1}$. GRU is a novel approach to recurrent neural networks (RNN) currently being a target of lively research. GRUs provide similar accuracy as other RNN approaches but are computationally less expensive [17], [18]. In **Step 4** the sequence of occurrence probability estimates $p_1, p_2, \ldots$ is evaluated to determine possible anomalies. If the occurrence probabilities p_i of a sufficient number of packets in a window of consecutive packets fall below a detection threshold, as described in detail in Sect. III-B, the packet sequence is deemed anomalous and an alarm is raised.

A. Modelling Packet Sequences

Data packets pkt_i in the packet sequence $pkt_1, pkt_2, \ldots$ emitted by an IoT device are mapped into *packet symbols* s_i based on 7-tuples $(c_1, c_2, \ldots, c_7)$ of discrete packet characteristics c_i of packet pkt_i. This mapping is defined by

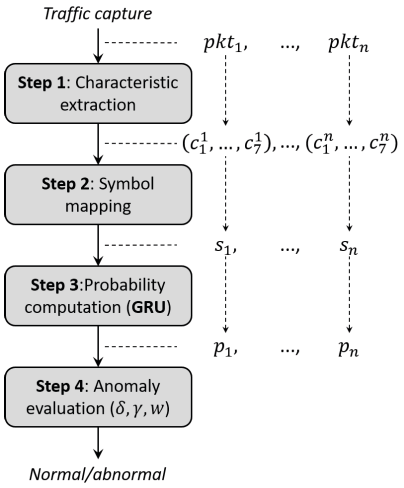
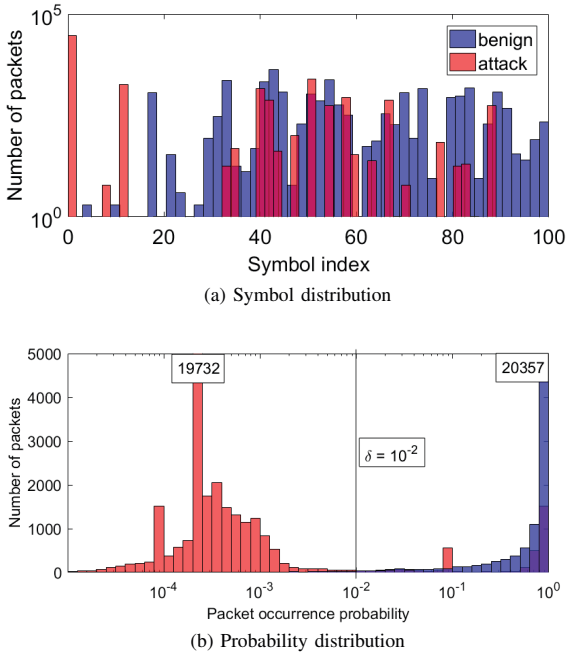


Fig. 2: Overview of device-type-specific anomaly detection

a device-type-specific mapping function $mapping_{type\#k} : A \rightarrow B_{type\#k}$ s.t. $mapping_{type\#k}(pkt_i) = s_i$ where A is the domain of raw network packets pkt and $B_{type\#k}$ is the domain of packet symbols s for device-type $type\#k$. Mapping $mapping_{type\#k}$ assigns each unique combination of packet characteristics $(c_1, \ldots, c_7)$ a dedicated symbol s representing the 'type' of the particular packet.

We use the following packet characteristics shown also in Tab. I:

- c_1 **direction:** (*incoming / outgoing*) Normal TCP traffic is usually balanced two-way communication but abnormal is not as, e.g., a bot only sends packets to a victim without receiving replies when running DDoS attacks.
- c_2 **and** c_3 **local and remote port type:** (*system / user / dynamic*) Each device-type uses specific ports designed by the manufacturers while malicious attack patterns usually use different ports.
- c_4 **packet length:** (*bin index of packet's length where eight most frequently occurring packet lengths receive dedicated bins and one bin for other packet length values*) Each device-type communicates using specific packet patterns with specific packet lengths that are mostly different in malicious attack patterns.
- c_5 **TCP flags:** Normal communications contain packets with specific TCP flag sequences e.g., $SYN \rightarrow SYNACK \rightarrow ACK \rightarrow PUSH \rightarrow FIN$. However, many attacks do not follow standard protocols, e.g., SYN flood (DDoS attack) only sends SYN messages.
- c_6 **encapsulated protocol types:** Each device type usually uses a set of specific protocols, which is likely different from protocol types used in attacks.
- c_7 **IAT bin:** (*bin index of packet inter-arrival time (IAT) using three bins:* $< 0.001\,\text{ms}$, $0.001\,\text{ms}$ *to* $0.05\,\text{ms}$, *and* $> 0.05\,\text{ms}$) Many attacks (e.g., DDoS) usually generate traffic at a high packet rate, resulting in smaller IAT values in than normal communications.



(a) Symbol distribution

(b) Probability distribution

Fig. 3: Packet symbol occurrence frequencies and occurrence probability estimates for benign and attack traffic for Edimax smart power plugs

TABLE I: Packet characteristics used in symbol mapping

ID	Characteristic	Value
c_1	direction	$1 =$ incoming, $0 =$ outgoing
c_2	local port type	bin index of port type
c_3	remote port type	bin index of port type
c_4	packet length	bin index of packet length
c_5	TCP flags	TCP flag values
c_6	protocols	encapsulated protocol types
c_7	IAT bin	bin index of packet inter-arrival time

B. Detection Process

Fig. 3a shows an example of the occurrence frequencies of individual packet symbols for benign and attack traffic (as generated by the Mirai malware) for Edimax smart power plugs. It can be seen that using packet symbols alone to distinguish between benign and attack traffic is not sufficient, as both traffic types contain packet types that are mapped to the same symbols. Our detection approach is therefore based on estimating the likelihood of observing individual packet types given the sequence of preceding packets. The rationale behind this approach is the observation that IoT device communications usually follow particular characteristic patterns. Traffic generated by IoT malware, however, doesn't follow these patterns and can therefore be detected. We will thus use the detection model to calculate an *occurrence probability* p_i

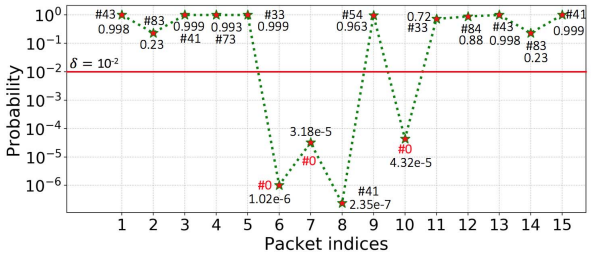


Fig. 4: Occurrence probabilities of 15 packets from Edimax Plug when Mirai was in standby stage. The red '#0' denotes the malicious packets.

for each packet symbol s_i given the sequence of k preceding symbols $< s_{i-k}, s_{i-k+1}, \ldots, s_{i-1} >$, i.e.,

$$p_i = P(s_i | < s_{i-k}, s_{i-k+1}, \ldots, s_{i-1} >) \tag{1}$$

Parameter k is a property of the used GRU network and denotes the length of the lookback history, i.e., the number of preceding symbols that the GRU takes into account when calculating the probability estimate. From Fig. 3b we can see that these probability estimates are on average higher for packets belonging to benign traffic patterns, and lower for packets generated by malware on an infected device and can therefore be flagged as anomalous.

Definition 1 (Anomalous packets): Packet pkt_i mapped to packet symbol s_i is *anomalous*, if its occurrence probability p_i is below *detection threshold* δ, i.e., if

$$p_i < \delta \tag{2}$$

We performed an extensive empirical analysis of the probability estimates provided by device-specific detection models for both benign and attack traffic for the datasets described in Sect. VI and could determine that a value of $\delta = 10^{-2}$ provides a good separation between benign and attack traffic, as can be also seen in Fig. 3b. An example of our approach is shown in Fig. 4. Malicious packets (represented by symbol '#0') get very low probability estimates ($<10^{-4}$), distinguishing them clearly from benign packets. However, their presence at indices $6-7$ also affects the estimate of the benign packet '#41' at index 8 ($<10^{-6}$), since the sequence of packets preceding this packet is unknown to the detection model.

Triggering an anomaly each time an anomalous packet is observed would lead to numerous false positive detections, as also benign traffic may contain noise that is not covered by the GRU model and will therefore receive low occurrence probability estimates. An anomaly is therefore triggered only in the case that a significant number of packets in a window of consecutive packets are anomalous.

Definition 2 (Anomaly triggering condition): Given a window W of w consecutive packets $W = (pkt_1, pkt_2, \ldots, pkt_w)$ represented by symbol sequence $S = (s_1, s_2, \ldots s_w)$, we

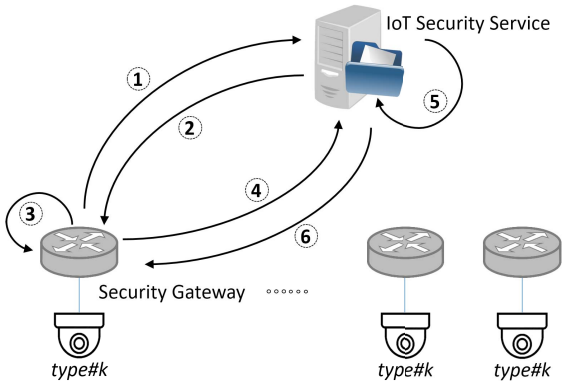


Fig. 5: Overview of federated learning process

trigger an anomaly alarm, if the fraction of anomalous packets in W is larger than an anomaly triggering threshold γ, i.e., if

$$\frac{|\{s_i \in S | p_i < \delta\}|}{w} > \gamma \tag{3}$$

IV. Federated Learning Approach

The GRU models are learned using traffic collected at several *Security Gateway*s, each monitoring a client IoT network. Each *Security Gateway* observing a device of a particular type $type\#k$ contributes to training its anomaly detection model. We take a *federated learning* approach to implement the distributed learning of models from several clients. Federated learning is a communication-efficient and privacy-preserving learning approach suited for distributed optimization of Deep Neural Networks (DNN) [19], [20]. In federated learning, clients do not share their training data but rather train a local model and send model updates to a centralized entity which aggregates them. Federated learning is chosen because it is suitable [21] for scenarios where:

- data are massively distributed, so that there is a large number of clients each having a small amount of data. IoT devices typically generate little traffic, which means only little data can be provided by each client alone.
- contributions from clients are imbalanced. In our system, the training data available at each *Security Gateway* depends on the duration that an IoT device has been in the network and the amount of interaction it has had, which varies largely between clients.

A. Learning Process

The federated training process is illustrated in Fig. 5. Each *Security Gateway* having devices of a particular type $type\#k$ in its network requests a detection profile for this type from *IoT Security Service* in **Step 1** and gets an initial GRU model for this type in **Step 2**. At the start of DÏoT, this model is random, otherwise it is already trained through several rounds of the following process. In **Step 3** the global model is retrained locally by each *Security Gateway* with traces collected by monitoring communication of the $type\#k$ devices. Then

in **Step 4** local updates made to the model by each *Security Gateway* are reported to *IoT Security Service* which in **Step 5** aggregates them as defined in Def.3 [21] to improve the global model. Finally, the updated global model for $type\#k$ devices is then pushed back to *Security Gateway* and used for anomaly detection (**Step 6**). The re-training of the model is performed on a regular basis to improve its accuracy.

Definition 3 (Global Model Aggregation): Given n clients with their associated model weights $W_1, \ldots, W_n$ trained by associated number of data samples $s_1, \ldots, s_n$. We define the global model G which is aggregated from those local models as follows:

$$G = \sum_{i=1}^{n} \frac{s_i}{s} W_i \quad (\text{where } s = \sum_{i=1}^{n} s_i) \tag{4}$$

To train our models we adopt an approach introduced by McMahan *et al.* [21]. Each client (*Security Gateway*) trains its GRU model locally for several epochs before reporting updates to *IoT Security Service*. This limits the communication overhead by reducing the number of updates to send to the *IoT Security Service*. To the best of our knowledge we are the first to employ a federated learning approach for anomaly detection-based intrusion detection.

B. Federated Learning Setup

We implemented the federated learning algorithm utilizing the *flask* [22] and *flask_socketio* [23] libraries for the server-side application and the *socketIO-client* [24] library for the client-side application. The socketIO-client uses the *gevent* asynchronous framework [25] which provides a clean API for concurrency and network related tasks. We used the *Keras* [26] library with *Tensorflow* backend to implement the GRU network with the parameters selected in Sect. V-B.

V. Experimental Setup

To evaluate DÏoT, we apply it on the use case of detecting real-life IoT malware. We selected Mirai for this purpose, since its source code is publicly available and several infamous malware variants like Hajime [2] or Persirai [27] have been implemented using the same code base. Mirai also realizes similar attack stages (detailed in Sect. V-A3 below) as state-of-the-art IoT malware [3], [28]. This makes Mirai a highly relevant baseline for IoT malware behavior.

A. Datasets

We collected extensive datasets about the communication behavior of IoT devices in laboratory and real-world deployment settings. The monitored devices included 33 typical consumer IoT devices like IP cameras, smart power plugs and light bulbs, sensors, etc. The devices were mapped by our device-type-identification method to 23 unique device types. The detailed list of devices and assignment to device-types can be found in Tab. II. We collected datasets by setting up a laboratory network as shown in Fig. 6 using `hostapd` on a laptop running Kali Linux to create a gateway acting as an access point with WiFi and Ethernet interfaces to which

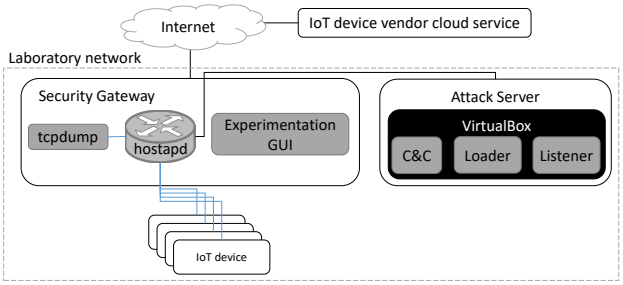


Fig. 6: Laboratory network setup

IoT devices were connected. On the gateway we collected all network traffic packets originating from the monitored devices using `tcpdump`.

1) Activity dataset: A key characteristic of IoT devices is that they expose only a few distinct actions accessible to users, e.g., ON, OFF, ADJUST, etc. To capture the communication patterns related to user interactions with IoT devices, we collected a dataset encompassing all such actions being invoked on the respective IoT devices. We repeatedly performed actions shown in Tab. IV. Each of the actions was repeated 20 times (20-time repetition chosen as a rule of thumb). To capture also less intensive usage patterns, the dataset was augmented with longer measurements of two to three hours, during which actions were triggered only occasionally. This dataset contains data from 33 IoT devices out of which 27 have both action and standby data. Six devices (lighting and home automation hubs) have standby data only because they do not provide meaningful actions that users could invoke.

2) Deployment dataset: To evaluate DÏoT in a realistic smart home deployment setting, in particular with regard to how many false alarms it will raise, we installed a number of ($n = 14$) different smart home IoT devices[1] in several different domestic deployment scenarios. This deployment involved real users and collected communication traces of these devices under realistic usage conditions. We used the same set-up as in the laboratory network for the domestic deployment, albeit we excluded the attack server. Users used and interacted with the IoT devices as part of their everyday life. Packet traces were collected continuously during one week.

3) Attack dataset: For evaluating the effectiveness of DÏoT at detecting attacks, we collected a dataset comprising malicious traffic of IoT devices infected with Mirai malware [1], [3] in all four different attack stages discussed below: *pre-infection*, *infection*, *scanning* and *DoS attacks* (as a monetization stage). Additionally, we collected traffic when Mirai was in a *standby* mode, i.e., not performing any attack but awaiting commands from its *Command & Control* server.

Among 33 experimental devices, we found 5 devices which are vulnerable to the Mirai malware. The *Attack* dataset was collected from those five devices: *D-LinkCamDCS930L*,

[1]The number of devices was limited, as the driver of the used WiFi interface allowed at most 16 devices to reliably connect to it simultaneously.

TABLE II: 33 IoT devices used in the *Activity*, *Deployment* and *Attack* datasets and their connectivity technologies + Affectation of these devices to 23 DÏoT device types during evaluation.

Device-type	Identifier	Device model	WiFi	Ethernet	Other	Activity	Deployment	Attack
type#01	ApexisCam	Apexis IP Camera APM-J011	•	•	○	•	○	○
type#02	CamHi	Cooau Megapixel IP Camera	•	•	○	•	○	○
type#03	D-LinkCamDCH935L	D-Link HD IP Camera DCH-935L	•	○	○	•	○	○
type#04	D-LinkCamDCS930L	D-Link WiFi Day Camera DCS-930L	•	•	○	•	•	•
	D-LinkCamDCS932L	D-Link WiFi Camera DCS-932L	•	•	○	•	•	•
type#05	D-LinkDoorSensor	D-Link Door & Window sensor	○	○	•	•	○	○
	D-LinkSensor	D-Link WiFi Motion sensor DCH-S150	•	○	○	•	•	○
	D-LinkSiren	D-Link Siren DCH-S220	•	○	○	•	○	○
	D-LinkSwitch	D-Link Smart plug DSP-W215	•	○	○	•	•	○
	D-LinkWaterSensor	D-Link Water sensor DCH-S160	•	○	○	•	○	○
type#06	EdimaxCamIC3115	Edimax IC-3115W Smart HD WiFi Network Camera	•	•	○	•	○	○
	EdimaxCamIC3115(2)	Edimax IC-3115W Smart HD WiFi Network Camera	•	•	○	•	○	○
type#07	EdimaxPlug1101W	Edimax SP-1101W Smart Plug Switch	•	•	○	•	•	•
	EdimaxPlug2101W	Edimax SP-2101W Smart Plug Switch	•	○	○	•	•	•
type#08	EdnetCam	Ednet Wireless indoor IP camera Cube	•	•	○	•	○	○
type#09	EdnetGateway	Ednet.living Starter kit power Gateway	•	○	•	•	•	○
type#10	HomeMaticPlug	Homematic pluggable switch HMIP-PS	○	○	•	•	○	○
type#11	Lightify	Osram Lightify Gateway	•	○	•	•	•	○
type#12	SmcRouter	SMC router SMCWBR14S-N4 EU	•	•	○	•	○	○
type#13	TP-LinkPlugHS100	TP-Link WiFi Smart plug HS100	•	○	○	•	○	○
	TP-LinkPlugHS110	TP-Link WiFi Smart plug HS110	•	○	○	•	○	○
type#14	UbnTAirRouter	Ubnt airRouter HP	•	•	○	•	○	•
type#15	WansviewCam	Wansview 720p HD Wireless IP Camera K2	•	○	○	•	○	○
type#16	WeMoLink	WeMo Link Lighting Bridge model F7C031vf	•	○	•	•	○	○
type#17	WeMoInsightSwitch	WeMo Insight Switch model F7C029de	•	○	○	•	○	○
	WeMoSwitch	WeMo Switch model F7C027de	•	○	○	•	○	○
type#18	HueSwitch	Philips Hue Light Switch PTM 215Z	○	○	•	•	•	○
type#19	AmazonEcho	Amazon Echo	•	○	○	•	•	○
type#20	AmazonEchoDot	Amazon Echo Dot	•	○	○	•	○	○
type#21	GoogleHome	Google Home	•	○	○	•	•	○
type#22	Netatmo	Netatmo weather station with wind gauge	•	○	•	•	•	○
type#23	iKettle2	Smarter iKettle 2.0 water kettle SMK20-EU	•	○	○	•	•	○
	SmarterCoffee	Smarter SmarterCoffee coffee machine SMC10-EU	•	○	○	•	•	○

TABLE III: Characteristics of used datasets

Dataset (Number of devices)	Time (hours)	Size (MiB)	Flows	Packets
Activity (33)	165	465	115,951	2,087,280
Deployment (14)	2,352	578	95,518	2,286,697
Attack (5)	84	7,734	8,464,434	21,919,273

TABLE IV: Actions for different IoT device categories

Category (count)	Typical actions
IP cameras (6)	START / STOP video, adjust settings, reboot
Smart plugs (9)	ON, OFF, meter reading
Sensors (3)	trigger sensing action
Smart lights (4)	turn ON, turn OFF, adjust brightness
Actuators (1)	turn ON, turn OFF
Appliances (2)	turn ON, turn OFF, adjust settings
Routers (2)	browse amazon.com
Hub devices (6)	no actions

D-LinkCamDCS932L, *EdimaxPlug1101W*, *EdimaxPlug2101W* and *UbntAirRouter*. This was done by installing the *Command & Control*, *Loader* and *Listener* server modules on the laboratory network for infecting target devices with Mirai and controlling them. Infection was achieved using security vulnerabilities like easy-to-guess default passwords to open a terminal session to the device and issuing appropriate commands to download the malware binary onto the device.

In the *pre-infection* stage, *Loader* sends a set of commands via telnet to the vulnerable IoT device to prepare its environment and identify an appropriate method for uploading the Mirai binary files. We repeated the pre-infection process 50 times for each device. During each run, around 900 pre-infection-related packets were generated.

After pre-infection the *infection stage* commences, during which *Loader* uploads Mirai binary files to the IoT device. It supports three upload methods: `wget`, `tftp` and `echo` (in this priority order). To infect the two D-Link cameras and the Ubnt router *Loader* uses `wget`, on the Edimax plugs it will resort to using `tftp` as these are installed on the devices by default. We repeated the infection process 50 times for each device, each run generating approximately 700 data packets.

In the *scanning stage* we collected packets while the infected devices were actively performing a network scan in order to locate other vulnerable devices. Data collection was performed for five minutes per device, resulting in a dataset of more than 446,000 scanning data packets.

We extensively tested the *DoS attack stage*, utilizing all ten different DoS attack vectors (for details, see [29]) available in the Mirai source code [30]. We ran all attacks separately on

all five compromised devices for five minutes each, generating more than 20 million packets of attack traffic in total.

Tab. III summarizes the sizes and numbers of distinct packets and packet flows in the different datasets. While packet flows can't be directly mapped to distinct device actions, they do provide a rough estimate of the overall level of activity of the targeted devices in the dataset.

B. Parameter Selection

Based on initial experiments with our datasets (Tab. III) we inferred that a lookback history of $k = 20$ symbols is sufficient to capture most communication interactions with sufficient accuracy. We used a GRU network with three hidden layers of size 128 neurons each. The size of the input and output layers is device-type-specific and equal to the number of mapping symbols of the function $mapping_{type\#k}$, which is equal to $\mid B_{type\#k} \mid$ (cf. Sect. III-A). We learned 23 anomaly detection models, each corresponding to a device type identified using the method described in Sect. II-C. Each anomaly detection model was trained with, and respectively tested on, communication from all devices matching the considered type.

C. Evaluation Metrics

We use false positive and true positive rate (FPR and TPR) as measures of fitness. FPR measures the rate at which benign communication is incorrectly classified as anomalous by our method causing a false alarm to be raised. TPR is the rate at which attacks are correctly reported as anomalous. We seek to minimize FPR, since otherwise the system easily becomes unusable, as the user would be overwhelmed with false alarms. At the same time we want to maximize TPR so that as many attacks as possible will be detected by our approach.

Testing for false positives was performed by four-fold cross-validation for device types in the *Activity* and *Deployment* datasets. The data were divided equally into four folds using three folds for training and one for testing. To determine the FPR, we divided the testing dataset according to Def. 2 into windows of $w = 250$ packets. Since the testing data contained only benign communications, any triggered anomaly alarm for packets of the window indicated it as a false positive, whereas windows without alarms were considered a true negative.

Testing for true positives was done by using the *Activity* and *Deployment* datasets as training data and the *Attack* dataset for testing with the same settings as for false positive testing. Moreover, as we know that the *Attack* dataset also contains benign traffic corresponding to normal operations of the IoT devices, we were interested in the average duration until detection. Therefore, in each window of $w = 250$ packets we calculated the number of packets required until an anomaly alarm was triggered in order to estimate the average detection time. In terms of TPR, such windows were considered true positives, whereas windows without triggered alarms were considered false negatives.

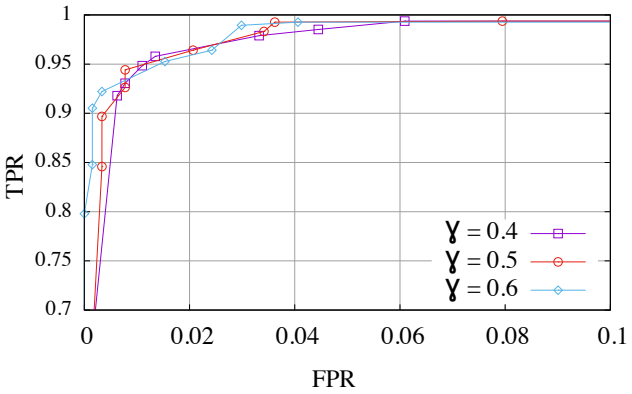


Fig. 7: ROC curve of TPR and FPR in dependence of detection threshold δ and anomaly triggering threshold γ.

VI. Experimental Results

A. Accuracy

To determine appropriate values for the detection threshold δ and anomaly triggering threshold γ, we evaluated FPR using the *Activity (33 devices, 23 device types)* dataset and TPR using the *Attack (5 devices, 3 device types)* dataset for a fixed window size of $w = 250$. Fig. 7 shows the receiver operating characteristic (ROC) curve of FPR and TPR in dependence of these parameters. We can see that all curves quickly reach over 0.9 TPR while keeping a very low FPR (<0.01), which is one of the main objectives for our approach. We therefore select $\delta = 0.01$ and $\gamma = 0.5$ at $w = 250$, which achieves 94.01% TPR at <0.01 FPR.

Using these selected parameters in the *Deployment (14 devices, 10 device types)* dataset and *Attack (5 devices)* dataset, we achieved an attack detection rate of 95.60% TPR and **no false positives**, i.e., 0% FPR during one week of evaluation. These results show that DÏoT can successfully address challenge C3, *reporting no false alarms in a real-world deployment setting*. Tab. V shows the detailed performance of our system for different attack scenarios (cf. Sect. V). The time to detect attacks varies according to the traffic intensity of the attacks. The average detection delay over all tested attacks is 257 ± 194 ms. DÏoT can detect an attack in the pre-infection stage after 223 packets while Mirai generates more than 900 packets during pre-infection. It means DÏoT is able to detect the attack *even before the attack proceeds to the infection stage*.

The detection rate for DoS attacks is lower than for other attack stages. However, *all DoS attacks are eventually detected* because DoS attacks have a high throughput ($1,412.94$ packets/s.) and we analyze five windows of 250 packets per second at this rate. Considering the 88.96% TPR we achieve on DoS attacks, four windows out of five are detected as anomalous and trigger an alarm. It is also worth noting that infected devices in *standby* mode get detected in *33.33%* of cases, while this activity is very stealthy (0.05 packets/s).

TABLE V: Average detection times of analyzed Mirai attacks

Attack	packets/s.	det. time (ms.)	TPR
standby	*0.05*	*4,051,889*	*33.33%*
Pre-Infection	426.66	524	100.00%
Infection	721.18	272	93.45%
Scanning	752.60	166	100.00%
DoS	1,412.94	92	88.96%
Average	866.88	257±194	95.60%

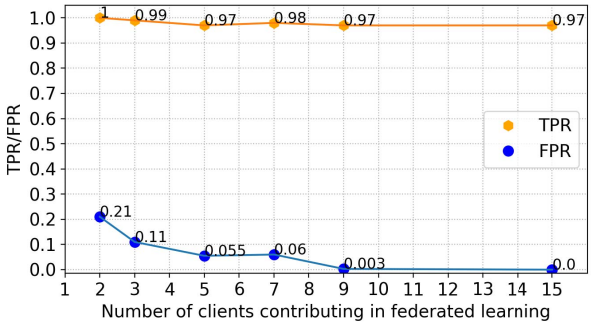


Fig. 8: Evolution of TPR and FPR as we increase the number of clients in federated learning. TPR decreases slightly (-3%) while FPR reaches 0 (-21%) when using 15 clients.

B. Efficiency of Federated Learning

We conducted a set of experiments to evaluate federated learning performance with different numbers of clients (ranging from 2 to 15) contributing to the training of the models. We selected the *number of epochs* that each client trains its local model to be 17 and specified the *number of communication rounds* between clients and server to be 3. Therefore, the local models were trained a total of 51 epochs. This was deemed sufficient since in our initial experiments utilizing a centralized learning setting the models converged after approximately 50 epochs. Each client was allocated a randomized subset of training data from the *Deployment* dataset (ranging from 0.1% to 10% of the total training dataset size) and we evaluated the system's performance for different numbers of clients involved in building the federated model. In average, each client takes approximately one second to train one local epoch on its data. We repeated our experiment three times for each device type, with random re-sampling of the training datasets. As expected, Fig. 8 shows that the federated models with more participating clients achieve better FPR, while TPR deteriorates only slightly.

Federated learning provides better privacy for clients contributing to training as they do not need to share their training data. However, this may result in a loss of accuracy of the obtained model in comparison to training the model in a centralized manner. To evaluate this possible loss in accuracy, we trained three federated models using the entire training dataset by dividing it among 5, 9 or 15 clients and comparing these to a model trained in a centralized manner. Tab. VI shows a small decrease in TPR as we increase the number of clients

TABLE VI: Effect of using federated learning comparing to centralizing approach

Type	Centralized learning	Federated learning		
		5 clients	9 clients	15 clients
FPR	0.00%	0.00%	0.00%	0.00%
TPR	95.60%	95.43%	95.01%	94.07%

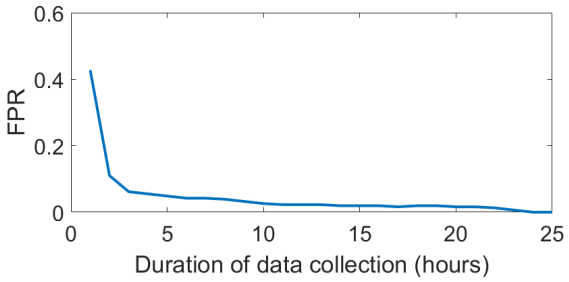


Fig. 9: Effect of training data size in time to FPR

while FPR is not deteriorated (remaining constant at 0.00%). This small drop in TPR is not a concern since a large number of packet windows would still trigger an alarm for any attack stage.

C. Data Needed for Training

Fig. 9 shows an example of detection model performance for two Edimax smart plug devices (models 1101W & 2101W) in dependency of the amount of data used for training the model. We divided the 7-day *Deployment* dataset into one-hour data chunks and randomly sampled different amounts of data chunks for training the model, gradually increasing the training dataset size. The figure shows that the FPR decreases noticeably when the training dataset grows. More importantly, the model needs less than 25 hours of data to achieve FPR = 0. It shows that our detection model needs little data for training and it means DÏoT can address challenge C4. Moreover, with the help of our federated learning approach leveraging several clients contributing to training the model, each client needs only a small amount of data i.e, 2.5 hours if there are ten clients involved. It justifies our assumption A1 as mentioned in Sect. II-B.

D. Efficiency of Device-Type-Specific Models and Scalability

Traditional anomaly detection approaches utilizing a single model for modeling benign behavior easily suffer from increasing false positive rates or decreasing sensitivity when the number of different types of behaviors (i.e., device types) captured by the model grows. This makes them unsuitable for real-world deployments with hundreds or thousands of different device types. Our solution, however, does not have this drawback, as it uses a dedicated detection model for each device type (details in Sect. III). Each of these models focuses solely on the characteristic behavior of one single device type, resulting in more specific and accurate behavioral models, independent of the number of different device types handled

by the system. To evaluate the benefit of using device-type-specific anomaly detection models compared to using a single model for all devices, we evaluated a single model on the whole *Deployment* dataset using 4-fold-cross validation and evaluated detection accuracy on the *Attack* dataset. The result is as expected: FPR increases from 0% to 0.67% while TPR increases from 95.6% to 97.21%. However, as mentioned in Sect. II, a high false alarm rate would make the anomaly detection system impractical. If the system had FPR of 0.67% in our deployment setup, it would trigger around eight alarms per day. It means a smarthome with dozens of devices could have hundreds of false alarms per day.

E. Performance

We evaluated the processing performance of GRU without specific performance optimizations on a laptop and a desktop computer. The laptop ran Ubuntu Linux 16.04 with an Intel©Core™i7-4600 CPU with 8GB of memory, whereas the desktop ran Ubuntu Linux 18.04 with an Intel©Core™i7-7700 CPU with 8GB of memory and a Radeon RX 460 core graphic card. We evaluated the processing performance of GRU without specific optimizations on a laptop and a desktop computer. The laptop ran Ubuntu Linux 16.04 with an Intel i7-4600 CPU with 8GB of memory, whereas the desktop ran Ubuntu Linux 18.04 with an Intel i7-7700 CPU with 8GB of memory and a Radeon RX 460 core graphics card with GPU. Average processing time per symbol (packet) for prediction was $0.081(\pm 0.001)$ ms for the desktop utilizing its GPU and $0.592(\pm 0.001)$ ms when executed on the laptop with CPU. On average, training a GRU model for one device type took 26 minutes on the desktop and 71 minutes on the laptop hardware when considering a week's worth of data in the *Deployment* dataset. We conclude from this that model training will be feasible to realize in real deployment scenarios, as training will in any case be done gradually as data are collected from the network over longer periods of time.

VII. Effectiveness

A. Generalizability of Anomaly Detection

Although we focused our evaluation on the most well-known IoT malware so far: Mirai [1] for the use case, DÏoT is likely effective also in detecting other botnet malware like Persirai [27], Hajime [2], etc. DÏoT's anomaly detection leverages deviations in the behavior of infected IoT devices caused by the malware. Such deviations will be observable for any malware.

B. Evolution of IoT Device Behavior

The behavior of an IoT device type can evolve due to, e.g., firmware updates that bring new functionality. This modifies its behavior and may trigger false alarms for legitimate communication. We prevent these false alarms by correlating anomaly reports from all *Security Gateway*s at the *IoT Security Service*. Assuming firmware updates would be propagated to many client networks in a short time, if alarms are reported from a large number of security gateways for the same device type in a short time, we can cancel the alarm and trigger re-learning of the corresponding device identification and anomaly detection models to adapt to this new behavior. To ensure that sudden widespread outbreaks of an IoT malware infection campaign are not erroneously interpreted as firmware updates, the canceling of an alarm can be confirmed by a human expert at the *IoT Security Service*. This should represent a small burden, as the roll-out of firmware updates is a relatively seldom event.

C. Mimicking Legitimate Communication

An adversary that has compromised an IoT device can attempt to mimic the device's legitimate communication patterns to try to remain undetected. However, as the device-type-specific detection model is restricted to the (relatively limited) functionality of the IoT device, it is in practice very difficult for the adversary to mimic legitimate communication and at the same time achieve a malicious purpose, e.g., scanning, flooding, etc., especially when considering that any change in packet flow semantics is also likely to change the characteristics (protocol, packet size, port, etc.) of packets and their ordering, which are both used for detecting anomalies in the packet sequence. Moreover, adversaries would need to know the device-type-specific communication patterns in order to mimic them. This makes it significantly harder for adversaries to develop large scale IoT malware that affects a wide range of different IoT device types in the way that, e.g., Mirai does.

D. Adversarial Machine Learning

Adversarial examples. If an adversary manages to compromise an IoT device while remaining undetected, it can attempt to 'poison' the training process of the system by forging packets as *adversarial examples* that are specifically meant to influence the learning of the model in such a way that malicious activities are not detected by it. There exist techniques to forge adversarial examples to neural networks [31]. However, these apply to images [32], [33] and audio inputs [34], [35], where objective functions for the underlying optimization problem are easy to define. Forging adversarial examples consists of finding minimal modifications ϵ for an input x of class C such that $x+\epsilon$ is classified as $C' \neq C$. For example, in our case this would mean that a malicious packet is incorrectly classified as a benign one. In contrast to image or audio processing, however, our features (symbols) are not raw but processed from packet properties. First, it means that modifications ϵ are computed for our symbolic representation of packet sequences which are difficult to realize in a way that would preserve their utility for the adversary, i.e., realize 'useful' adversarial functionality required for malicious activities like scanning or DoS. Second, it is difficult to define the objective distance to minimize in order to achieve "small modifications" since modifying the value of one single packet characteristic (protocol, port, etc.) can change the semantics of a packet entirely.

Poisoning federated learning. For initial model training, we can assume the training data contain only legitimate network traffic, as devices are assumed initially to be benign (assumption A1 (Sect. II-B)). However, the federated setting can be subject to *poisoning attacks* during re-training, where the adversary uses adversarial examples as described above to corrupt the anomaly detection model so that it eventually will accept malicious traffic as benign [36] (or vice versa). Techniques have been developed for preventing poisoning attacks by using local outlier detection-based filtering of adversarial examples to pre-empt model poisoning [37].

In the scope of this paper we assume that the *Security Gateway* is not compromised by the adversary (assumption A2 (Sect. II-B)). However, since a malicious user can have physical access to his *Security Gateway*, it is thinkable that he could compromise it in order to stage a poisoning attack against the system using adversarial examples. In this case, local filtering of adversarial examples is not possible, as it can not be enforced by the compromised *Security Gateway*. We are therefore currently focusing our ongoing research efforts on applying poisoning mitigation approaches applied at the *IoT Security Service*. These include using more robust learning approaches less resilient to adversarial examples that will 'average out' the effects of adversarial examples, as well as approaches similar to, e.g., Shen *et al.* [38], where malicious model updates are detected before they are incorporated in global detection models.

VIII. Related Work

Several solutions have been proposed for the detection and prevention of intrusions in IoT networks [39], [40], sensor networks [9] and industrial control systems [41], [42]. SVELTE [40] is an intrusion detection system for protecting IoT networks from already known attacks. It adapts existing intrusion detection techniques to IoT-specific protocols, e.g., 6LoWPAN. Similarly, Doshi at al. [6] proposed a signature-based approach to detect known DDoS attacks using features representing the density of the network traffic. In contrast, DÏoT performs dynamic detection of any unknown attacks that deviate from the legitimate behavior of the device, since it only models legitimate network traffic. Jia *et al.* [39] proposed a context-based system to automatically detect sensitive actions in IoT platforms. This system is designed for patching vulnerabilities in appified IoT platforms such as Samsung SmartThings. It is not applicable to multi-vendor IoT systems while DÏoT is platform independent.

Detecting anomalies in network traffic has a long history [7], [8], [43], [44]. Existing approaches rely on analysing single network packets [7] or clustering large numbers of packets [8], [9] to detected intrusions or compromised services. Some works have proposed, as we do, to model communication as a language [42], [43]. For instance, authors of [43] derive finite state automatons from layer 3-4 communication protocol specifications. Monitored packets are processed by the automaton to detect deviations from protocol specification or abnormally high usage of specific transitions. Automatons can only model short sequences of packets while we use GRU to model longer sequences, which enables the detection of stealthy attacks. Also, modelling protocol specifications is coarse and leaves room for circumventing detection. In contrast, we use finer grained-features that are difficult to forge while preserving the adversarial utility of malicious packets.

Lately, recurrent neural networks (RNN) have been used for several anomaly-detection purposes. Most applications leverage Long Short-Term Memory (LSTM) networks for detecting anomalies in time series [45], aircraft data [46] or system logs [47]. Oprea at al. [48] use deep belief networks for mining DNS log data and detect infections in enterprise networks. In contrast to these works, DÏoT uses a different flavor of RNN, namely GRU that can be learned using less training data, enabling DÏoT to be trained faster, and operate in real-time, detecting anomalies in live network traffic instead of utilizing off-line analysis.

IX. Summary

In this paper we introduced DÏoT: a self-learning system for detecting compromised devices in IoT networks. Our solution relies on novel automated techniques for *device-type-specific anomaly detection*. DÏoT does *not require any human intervention or labeled data* to operate. It learns anomaly detection models autonomously, using unlabeled crowdsourced data captured in client IoT networks. We demonstrated the efficacy of anomaly detection in detecting a large set of malicious behavior from devices infected by the Mirai malware. DÏoT detected 95.6% of attacks in 257 milliseconds on average and without raising any false alarm when evaluated in a real-world deployment.

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FLAME: TAMING BACKDOORS IN FEDERATED LEARNING

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FLAME: Taming Backdoors in Federated Learning

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Abstract

Federated Learning (FL) is a collaborative machine learning approach allowing participants to jointly train a model without having to share their private, potentially sensitive local datasets with others. Despite its benefits, FL is vulnerable to so-called *backdoor attacks*, in which an adversary injects manipulated model updates into the federated model aggregation process so that the resulting model will provide targeted false predictions for specific adversary-chosen inputs. Proposed defenses against backdoor attacks based on detecting and filtering out malicious model updates consider only very specific and limited attacker models, whereas defenses based on differential privacy-inspired noise injection significantly deteriorate the benign performance of the aggregated model. To address these deficiencies, we introduce FLAME, a defense framework that estimates the sufficient amount of noise to be injected to ensure the elimination of backdoors. To minimize the required amount of noise, FLAME uses a model clustering and weight clipping approach. This ensures that FLAME can maintain the benign performance of the aggregated model while effectively eliminating adversarial backdoors. Our evaluation of FLAME on several datasets stemming from application areas including image classification, word prediction, and IoT intrusion detection demonstrates that FLAME removes backdoors effectively with a negligible impact on the benign performance of the models.

1 Introduction

Federated learning (FL) is an emerging collaborative machine learning trend with many applications, such as next word prediction for mobile keyboards [39], medical imaging [49], and intrusion detection for IoT [44] to name a few. In FL, clients locally train models based on local training data and then provide these model updates to a central aggregator who combines them into a global model. The global model is then propagated back to the clients for the next training iteration.

FL promises efficiency and scalability as the training is distributed among many clients and executed in parallel. In particular, FL improves privacy by enabling clients to keep their training data locally [38]. Despite its benefits, FL has been shown to be vulnerable to so-called *poisoning attacks* where the adversary manipulates the local models of a subset of clients participating in the federation so that the malicious updates get aggregated into the global model. Untargeted poisoning attacks merely aim at deteriorating the performance of the global model and can be defeated by validating the performance of uploaded models [12]. In this paper, we therefore focus on the more challenging problem of *backdoor attacks* [7, 45, 57, 59], i.e., targeted poisoning attacks in which the adversary seeks to stealthily manipulate the resulting global model in a way that attacker-controlled inputs result in incorrect predictions chosen by the adversary.

Deficiencies of existing defenses. Existing defenses against backdoor attacks can be roughly divided into two categories: The first one comprises anomaly detection-based approaches [4,9,22,51] for identifying and removing potentially poisoned model updates. However, these solutions are effective only under very specific adversary models, as they make detailed assumptions about the attack strategy of the adversary and/or the underlying distribution of the benign or adversarial datasets. If these very specific assumptions do not hold, the defenses may fail. The second category is inspired by differential privacy (DP) techniques [7,56], where individual weights[1] of model updates are clipped to a maximum threshold and random noise is added to the weights for diluting/reducing the impact of potentially poisoned model updates on the aggregated global model. In contrast to the first category, DP techniques [7,56] are applicable in a generic adversary model without specific assumptions about adversarial behavior and data distributions and are effective in eliminating the impact of malicious model updates. However, straightforward application of DP approaches severely deteriorates the benign

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[1]Parameters of neural network models typically consist of 'weights' and 'biases'. For the purposes of this paper, however, these parameters can be treated identically and we will refer to them as 'weights' for brevity.

performance of the aggregated model because the amount of noise required to ensure effective elimination of backdoors also results in significant modifications of individual weights of benign model updates [7, 57].

In this paper, we develop a resilient defense against backdoors by combining the benefits of both defense types without suffering from the limitations (narrow attacker model, assumptions about data distributions) and drawbacks (loss of benign performance) of existing approaches. To this end, we introduce an approach in which detection of anomalous model updates and tuned clipping of weights are combined to minimize the amount of noise needed for backdoor removal of the aggregated model while preserving its benign performance.

Our Goals and Contributions. We present FLAME, a resilient aggregation framework for FL that eliminates the impact of backdoor attacks while maintaining the benign performance of the aggregated model. This is achieved by three modules: DP-based noising of model updates to remove backdoor contributions, automated model clustering approach to identify and eliminate potentially poisoned model updates, and model weight clipping before aggregation to limit the impact of malicious model updates on the aggregation result. The last two modules can significantly reduce the amount of random noise required by DP noising for backdoor elimination. In particular, our contributions are as follows:

- We present FLAME, a defense framework against backdoor attacks in FL that is capable of eliminating backdoors without impacting the benign performance of the aggregated model. Contrary to earlier backdoor defenses, FLAME is applicable in a *generic* adversary model, i.e., it does not rely on strong assumptions about the attack strategy of the adversary, nor about the underlying data distributions of benign and adversarial datasets (§4.1).
- We show that the amount of required Gaussian noise can be radically reduced by: a) applying our clustering approach to remove potentially malicious model updates and b) clipping the weights of local models at a proper level to constrain the impact of individual (especially malicious) models on the aggregated model. (§4.3)
- We provide a noise boundary proof for the amount of Gaussian noise required by noise injection (inspired by DP) to eliminate backdoor contributions (§5).
- We extensively evaluate our defense framework on real-world datasets from three very different application areas. We show that FLAME reduces the amount of required noise so that the benign performance of the aggregated model does not degrade significantly, providing a crucial advantage over state-of-the-art defenses using straightforward injection of DP-based noise (§7).

As an orthogonal aspect, we also consider how the privacy of model updates against an honest-but-curious aggregator can be preserved and develop a secure multi-party computation approach that can preserve the privacy of individual model updates while realizing our backdoor defense approach (§8).

2 Background and Problem Setting

2.1 Federated Learning

Federated Learning [38, 50] is a concept for distributed machine learning that links n clients and an aggregator to collaboratively build a global model G. In a training iteration $t \in \{1,\ldots,T\}$, each client $i \in \{1,\ldots,n\}$ locally trains a local model W_i with p parameters (indicating both weights and biases) $w_i^1,\ldots,w_i^p$ based on the previous global model G_{t-1} using its local data D_i and sends it to the aggregator which aggregates the received models W_i into the global model G_t.

Several aggregation mechanisms have been proposed recently: 1) *Federated Averaging* (FedAvg) [38], 2) *Krum* [9], 3) *Adaptive Federated Averaging* [42], and 4) *Trimmed mean or median* [60]. Although we evaluate FLAME's effectiveness on several aggregation mechanisms in §7.1, we generally focus on FedAvg in this work as it is commonly applied in FL [21, 28, 39, 44, 47, 50, 54] and related work on backdoor attacks [7, 22, 51, 57, 59]. In FedAvg, the global model is updated by averaging the weighted models as follows: $G_t = \Sigma_{i=1}^{n} s_i \times W_i / s$, where $s_i = \|D_i\|, s = \Sigma_{i=1}^{n} s_i$. However, in practice, a malicious client might provide falsified information about its dataset size (i.e., a large number) to amplify the relative weight of its updates [57]. Previous works often employed equal weights ($s_i = 1/n$) for the contributions of all clients [7, 51, 59]. We adopt this approach in this paper, i.e., we set $G_t = \Sigma_{i=1}^{n} W_i / n$. Further, other state-of-the-art aggregation rules, e.g., *Krum* [9], *Adaptive Federated Averaging* [42], and *Trimmed mean or median* [60] also do not consider the sizes of local training datasets by design.

2.2 Backdoor Attacks on Federated Learning

In backdoor attacks, the adversary $\mathcal{A}$ manipulates the local models W_i of k compromised clients to obtain poisoned models W_i' that are then aggregated into the global model G_t and thus affect its properties. In particular, $\mathcal{A}$ wants the poisoned model G_t' to behave normally on all inputs except for specific attacker-chosen inputs $x \in I_{\mathcal{A}}$ (where $I_{\mathcal{A}}$ denotes the so-called *trigger set*) for which attacker-chosen (incorrect) predictions should be output. Figure 1 shows common techniques used in FL backdoor attacks, including 1) data poisoning, e.g., [45, 51, 59], where $\mathcal{A}$ manipulates training datasets of models, and 2) model poisoning, e.g., [7, 57] where $\mathcal{A}$ manipulates the training process or the trained models themselves. Next, we will briefly discuss these attack techniques.

Data Poisoning. In this attack, $\mathcal{A}$ adds manipulated data $D^{\mathcal{A}}$ to the training datasets of compromised clients i by flipping data labels, e.g., by changing the labels of a street sign database so that pictures showing a 30 km/h speed limit are labeled as 80 km/h [51], or, by adding triggers into data samples (e.g., a specific pixel pattern added to images [59]) in combination with label flipping. We denote the fraction

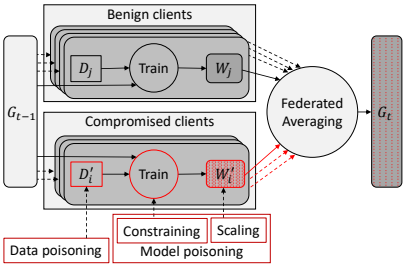


Figure 1: An overview of backdoor attacks.

of injected poisoned data $D_i^{\mathcal{A}}$ in the overall poisoned training dataset D'_i of client i as *Poisoned Data Rate (PDR)*, i.e., $PDR_i = \frac{|D_i^{\mathcal{A}}|}{|D'_i|}$.

Model Poisoning. This attack technique requires that $\mathcal{A}$ can fully control a number of clients. $\mathcal{A}$ poisons the training datasets of these clients and manipulates how they execute the training process by modifying parameters and scaling the resulting model update to maximize the attack impact while evading the aggregator's anomaly detector [7, 57]. This is done by (1) scaling up the weights of malicious model updates to maximize attack impact (e.g., *model-replacement* attack [7], or, *projected gradient descent (PGD) attack with model replacement* [57]), or, scaling down model updates to make them harder to detect (e.g., *train-and-scale* [7]) and (2) constraining the training process itself to minimize the deviation of malicious models from benign models to evade anomaly detection (e.g., *constrain-and-scale* attack [7]).

2.3 Adversary Goals and Capabilities

The goals of the adversary are two-fold:

Impact: The adversary $\mathcal{A}$ aims to manipulate the global model G so that the modified model G' provides incorrect predictions $f(G',x) = c' \neq f(G,x)$ for any inputs $x \in I_{\mathcal{A}}$, where $I_{\mathcal{A}}$ is the so-called *trigger set* consisting of specific attacker-chosen inputs and c' denotes the incorrect prediction chosen by the adversary.

Stealthiness: To make the poisoned model G' hard to detect by aggregator A, it should closely mimic the behavior of G on all other inputs not in $I_{\mathcal{A}}$, i.e.:

$$f(G',x) = \begin{cases} c' \neq f(G,x) & \forall x \in I_{\mathcal{A}} \\ f(G,x) & \forall x \notin I_{\mathcal{A}} \end{cases} \quad (1)$$

Additionally, to make poisoned models as indistinguishable as possible from benign models, the distance (e.g., euclidean) between a poisoned model W' and a benign model W must be smaller than a threshold η denoting the distinction capability of the anomaly detector of aggregator A, i.e., $dist(W,W') < \eta$. The adversary can estimate this distance by comparing the local malicious model to the global model or to a local model trained on benign data.

Adversarial Capabilities. In this paper, we make no specific assumptions about the adversary's behavior. We assume that the adversary $\mathcal{A}$ has full control over $k < \frac{n}{2}$ clients and their training data, processes, and parameters [7, 59]. We denote the fraction of compromised clients as Poisoned Model Rate $PMR = \frac{k}{n}$. Furthermore, $\mathcal{A}$ has full knowledge of the aggregator's operations, including potentially applied backdoor defenses. However, $\mathcal{A}$ has no control over any processes executed at the aggregator nor over the honest clients.

2.4 Preliminaries

HDBSCAN [11] is a density-based clustering algorithm that uses the distance of data points in n-dimensional space to group data points that are located near each other together into a cluster. Hereby the number of clusters is determined dynamically. Data points that do not fit to any cluster are considered outliers. However, while HDBSCAN's predecessor DBSCAN [19] uses a predefined maximal distance to determine whether two points belong to the same cluster, HDBSCAN determines this maximal distance for each cluster independently, based on the density of points. Thus, in HDBSCAN, neither the maximal distance nor the total number of clusters need to be predefined.

Differential Privacy (DP). DP is a privacy technique that aims to ensure that the outputs do not reveal individual data records of participants. DP is formally defined as follows:

Definition 1 ((ε,δ)-differential privacy)**.** *A randomized algorithm $\mathcal{M}$ is (ε,δ)-differentially private if for any datasets D_1 and D_2 that differ on a single element, and any subset of outputs $\mathcal{S} \in Range(\mathcal{M})$, the following inequality holds:*

$$Pr[\mathcal{M}(D_1) \in \mathcal{S}] \leq e^{\varepsilon} \cdot Pr[\mathcal{M}(D_2) \in \mathcal{S}] + \delta.$$

Here, ε denotes the privacy bound and δ denotes the probability of breaking this bound [18]. Smaller values of ε and δ indicate stronger privacy. A commonly used approach to enforce differential privacy is adding random Gaussian noise $N(0,\sigma^2)$ to the output of the algorithm [3, 18].

3 Problem Setting and Objectives

Backdoor Characterization. Following common practice in FL-related papers (e.g., [7, 12, 22]), we represent Neural Networks (NNs) using their weight vectors, in which the extraction of weights is done identically for all models by flattening/serializing the weight/bias matrices in a predetermined order. Figure 2 shows an abstract two-dimensional representation of the weight vectors of local models compared to the global model G_{t-1} of the preceding aggregation round. Each model W_i can be characterized with two factors: *direction (angle)* and *magnitude (length)* of its weight vector $(w^1, w^2, \ldots, w^p)$. The angle between two updates W_i and W_j can be measured, e.g., by using the cosine distance metric c_{ij} as defined in (2) while their magnitude difference is measured by the L_2-norm e_{ij} as defined in (3).

$$c_{ij} = 1 - \frac{W_i W_j}{\|W_i\| \|W_j\|} = 1 - \frac{\sum_{k=1}^{p} w_i^k w_j^k}{\sqrt{\sum_{k=1}^{p} (w_i^k)^2} \sqrt{\sum_{k=1}^{p} (w_j^k)^2}} \quad (2)$$

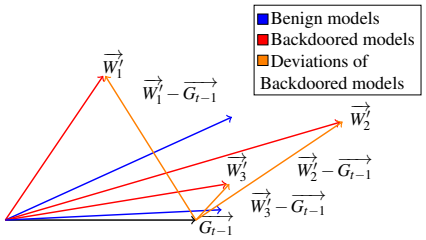


Figure 2: Weight vectors of benign and backdoored models.

$$e_{ij} = \|W_i - W_j\| = \sqrt{\sum_{k=1}^{p} (w_i^k - w_j^k)^2} \tag{3}$$

Benign and backdoored local models are shown in blue and red colors and are labeled with W_i or W_i', respectively. Note that the benign models are typically not identical due to the potentially partially non-iid nature of their training data.

The impact of the adversarial goal (injection of a backdoor) causes a deviation in the model parameters that manifests itself as a difference in the direction and/or magnitude of the backdoored model's weight vector in comparison to benign models, e.g., the deviations among local models and to the global model G_{t-1} of the previous aggregation round. Since the adversary has full control over the training process of compromised clients, he can fully control these distances, e.g., by changing the direction (in the case of W_1') or magnitude (in the case of W_2') of the backdoored models' weight vectors.

Figure 2 also shows three kinds of backdoored models resulting from different types of backdoor attacks. The first type W_1' has a similar weight vector, but a *large angular deviation* from the majority of local models and the global model. This is because such models are trained to obtain high accuracy on the backdoor task, which can be achieved by using a large poisoned data rate (*PDR*) or a large number of local training epochs (cf. Distributed Backdoor Attack (DBA) [59]). The second backdoor type W_2' has a small angular deviation but a *large magnitude* to amplify the impact of the attack. Such models can be crafted by the adversary by *scaling up* the model weights to boost its effect on the global model (cf. *Model-replacement* attack in [7]). The third backdoor type W_3' has a similar weight vector as benign models, the angular difference and the magnitude are not substantially different compared to benign models and, thus less distinguishable from benign models. Such *stealthy* backdoored models can be crafted by the adversary by carefully constraining the training process or scaling down the poisoned model's weights (cf. *Constrain-and-scale* attack [7] or FLIoT attack [45]).

Defense Objectives. A generic defense that can effectively mitigate backdoor attacks in the FL setting needs to fulfill the following objectives: (i) *Effectiveness*: To prevent the adversary from achieving its attack goals, the impact of backdoored model updates must be eliminated so that the aggregated global model does not demonstrate backdoor behavior. (ii) *Performance*: Benign performance of the global model must be preserved to maintain its utility. (iii) *Independence from data distributions and attack strategies*: The defense method must be applicable to generic adversary models, i.e., it must not require prior knowledge about the backdoor attack method, or make assumptions about specific data distributions of local clients, e.g., whether the data are iid or non-iid.

4 FLAME Overview and Design

We present the high-level idea of FLAME and the associated design challenges to fulfill the objectives identified in §3.

4.1 High-level Idea

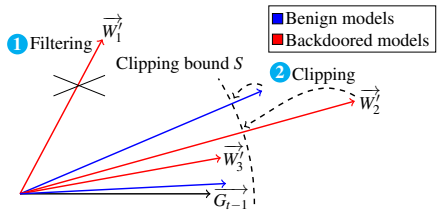
Motivation. Earlier works (e.g., Sun *et al.* [56]) use differential privacy-inspired noising of the aggregated model for eliminating backdoors. They determine the sufficient amount of noise to be used empirically. In the FL setting this is, however, challenging, as one cannot in general assume the aggregator to have access to training data, in particular to poisoned datasets. What is therefore needed is a generic method for determining how much noise is sufficient to remove backdoors effectively. On the other hand, the more noise is injected into the model, the more its benign performance will be impacted.

FLAME Overview. FLAME estimates the noise level required for backdoor removal in the FL setting without extensive empirical evaluation and having access to training data (this noise bound is formally proven in §5). In addition, to effectively limit the amount of required noise, FLAME uses a novel clustering-based approach to identify and remove adversarial model updates with high impact and applies a dynamic weight-clipping approach to limit the impact of models that the adversary has scaled up to boost their performance. As discussed in §3, one cannot guarantee that all backdoored models can be detected since the adversary can fully control both the angular and magnitude deviation to make the models arbitrarily hard to detect. Our clustering approach therefore aims to remove models with high attack impact (having larger angular deviation) rather than all malicious models. Fig. 3 illustrates the high-level idea of FLAME consisting of the above three components: filtering, clipping, and noising. We emphasize, however, that each of these components needs to be applied with great care, since, a naïve combination of noising with clustering and clipping leads to poor results as it easily fails to mitigate the backdoor and/or deteriorates the benign performance of the model, as we show in §C. We detail the design of each component and its use in the FLAME defense approach in §4.3.

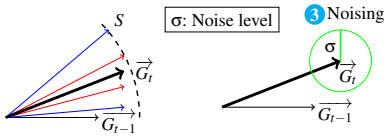
4.2 Design Challenges

To realize the high-level idea presented above, we need to solve the following technical challenges.

C_1 - Filtering out backdoored models with large angular deviations in dynamic scenarios. As discussed in §3, the weight vector of a well-trained backdoored model, W', has a *higher angular difference* in comparison to weight vectors of benign models W. FLAME deploys a clustering approach to



(a) Applying clustering and clipping.



(b) Applying noising

Figure 3: High-level idea of FLAME defense.

identify such poisoned models and *remove* them from FL aggregation (detailed in §4.3.1). The effect of clustering-based filtering is shown in Fig. 3a where model W_1' is removed from the aggregated model as it does not align with the directions of benign models. In contrast to existing clustering-based defenses, we need an approach that can also work in a *dynamic attack setting*, i.e., the number of injected backdoors is unknown and may vary between training rounds. To this end, we make a key observation: clustering approaches using a fixed number of clusters $n_{cluster}$ for identifying malicious models are inherently vulnerable to attacks with varying numbers of backdoors[2] $n_{backdoor}$. This is because the adversary can likely cause at least one backdoor model to be clustered together with benign models due to the pigeonhole principle by simultaneously injecting $n_{backdoor} \geq n_{cluster}$ backdoors. We seek to solve this challenge by employing a clustering solution that dynamically determines the clusters for model updates, thereby allowing it to adapt to dynamic attacks.

C_2-Limiting the impact of scaled-up backdoors. To limit the impact of backdoored models that the adversary artificially scales up to boost the attack (e.g., W_2' in Fig. 2), the weight vectors of models with high magnitudes can be clipped [56]. The effect of clipping is shown in Fig. 3a where the weight vectors of all models with a magnitude beyond the clipping bound S (in particular, backdoored model W_2') are clipped to S by scaling down the weight vectors. The resulting clipped weight vectors are shown on the left side of Fig. 3b. The challenge here is how to select a proper clipping bound without empirically evaluating its impact on the training datasets (which are not available in the FL setting). If the applied clipping bound is too large, an adversary can boost its model W' by scaling its weights up to the clipping bound, thereby maximizing the backdoor impact on the aggregated global model G. However, if the applied clipping bound is too small, a large fraction of benign model updates W will be clipped, thereby leading to performance deterioration of the aggregated global model G on the main task. We tackle this challenge in §4.3.2, where we show how to select a clipping bound that can not be influenced by the adversary and that effectively limits the impact of scaled-up backdoored models.

C_3-Selecting suitable noise level for backdoor elimination. As mentioned in §4.1, FLAME uses model noising that applies Gaussian noise with noise level σ to mitigate the adversarial impact of backdoored models (e.g., W_3' in Fig. 2). Similar to the clipping bound, however, also here the noise level σ must be carefully selected, as it has a direct impact on the effectiveness of the defense and the model's benign performance. If it is too low, the aggregated model might retain backdoor behavior after model noising, rendering the defense ineffective, while excessive noise will degrade the utility of the aggregated model. To address this challenge, we develop an approach for reliably estimating a sufficient but minimal bound for the applied noise in §5.

4.3 FLAME Design

As discussed in §4.1, our defense consists of three main components: filtering, clipping, and noising. Figure 4 shows these components and the workflow of FLAME during training round t. Algorithm 1 outlines the procedure of FLAME. In the rest of this section, we detail the design of these components to resolve the challenges in §4.2.

Algorithm 1 FLAME

Input: n, G_0, T ▷ n is the number of clients, G_0 is the initial global model, T is the number of training iterations
Output: G_T^* ▷ G_T^* is the updated global model after T iterations
for each training iteration t in $[1,T]$ **do**
  for each client i in $[1,n]$ **do**
    $W_i \leftarrow \text{CLIENTUPDATE}(G_{t-1}^*)$ ▷ The aggregator sends G_{t-1}^* to Client i who trains G_{t-1}^* using its data D_i locally to achieve local modal W_i and sends W_i back to the aggregator.
  $(c_{11},\ldots,c_{nn}) \leftarrow \text{COSINEDISTANCE}(W_1,\ldots,W_n)$ ▷ $\forall i,j \in (1,\ldots,n)$, c_{ij} is the cosine distance between W_i and W_j
  $(b_1,\ldots,b_L) \leftarrow \text{CLUSTERING}(c_{11},\ldots,c_{nn})$ ▷ L is the number of admitted models, b_l is the index of the l^{th} model
  $(e_1,\ldots,e_n) \leftarrow \text{EUCLIDEANDISTANCES}(G_{t-1}^*,(W_1,\ldots,W_n))$ ▷ e_i is the Euclidean distance between G_{t-1}^* and W_i
  $S_t \leftarrow \text{MEDIAN}(e_1,\ldots,e_n)$ ▷ S_t is the adaptive clipping bound at round t
  for each client l in $[1,L]$ **do**
    $W_{b_l}^c \leftarrow G_{t-1} + (W_{b_l} - G_{t-1}) \cdot \text{MIN}(1,\gamma)$ ▷ Where γ $(= S_t/e_{b_l})$ is the clipping parameter, $W_{b_l}^c$ is the admitted model after clipped by the adaptive clipping bound S_t
  $G_t \leftarrow \sum_{l=1}^{L} W_{b_l}^c / L$ ▷ Aggregating, G_t is the plain global model before adding noise
  $\sigma \leftarrow \lambda \cdot S_t$ where $\lambda = \frac{1}{\varepsilon} \cdot \sqrt{2ln\frac{1.25}{\delta}}$ ▷ Adaptive noising level
  $G_t^* \leftarrow G_t + N(0,\sigma^2)$ ▷ Adaptive noising

4.3.1 Dynamic *Model Filtering*

The *Model Filtering* component of FLAME utilizes a *dynamic clustering* technique based on HDBSCAN [11] that

[2] We consider two backdoors to be independent if they use different triggers.

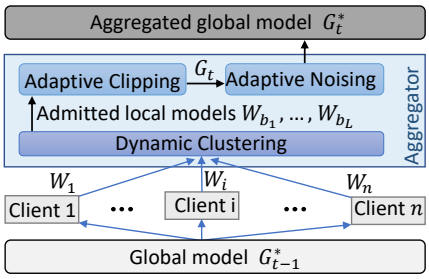
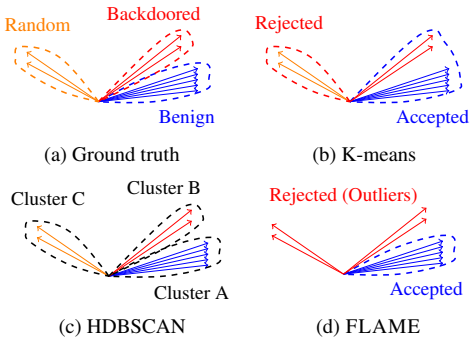


Figure 4: Illustration of FLAME's workflow in round t.

identifies poisoned models with high angular deviations from the majority of updates (e.g., W_1' in Fig. 3a). Existing clustering-based defenses [9, 51] identify potentially malicious model updates by clustering them into two groups where the smaller group is always considered malicious and thus removed. However, if no malicious models are present in the aggregation, this approach may lead to many models being incorrectly removed and thus a reduced accuracy of the aggregated model. These approaches also do not protect against attacks in which adversary $\mathcal{A}$ simultaneously injects multiple backdoors by using different groups of clients to inject different backdoors. If the number of clusters is fixed, there is the risk that poisoned and benign models end up in the same cluster, in particular, if models with different backdoors differ significantly. Consequently, existing model clustering methods do not adequately address challenge C_1 (§4.2). Fig. 5 shows the behavior of different clustering methods on a set of model updates' weight vectors. Fig. 5a shows the ground truth of an attack scenario where $\mathcal{A}$ uses two groups of clients: one group is used to inject a backdoor, whereas the other group provides random models with the goal of fooling clustering-based defenses. Fig. 5b shows how in this setting, K-means (as used in Auror [51]) fails to successfully separate benign and poisoned models as all poisoned models end up in the same cluster with the benign models.

To overcome the limitations of existing defenses, we design our clustering solution and ensure that: (i) it is able to handle dynamic attack scenarios where multiple backdoors are injected simultaneously, and (ii) it minimizes false positives of poisoned model identification. In contrast to existing approaches that try to place poisoned models into one cluster, our approach considers each poisoned model individually as an outlier, so that it can gracefully handle multiple simultaneous backdoors and thus address challenge C_1.

FLAME uses pairwise cosine distances to measure the angular differences between all model updates and applies the HDBSCAN clustering algorithm [11]. The advantage here is that cosine distances are not affected even if the adversary scales up model updates to boost their impact as this does not change the angle between the updates' weight vectors. Since the HDBSCAN algorithm clusters the models based on their density of the cosine distance distribution and *dynamically determines the required number of clusters*, we leverage it for our dynamic clustering approach. We describe HDBSCAN



(a) Ground truth (b) K-means

(c) HDBSCAN (d) FLAME

Figure 5: Comparison of clustering quality for (a) ground truth, (b) using K-means with 2 clusters as in Auror [51], (c) straightforward applied HDBSCAN and (d) our approach as in FLAME.

and how we apply it in detail in §E. In particular, HDBSCAN labels models as outliers if they do not fit into any cluster. This allows FLAME to effectively handle multiple poisoned models with different backdoors by labeling them as outliers. To realize this, we set the minimum cluster size to be at least 50% of the clients, i.e., $\frac{n}{2}+1$, so that the resulting cluster will contain the majority of updates (which we assume to be benign, cf. §2.3). All remaining (potentially poisoned) models are marked as *outliers*. This behavior is depicted in Fig. 5d where all the models from Clusters B and C from Fig. 5c are considered as outliers. Hence, to the best of our knowledge, our approach is the first FL backdoor defense that is able to gracefully handle also dynamic attacks in which the number of injected backdoors may vary. The clustering step is shown in lines 6-7 of Alg. 1 where L models are retained after clustering.

4.3.2 Adaptive Clipping and Noising

As discussed in §4.2 (challenges C_2 and C_3), determining a proper clipping bound and noise level for model weight clipping and noising is not straightforward. We present our new approach for selecting an effective clipping bound and reliably estimating a sufficient noise level that can effectively eliminate backdoors while preserving the performance of the main task. Furthermore, our defense approach is resilient to adversaries that dynamically adapt their attacks.

Adaptive Clipping. Fig. 6 shows the variation of the average L_2-norms of model updates of benign clients in three different datasets (cf. §6) over subsequent training rounds. We can observe that the *L_2-norms of benign model updates become smaller in later training rounds*. To effectively remove backdoors while minimizing the impact on benign updates, the clipping bound S needs to be dynamically adapted to this decreasing trend of the L_2-norm. Recall that clipping is performed after clustering by scaling down model weights so that the L_2-norm of the scaled model becomes smaller or equal to the clipping threshold. We describe how FLAME determines a proper scaling factor for each model update W_i in t^{th} training round as follows: Given the index set $(b_1, \ldots b_L)$ of the models admitted by the clustering method (line 7 of Alg. 1), the aggregator first computes the clipping bound

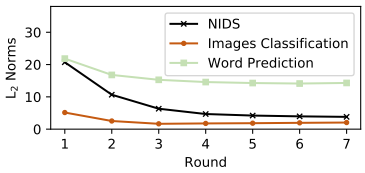


Figure 6: L_2-norms of model updates depending on the number of training rounds for different datasets.

S_t as the median of the L_2-norms of all n model updates: $S_t = \text{MEDIAN}(e_1, \ldots, e_n)$. It should be noted that for determining the clipping bound, the rejected models are also considered to ensure that even if benign models were filtered, the computed median S_t is still determined based on benign values. However, after determining the clipping bound, only the admitted models $W_1, \ldots, W_L$ are considered for later processing. The scaling factor for the l^{th} admitted model is computed as $\gamma = \frac{S_t}{e_{b_l}}$ where e_{b_l} is the L_2-norm of the model update W_{b_l}. Clipping scales down model updates as follows: $W^c_{b_l} = G_{t-1} + (W_{b_l} - G_{t-1}) \cdot \text{MIN}(1, \gamma)$ (detailed in line 8-11 of Alg. 1) where the multiplication is computed coordinate-wise. It is worth noting that weighting contributions (i.e., adjusting scaling factor) based on client data sizes is insecure. As we point out in §2.1, the reported dataset sizes by clients cannot be trusted, i.e., the adversary can lie about their dataset sizes to maximize attack impact [57]. Hence, we follow common practice in literature and weight the contributions of all clients equally regardless of their dataset size [7, 9, 12, 59]. By using the median as the clipping bound S_t, we ensure that S_t is always in the range of the L_2-norms between benign models and the global model since we assume that more than 50% of clients are benign (cf. §2.3). We evaluate the effectiveness of the clipping approach in §B.2.

Adaptive Noising. It has been shown that by adding noise to a model's weights, the impact of outlier samples can be effectively mitigated [17]. Noise can also be added to poisoned samples (special cases of outliers) used in backdoor injection. The more noise is added to the model during the training process, the less responsive the model will be to the poisoned samples. Thus, increasing model robustness against backdoors. Eliminating backdoors utilizing noise addition is conceptually the same in a centralized or federated setting (e.g., [7, 17]): In both cases, noise is added to the model weights to smooth out the effect of poisoned data (cf. Eq. 5). The challenge is to determine as small a noise level as possible to eliminate backdoors and at the same time not deteriorate the benign performance of the model. As we discuss in detail in §5.1, the amount of noise is determined by estimating the sensitivity based on the differences (distances) among local models, which can be done without access to training data. We then add Gaussian noise to the global model G_t to yield a noised global model G^*_t as follows: $G^*_t = G_t + N(0, \sigma^2)$, see Lines 13-14 of Alg. 1 for more details. This ensures that backdoor contributions are effectively eliminated from the aggregated model. In particular, we show in §5.1 how the noise-based backdoor elimination technique can be transferred from a centralized to a federated setting by analysing the relationship between aggregated Gaussian noise applied to the global model and individual noising of each local model.

5 Security Analysis

5.1 Noise Boundary Proof of FLAME

In this section, we provide a proof to corroborate that FLAME can neutralize backdoors in the FL setting by applying strategical noising with bound analysis on the noise level. We first formulate the noise boundary guarantee of FLAME in Theorem 1. Subsequently, we explain related parameters and prove how the noise level bound for σ can be estimated. This is done by generalizing theoretical results from previous works [17, 18] to the FL setting. Then, we show how the filtering and clipping component of FLAME helps to effectively reduce the noise level bound in Theorem 2. We provide a formal proof for linear models and extend the proof to DNNs using empirical evaluation. This is because providing formal proof for DP-based backdoor security for DNN models is still an open research problem even for centralized settings.

Theorem 1. *A (ε, δ)-differentially private model with parameters G and clipping bound S_t is backdoor-free if random Gaussian noise is added to the model parameters yielding a noised version G^* of the model: $G^* \leftarrow G + N(0, \sigma^2_G)$ where the noise scale σ_G is determined by the clipping bound S_t and a noise level factor λ: $\sigma_G \leftarrow \lambda \cdot S_t$ and $\lambda = \frac{1}{\varepsilon} \cdot \sqrt{2ln\frac{1.25}{\delta}}$.*

We explore the key observation that an ML model with a sufficient level of differential privacy is *backdoor-free*. With this new definition of backdoor-free models in the DP domain, the main challenge to defeat backdoors in the FL setting is to decide a proper noise scale for the global model without knowledge of the training datasets. Furthermore, we need to minimize the amount of noise added to the global model to preserve its performance on the main task. None of the prior DP-based FL backdoor defense techniques provide a solution to the noise determination problem [56]. For the first time, FLAME presents an approach to *estimate* the proper noise scale that ensures the global model is backdoor-free. The noise boundary proof in Theorem 1 consists of two steps:
Step 1 (S1). By introducing the data hiding property of DP (Def. 1) and its *implication as the theoretical guarantee for backdoor-free* models. We also discuss function sensitivity (Def. 2) which is an important factor for selection of the DP parameters (ε, δ).
Step 2 (S2). We show how FLAME *generalizes backdoor elimination from centralized setting to federated setting* with theoretical analysis of the noise boundary (Eq. 5 and 6). FLAME *is the first FL defense against backdoors that provides noise level proof with bounded backdoor effectiveness.*

(S1) DP foundations and re-interpretation as Backdoor-free. As discussed in §2.4, by definition, DP makes the differ-

ence between data points indistinguishable. FLAME leverages this property of DP for backdoor elimination. In particular, we can consider D_1 and D_2 in Def. 1 as the benign and backdoored dataset. The inequality of DP suggests that algorithm $\mathcal{M}$ has a high probability of producing the same outputs on the benign and the poisoned dataset, meaning that the backdoor is eliminated. The noise level σ is determined based on the DP parameters (ε, δ) and the *sensitivity* of the function f defined below:

Definition 2 (Sensitivity). *Given the function $f : \mathcal{D} \to \mathbb{R}^d$ where $\mathcal{D}$ is the data domain and d is the dimension of the function output, the sensitivity of the function f is defined as:*

$$\Delta = \max_{D_1,\, D_2 \in \mathcal{D}} ||f(D_1) - f(D_2)||_2, \tag{4}$$

where D_1 and D_2 differs on a single element $||D_1 - D_2||_1 = 1$.

As shown in Lemma 1 [18], this definition can be extended to datasets differing by more than one element, i.e., can be generalized to the DP in the multiple-point-difference setting.

(S2) Generalizing backdoor resilience from centralized to federated setting (FLAME). In the centralized setting, the defender has access to the model to be protected, the benign dataset, and the outlier (backdoored) samples. As such, he can estimate the sensitivity Δ for (ε, δ)-DP. When applying Gaussian noise with the noise scale $\sigma = \frac{\Delta}{\varepsilon}\sqrt{2ln\frac{1.25}{\delta}}$, the defender can enforce a lower bound on the prediction loss of the model on the backdoored samples for backdoor elimination [28]. However, this robustness rationale *cannot* be directly transferred from the centralized setting to the FL setting since the defender in the federated scenario (i.e., aggregator) only has access to received model updates, but not the datasets to estimate the sensitivity Δ for the global model.

FLAME extends DP-based noising for backdoor elimination to the federated setting based on the following observation: if one can ensure that all aggregated models are benign (i.e., backdoor-free), then it is obvious that the aggregated global model will also be backdoor-free. This intuition can be formally proven if the FL aggregation rule is Byzantine-tolerant. To ensure that any backdoor potentially present in the model is eliminated and the aggregated model is benign, a sufficient DP noise level is added to individual local models. However, since the local models are independent, adding noise to each local model is mathematically equivalent to the case where aggregated noise is added to the global model. This is conceptually equivalent to the conventional centralized setting, for which it has been formally shown that DP noise can eliminate backdoors [17]. In the following, we therefore show that adding DP noise to local models is equivalent to adding 'aggregated' DP noise to the global model.

We write the standard deviation of noise for the local models in the form $\sigma_i \leftarrow \frac{\alpha_i \cdot e_i}{\varepsilon} \cdot \sqrt{2ln\frac{1.25}{\delta}}$ where $\alpha_i = \frac{\Delta_i}{e_i}$, Δ_i and e_i is the sensitivity and the L_2 norm of the model W_i, respectively. Mathematically, the FL system with FLAME has:

$$\begin{aligned} G^* &= \frac{1}{n}\Sigma_{i=1}^n W_i^* = \frac{1}{n}[\,\Sigma_{i=1}^n\, W_i + N(0,\sigma_i^2)] \\ &= \frac{1}{n}\,\Sigma_{i=1}^2 W_i + \frac{1}{n}\Sigma_{i=1}^n N(0,\sigma_i^2) \\ &= \frac{1}{n}\,\Sigma_{i=1}^2 W_i + N(0, \frac{1}{n}\Sigma_{i=1}^n \sigma_i^2) \\ &= G + N(0,\sigma_G^2) \end{aligned} \tag{5}$$

in which W_i^* are local models and G^* the global model after adding noise $N(0,\sigma_i^2)$. Equation 5 represents the fact that adding DP noise to each local model (i.e., $W_i + N(0,\sigma_i^2)$) is equivalent to adding an 'aggregated' DP noise on the global model (i.e., $G + N(0,\sigma_G^2)$). More specifically, this equivalent Gaussian noise on the global model is the sum of Gaussian noise applied on each local model with a scaling factor $N_G = \frac{1}{n}\Sigma_{i=1}^n N_i$. Here, N_G and N_i are random variables with distribution $N(0,\sigma_G^2)$ and $N(0,\sigma_i^2)$, respectively. As such, we can compute the equivalent noise scale for the global model:

$$\begin{aligned} \sigma_G^2 &= \frac{1}{n^2}\Sigma_{i=1}^n \sigma_i^2 = (\frac{1}{\varepsilon}\sqrt{2ln\frac{1.25}{\delta}})^2 \cdot \frac{1}{n^2}\Sigma_{i=1}^n \Delta_i^2 \\ &= (\frac{1}{\varepsilon}\sqrt{2ln\frac{1.25}{\delta}})^2 \cdot \frac{1}{n^2}\Sigma_{i=1}^n \alpha_i^2 e_i^2. \end{aligned} \tag{6}$$

Equation 6 describes the relation between the DP noise added on FLAME's global model and the DP noise added on each local model. This noise scale relation in Eq. 6 together with the transformation in Eq. 5 enable FLAME to provide guaranteed security for the global model against backdoors, thereby addressing Challenge C_3 .

In Alg. 1, we use the median of Euclidean distances e_i as the upper bound S_t to clip the admitted local models (line 9-11). We hypothesize that the sensitivity of a model W_i is positively correlated with its weight magnitude $|W_i|$ (see Theorem 2 for details). In the case of linear models, the sensitivity Δ has a *linear* relation with the model weight $|\vec{w}|$ (see Eq. 8). Therefore, we use the following approximation:

$$\frac{1}{n^2}\Sigma_{i=1}^n \alpha_i^2 e_i^2 = \frac{1}{n^2}\Sigma_{i=1}^n \Delta_i^2 \approx S_t^2,$$

where S_t is the weight clipping bound. Having substituted the above approximation into Eq. 6, we can compute the noise scale of DP that FLAME deploys on the global model N_G:

$$\sigma_G \approx \frac{S_t}{\varepsilon}\sqrt{2ln\frac{1.25}{\delta}} \tag{7}$$

This concludes the proof of Theorem 1. □

FLAME's adaptive noising step applies the Gaussian noise with the noise scale computed in Eq. 7 on the global model for backdoor elimination as shown in Alg. 1, line 13-14. Note that FLAME's noising scheme is *adaptive* since the clipping bound S_t is obtained dynamically in each t^{th} epoch.

Next, we present Theorem 2 and justify how FLAME design reduces the derived noise level with *step 3 (S3)* below.

(S3) Clustering and clipping components in FLAME help to reduce the DP noise boundary. Recall that FLAME protects the FL system against backdoor attacks using three steps:

clustering, clipping, and adding DP noise. The overall workflow of FLAME is shown in Fig. 4. If multiple backdoors exist in the FL system, the first two steps (clustering and clipping) can remove a subset of backdoors as shown in Fig. 3a. Note that the remaining backdoors are *'closer'* to the benign model updates in terms of both magnitude and direction. This gives us the *intuition* that removing the remaining backdoors by adding DP noise becomes easier (i.e., the noise scale σ_G is smaller) after the first two steps of FLAME.

We can see from Theorem 1 that the Gaussian noise scale σ required for backdoor resilience increases with the sensitivity of each local model Δ_i. We describe two characteristics of the model parameter W, i.e., direction and magnitude in §4. We discuss how these two factors impact the sensitivity of the model defined in Eq. 4 below.

Theorem 2. *Backdoor models with large angular deviation from benign ones, or with large parameter magnitudes have high sensitivity values* Δ.

Proving DP-based backdoor security for DNN models is still an open problem, even in the centralized setting. We, therefore, adopt a common approach in literature (e.g., [17]) by providing theoretical proof for linear models and validating it for DNNs empirically.

Proof: for a linear model f where the function output is determined by the inner product of model weight vector $\overrightarrow{w}$ and the data vector $\overrightarrow{x}$, we have

$$f(w;\, x) = \overrightarrow{w} \cdot \overrightarrow{x} = |w| \cdot |x| \cdot cos\theta, \tag{8}$$

where $\theta = < \overrightarrow{w}, \overrightarrow{x} >$ is the angle between two vectors. In this case, it is straightforward to see that if the backdoor attack changes the parameter magnitude $|w|$ or the direction θ of the model f, the resulting poisoned model f' has a large sensitivity value based on the definition in Eq. 4. □

This analysis suggests that backdoor models with large angular deviations or with large weight magnitudes have a high sensitivity value Δ. Recall that FLAME deploys dynamic clustering (§4.3.1) to remove poisoned models with large cosine distances, and employs adaptive clipping (§4.3.2) to remove poisoned models with large magnitudes. Therefore, the sensitivity of the remaining backdoor models is lower compared to the one before applying these two steps. As a result, FLAME *can use a small Gaussian noise to eliminate the remaining backdoors after applying clustering and clipping, which is beneficial for preserving the main task accuracy.*

We empirically show how the noise scale for backdoor elimination changes after applying each step of FLAME. Particularly, we measure the *smallest* Gaussian noise scale σ required to defeat *all backdoors* (i.e., $BA = 0\%$) in three settings: i) No defense components applied (which is equivalent to the previous DP-based defense [7, 18]); ii) After applying dynamic clustering; iii) After applying both dynamic clustering and adaptive clipping (which is the setting of FLAME). We conduct this comparison experiment on the IoT-Traffic dataset (cf. §6). For each communication round, 100 clients are selected where $k = 40$ are adversaries. We remove the backdoor by adding Gaussian noise $N(0, \sigma^2)$ to the aggregated model. Table 1 summarizes the evaluation results in the above three settings. We can observe from the comparison results that the noise scale required to eliminate backdoors decreases after individual deployment of clustering and clipping. This corroborates the correctness of Theorem 2.

Table 1: Effect of clustering and clipping in FLAME on minimal Gaussian noise level σ for backdoor elimination in the NIDS scenario, in terms of Backdoor Accuracy (*BA*) and Main Task Accuracy (*MA*).

σ	Only Noising		After Clustering		After Clustering & Clipping	
	BA	MA	BA	MA	BA	MA
0.01	100.0%	100.0%	0.0%	80.5%	0.0%	100.0%
0.08	3.5%	66.7%	0.0%	66.7%	0.0%	100.0%
0.10	0.0%	54.2%	0.0%	66.1%	0.0%	87.6%

5.2 Attack and Data Distribution Assumption

In FLAME, we do not make specific assumptions about the attack and data distribution compared to the existing clustering-based defenses. Let $X = (X_1, \ldots, X_b)$ be a set of distributions of benign models $(W_1, \ldots, W_{n-k})$ where $b \leq n-k$. The deviation in X is caused by the diversity of the data. Let $X' = (X'_1, \ldots, X'_a)$ be a set of distributions of poisoned models $(W'_1, \ldots, W'_k)$ where $a \leq k$. The deviation in X' is caused by the diversity of the benign data and backdoors (e.g., poisoned data or model crafting). Existing works assume that $X'_i \approx X'_j \quad (\forall i, j : 1 \leq i, j \leq a)$ (see e.g., [22] or $X' \neq X$ [9,51]). However, this assumption does not hold in many situations because (i) there can be one or multiple attackers injecting multiple backdoors [7], or (ii) the adversary can inject one or several random (honeypot) models having a distribution X'_r that is significantly different from $X \cup (X' \setminus X'_r)$, and (iii) the adversary can control how much the backdoored models deviate from benign ones as discussed in §3. Therefore, approaches that purely divide models into two groups, e.g., K-means [51] will incorrectly classify models having distribution X'_r into the malicious group and all remaining models (having distributions drawn from $(X \cup (X' \setminus X'_r))$ into the benign group. As a result, all backdoored models having distributions drawn from $(X' \setminus X'_r)$ are classified as benign, as demonstrated in Fig. 5b. In contrast, FLAME does not rely on such specific assumptions (the adversary can arbitrarily choose X'). If the distribution X'_i of a poisoned model is similar to benign distributions in X, FLAME will falsely classify X'_i as being. But if the distribution X'_j of a poisoned model is different from the distributions in X, FLAME will identify X'_j as an outlier and classify the associated model as malicious. To identify deviating and thus potentially malicious models, FLAME leverages the HDBSCAN algorithm to identify regions of high density in the model space. Any models that are not located in the dense regions will be categorized as outliers, as shown in Fig. 5d. As discussed in §3, FLAME aims to remove models with distributions X'_j that have a higher

attack impact compared to models with distribution X_i'. It is worth noting, however, that the impact of such remaining backdoored models will be eliminated by the noising component as shown in §5.1

Striking a balance between accuracy and security: Clustering and DP-based approaches affect model accuracy as discussed in §4.2 (Challenges C_2 and C_3). In particular, an approach that aims to maximize the number of filtered malicious models may lead to many false positives, i.e., many benign models being filtered out. Moreover, applying a very low clipping bound or a very high level of injected noise will degrade model accuracy. To address these problems, FLAME is configured so that the clustering component removes only models with high attack impact rather than all malicious models, i.e., it aims to remove the first backdoor type W_1' as shown in Fig. 3. In addition, FLAME carefully estimates the clipping bound and noise level to ensure backdoor elimination while preserving model performance. As discussed in §4.3.2, the L_2-norms of model updates depend on the number of training rounds, dataset types, and type of backdoors. Consequently, the clipping threshold and noise level should be adapted to L_2-norms. We therefore apply the median of the L_2-norms of model updates as the clipping bound S_t (cf. Lines 9-11 of Alg. 1). This ensures that S_t is always computed between a benign local model and the global model since we assume that more than 50% of clients are benign (cf. §2.3). Further, estimating noise level based on S_t (cf. Lines 13-14 of Alg. 1) also provides a noise boundary that ensures that the global model is resilient against backdoors as discussed in §5.1. Moreover, our comparison of potential values for S_t presented in §B.2 and §B.3 shows that the chosen clipping bound and noise level provide the best balance between accuracy and security, i.e., FLAME eliminates backdoor while retaining the global model's performance on the main task.

6 Experimental Setup

We conduct all the experiments using the PyTorch deep learning framework [2] and use the source code provided by Bagdasaryan *et al.* [7], Xie *et al.* [59] and Wang *et al.* [57] to implement the attacks. We reimplemented existing defenses to compare them with FLAME.

Datasets and Learning Configurations. Following recent research on poisoning attacks on FL, we evaluate FLAME in three typical application scenarios: word prediction [35, 38–40], image classification [13, 49, 50], and an IoT intrusion detection [44, 47, 48, 54] as summarized in Tab. 2. Verification of the effectiveness of FLAME against state-of-the-art attacks in comparison to existing defenses (cf. Tab. 3 and Tab. 4) are conducted on these three datasets in the mentioned application scenarios. Experiments for evaluating specific performance aspects of FLAME are performed on the IoT dataset as it represents a very diverse and real-world setting with clear security implications.

Evaluation Metrics. We consider a set of metrics for evaluating the effectiveness of backdoor attack and defense techniques as follows:

Table 2: Datasets used in our evaluations.

Application	Datasets	#Records	Model	#params
WP	Reddit	20.6M	LSTM	∼20M
NIDS	IoT-Traffic	65.6M	GRU	∼507k
IC	CIFAR-10	60k	ResNet-18 Light	∼2.7M
	MNIST	70k	CNN	∼431k
	Tiny-ImageNet	120k	ResNet-18	∼11M

BA - Backdoor Accuracy indicates the accuracy of the model in the backdoor task, i.e., it is the fraction of the trigger set for which the model provides the wrong outputs as chosen by the adversary. The adversary aims to maximize *BA*, while an effective defense prevents the adversary from increasing it.

MA - Main Task Accuracy indicates the accuracy of a model in its main (benign) task. It denotes the fraction of benign inputs for which the system provides correct predictions. The adversary aims at minimizing the effect on *MA* to reduce the chance of being detected. The defense system should not negatively impact *MA*.

TPR - True Positive Rate indicates how well the defense identifies poisoned models, i.e., the ratio of the number of models correctly classified as poisoned (True Positives - TP) to the total number of models being classified as poisoned: $TPR = \frac{TP}{TP+FP}$, where FP is False Positives indicating the number of benign clients that are wrongly classified as malicious.

TNR - True Negative Rate indicates the ratio of the number of models correctly classified as benign (True Negatives - TN) to the total number of benign models: $TNR = \frac{TN}{TN+FN}$, where FN is False Negatives indicating the number of malicious clients that are wrongly classified as benign.

7 Experimental Results

In this section, we evaluate FLAME against backdoor attacks in the literature (§7.1) and demonstrate that our defense mechanism is resilient to adaptive attacks (§7.2). In addition, we show the effectiveness of each of FLAME's components in §B and FLAME overhead in §D. Finally, we evaluate the impact of the number of clients (§7.3) as well as the degree of non-IID data (§7.4).

7.1 Preventing Backdoor Attacks

Effectiveness of FLAME. We evaluate FLAME against the state-of-the-art backdoor attacks called *constrain-and-scale* [7], DBA [59], PGD and Edge-Case [57] and an untargeted poisoning attack [20] (cf. §F) using the same attack settings as in the original works with multiple datasets. The results are shown in Tab. 3. FLAME completely mitigates the *constrain-and-scale* attack ($BA = 0\%$) for all datasets. Moreover, our defense does not affect the Main Task Accuracy (*MA*) of the system as MA reduces by less than 0.4% in all experiments. The DBA attack as well as the Edge-Case attack [57] are also successfully mitigated ($BA = 3.2\%/4.0\%$). Further, FLAME is also effective against PGD attacks ($BA =$ 0.5 %). It should be noted that suggesting words is a quite

Table 3: Effectiveness of FLAME against state-of-the-art attacks for the respective dataset, in terms of Backdoor Accuracy (*BA*) and Main Task Accuracy (*MA*). All metric values are reported as percentages.

Attack	Dataset	No Defense		FLAME	
		BA	*MA*	*BA*	*MA*
Constrain-and-scale [7]	Reddit	100	22.6	0	22.3
	CIFAR-10	81.9	89.8	0	91.9
	IoT-Traffic	100.0	100.0	0	99.8
DBA [59]	CIFAR-10	93.8	57.4	3.2	76.2
Edge-Case [57]	CIFAR-10	42.8	84.3	4.0	79.3
PGD [57]	CIFAR-10	56.1	68.8	0.5	65.1
Untargeted Poisoning [20]	CIFAR-10	-	46.72	-	91.31

Table 4: Effectiveness of FLAME in comparison to state-of-the-art defenses for the *constrain-and-scale* attack on three datasets, in terms of Backdoor Accuracy (*BA*) and Main Task Accuracy (*MA*). All values are percentages.

Defenses	Reddit		CIFAR-10		IoT-Traffic	
	BA	*MA*	*BA*	*MA*	*BA*	*MA*
Benign Setting	-	22.7	-	92.2	-	100.0
No defense	100.0	22.6	81.9	89.8	100.0	100.0
Krum [9]	100.0	9.6	100.0	56.7	100.0	84.0
FoolsGold [22]	**0.0**	**22.5**	100.0	52.3	100.0	99.2
Auror [51]	100.0	**22.5**	100.0	26.1	100.0	96.6
AFA [42]	100.0	22.4	**0.0**	91.7	100.0	87.4
DP [18]	14.0	18.9	**0.0**	78.9	14.8	82.3
Median [60]	**0.0**	22.0	**0.0**	50.1	0.0	87.7
FLAME	**0.0**	22.3	**0.0**	**91.9**	**0.0**	**99.8**

challenging task, causing the MA even without attack to be only 22.7%, aligned with previous work [7].

We extend our evaluation to various backdoors on three datasets. For NIDS, we evaluate 13 different backdoors (Mirai malware attacks) and 24 device types (78 IoT devices). The results show that FLAME is able to mitigate all backdoor attacks completely while achieving a high MA=99.8%. We evaluate 5 different word backdoors for WP, and 90 different image backdoors for IC, which change the output of a whole class to another class. In all cases, FLAME successfully mitigates the attack while still preserving the *MA*.

Comparison to existing defenses. We compare FLAME to existing defenses: Krum [9], FoolsGold [22], Auror [51], Adaptive Federated Averaging (AFA) [42], Median [60] and a generalized differential privacy (DP) approach [7, 40]. Tab. 4 shows that FLAME is effective for all 3 datasets, while previous works either fail to mitigate backdoors or reduce the main task accuracy. Krum, FoolsGold, Auror, and AFA do not effectively remove poisoned models and *BA* often remains at 100%. Also, some defenses make the attack even more successful than without defense. Since they remove many benign updates (cf. §B) but fail to remove a sufficient number of poisoned updates, these defenses increase the *PMR* and, therefore, also the impact of the attack. Some defenses, e.g., Krum [9], Auror [51] or AFA [42] are not able to handle non-iid data scenarios like Reddit. In contrast, FoolsGold is only effective on the Reddit dataset ($TPR = 100\%$) because it works well on highly non-independent and identically distributed (non-IID) data (cf. §9). Similarly, AFA only mitigates backdoors on the CIFAR-10 dataset since the data are highly IID (each client is assigned a random set of images) such that the benign models share similar distances to the global model (cf. §9). Additionally, the model's *MA* is negatively impacted. The DP-based defense is effective, but it significantly reduces *MA*. For example, it performs best on the CIFAR-10 dataset with $BA = 0$, but *MA* decreases to 78.9% while FLAME increases *MA* to 91.9% which is close to the benign setting (no attacks), where $MA = 92.2\%$.

Effectiveness of FLAME's Components. Further, we have also conducted an extensive evaluation of the effectiveness of each of FLAME's components. Due to space limitations, we would like to refer to §B for the details.

7.2 Resilience to Adaptive Attacks

Given sufficient knowledge about FLAME, an adversary may seek to use adaptive attacks to bypass the defense components. In this section, we analyze such attack scenarios and strategies including *changing the injection strategy*, *model alignment*, and *model obfuscation*.

Changing the Injection Strategy. The adversary $\mathcal{A}$ may attempt to inject several backdoors simultaneously to execute different attacks on the system in parallel or to circumvent the clustering defense (cf. §2.2). FLAME is also effective against such attacks (cf. Fig. 5). To further investigate the resilience of FLAME against such attacks, we conduct two experiments: 1) assigning different backdoors to malicious clients and 2) letting each malicious client inject several backdoors. To ensure that each backdoor is injected by a sufficient number of clients, we increased the PMR for this experiment. We conducted these experiments with $n = 100$ clients of which $k = 40$ are malicious on the IoT-Traffic dataset with each type of Mirai attack representing a backdoor. First, we evaluate FLAME for $0, 1, 2, 4$, and 8 backdoors, meaning that the number of malicious clients for each backdoor is $0, 40, 20, 10$, and 5. Our experimental results show that our approach is effective in mitigating the attacks as $BA = 0\% \pm 0.0\%$ in all cases, with $TPR = 95.2\% \pm 0.0\%$, and $TNR = 100.0\% \pm 0.0\%$. For the second experiment, 4 backdoors are injected by each of the 40 malicious clients. Also, in this case, the results show that FLAME can completely mitigate the backdoors.

Model Alignment. Using the same attack parameter values, i.e., *PDR* (cf. §2.2), for all malicious clients can result in high distances between benign and poisoned models. Those high distances can be illustrated as a gap between poisoned and benign models, s.t. the clustering can separate them. Therefore, a sophisticated adversary can generate models that bridge the gap between them such that they are merged to the same cluster in our clustering. We evaluate this attack on the IoT-Traffic dataset for $k = 80$ malicious clients and $n = 200$ clients in total. To remove the gap, each malicious client is assigned a random amount of malicious data, i.e., a random *PDR* ranging from 5% to 20%. As Tab. 5 shows, when we apply model filtering only, our clustering component cannot identify the

Table 5: Resilience to model alignment attacks in terms of Backdoor Accuracy (*BA*), Main Task Accuracy (*MA*), True Positive Rate (*TPR*), True Negative Rate (*TNR*) in percent.

	BA	*MA*	*TPR*	*TNR*
Model Filtering	100.0	91.98	0.0	33.04
FLAME	**0.0**	**100.0**	**5.68**	**33.33**

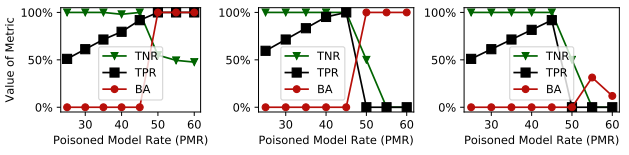
malicious clients well ($TPR = 0\%$), resulting in $BA = 100\%$. However, when we apply FLAME, although *TPR* remains low (5.68%) FLAME still mitigates the attack successfully (*BA* reduces from 100% to 0%). This can be explained by the fact that when the adversary $\mathcal{A}$ tunes malicious updates to be close to the benign ones, the attack's impact is reduced and consequently averaged out by our noising component.

Model Obfuscation. $\mathcal{A}$ can add noise to the poisoned models to make them difficult to detect. However, our evaluation of such an attack on the IoT-Traffic dataset shows that this strategy is not effective. We evaluate different noise levels to determine a suitable standard deviation for the noise. Thereby, we observe that a noise level of 0.034 causes the models' cosine distances in clustering to change without significantly impacting *BA*. However, FLAME can still efficiently defend this attack: *BA* remains at 0% and *MA* at 100%.

7.3 Effect of Number of Clients

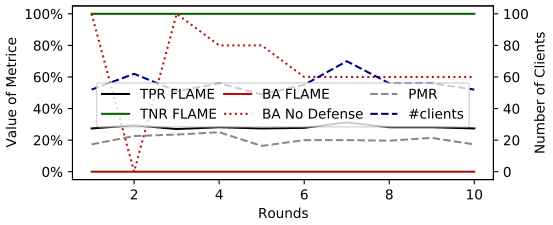
Impact of Number of Malicious Clients. We assume that the number of benign clients is more than half of all clients (cf. §2.2) and our clustering is only expected to be successful when $PMR = \frac{k}{n} < 50\%$ (cf. §4.3.1). We evaluate FLAME for different *PMR* values. Figure 7 shows how *BA*, *TPR*, and *TNR* change in the IC, NIDS, and WP applications for *PMR* values from 25% to 60%. It shows that FLAME is only effective if $PMR < 50\%$ so that only benign clients are admitted to the model aggregation ($TNR = 100\%$) and thus $BA = 0\%$. However, if $PMR > 50\%$, FLAME fails to mitigate the attack because the majority of poisoned models will be included resulting in low *TNR*. Interestingly, FLAME accepted all models for $PMR = 50\%$ ($TPR = 0\%$ and $TNR = 100\%$). For the IC application, since the IC data are non-IID, poisoned models are not similar. Therefore, some poisoned models were excluded from the cluster resulting in a high *TPR* even for *PMRs* higher than 50%. However, the majority of poisoned models were selected resulting in the drop in the *TNR*.

Varying number of clients in different training rounds. In general, FLAME is a round-independent defense, i.e., it

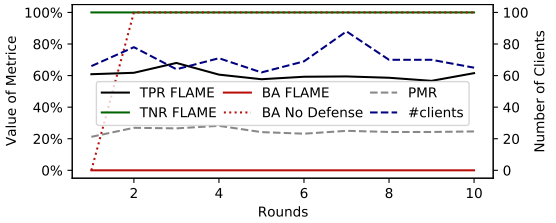


(a) IC (b) NIDS (c) WP

Figure 7: Impact of the poisoned model rate $PMR = \frac{k}{n}$ on the evaluation metrics. *PMR* is the fraction of malicious clients k per total clients n.



(a) Image Classification



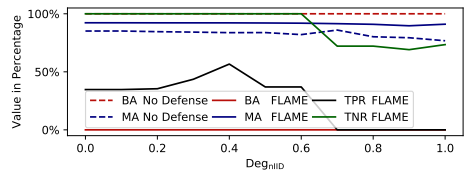
(b) Network Intrusion Detection

Figure 8: Impact of the number of clients on FLAME

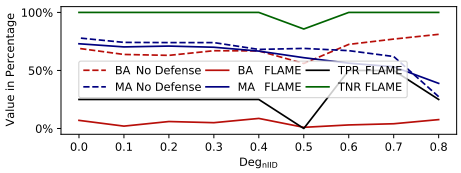
does not use information from previous rounds such as which clients were excluded in which rounds. Therefore, FLAME will not be affected if the number of clients or number of malicious clients varies as long as the majority of clients remain benign. To demonstrate this, we simulate realistic scenarios in which clients can join and drop out dynamically. We conducted an experiment where during each round, the total number of available clients is randomly selected. As the result, the number of malicious clients will also be random. In this experiment, we used a population of 100 clients in total, out of which 25 are malicious. In each round, a random number (from 60 to 90) of clients are selected, so that the fraction of malicious clients (*PMR*) varies in each round. Figure 8 shows the experimental results. One can see that the proportion of malicious clients (*PMR*) does not affect the effectiveness of FLAME, i.e., the backdoor is completely removed ($BA = 0\%$) in every round. Since all poisoned models are detected, their negative effect on the aggregated model is removed. Therefore, the MA with FLAME is better than the one without defense, and is almost always 100 % aligned with the results in Tab. 4.

7.4 Impact of the Degree of non-IID Data

Since clustering is based on measuring differences between benign and malicious updates, the distribution of data among clients might affect our defense. We conduct two experiments for both *Constrain-and-scale* and Edge-Case PGD on the CIFAR-10 dataset. For Reddit and IoT datasets, changing the degree of non-IID data is not meaningful since the data have a natural distribution as every client obtains data from different Reddit users or traffic chunks from different IoT devices. Following previous works [20, 57], we vary the degree of non-IID data Deg_{nIID} by changing the fraction of images belonging to a specific class assigned to clients. In particular, we divide the clients into 10 groups corresponding to the 10 classes of CIFAR-10. The clients of each group are assigned a fixed



(a) *Constrain-and-scale*



(b) Edge-Case PGD

Figure 9: Impact of degree of non-IID data on FLAME for *constrain-and-scale* using the $\text{Deg}_{\text{nIID}}$and for the Edge-Case PGD attack using the α parameter of the Dirichlet distribution.

fraction of $\text{Deg}_{\text{nIID}}$of the images from its designated image class, while the rest of the images will be assigned to it at random. Consequently, the data distribution is random, i.e., completely IID if $\text{Deg}_{\text{nIID}} = 0\%$ (all images are randomly assigned) and completely non-IID if $\text{Deg}_{\text{nIID}} = 100\%$ (a client only gets images from its designated class).

Figure 9a shows the evaluation results for the *constrain-and-scale* attacks. Although FLAME does not detect the poisoned models for very non-IID scenarios, it still mitigates the attack as the BA remains 0% for all values of Deg_{nIID}. For low Deg_{nIID}, FLAME effectively identifies the poisoned models ($TNR = 100\%$) and the MA remains on almost the same level as without defense. As shown in Fig. 9b, FLAME also mitigates the Edge-Case PGD attack effectively for all α values of the Dirichlet distribution and the MA also stays on the same level as without defense. However, since not all poisoned models are detected, a higher σ is determined dynamically to mitigate the *constrain-and-scale* backdoor, resulting in a slightly reduced MA for $\text{Deg}_{\text{nIID}} \geq 0.7$ (MA is 91.9% for $\text{Deg}_{\text{nIID}} = 0.6$, and is reduced to 91.0% for $\text{Deg}_{\text{nIID}} = 1.0$). Note that Fig. 9 shows the evaluation results in a training round t where the global model G_t is close to convergence [7], thus even though the TNR decreases with a large value of Deg_{nIID}, the drop of MA with FLAME is not substantial.

8 Privacy-preserving Federated Learning

A number of attacks on FL have been proposed that aim to infer from parameters of a model the presence of a specific training sample in the training dataset (*membership inference attacks*) [41,46,52], properties of training samples (*property inference attacks*) [23,41], try to assess the proportion of samples of a specific class in the data (*distribution estimation attacks*) [58]. Inference attacks by the aggregator $\mathcal{A}^s$ are significantly stronger, as $\mathcal{A}^s$ has access to the local models [43] and can also link gained information to a specific user, while the global model anonymizes the individual contributions. Therefore, enhanced privacy protection for FL is needed that prohibits access to the local model updates.

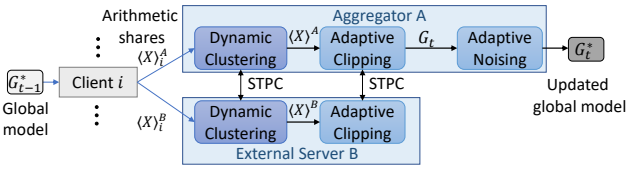


Figure 10: Overview of private FLAME in round t using Secure-Two-Party Computation (STPC).

Adversary Model (privacy). In this adversary type, $\mathcal{A}^s$ attempts to infer sensitive information about clients' data D_i from their model updates W_i [23,41,46,52] by maximizing the information $\phi_i = \text{INFER}(W_i)$ that $\mathcal{A}^s$ gains about the data D_i of client i by inferring from its corresponding model W_i.

Deficiencies of existing defenses. Generally, there are two approaches to protect the privacy of clients' data: differential privacy (DP; [18]) and cryptographic techniques such as homomorphic encryption [24] or multi-party computation [14]. DP is a statistical approach that can be efficiently implemented, but it can only offer high privacy protection at the cost of a significant loss in accuracy due to the noise added to the models [6,61]. In contrast, cryptographic techniques provide strong privacy guarantees as well as high accuracy at the cost of reduced efficiency.

Private FLAME. To securely implement FLAME using STPC, we use an optimized combination of three prominent STPC techniques as implemented with state-of-the-art optimizations in the ABY framework [14]. Fig. 10 shows an overview of private FLAME. It involves n clients and two non-colluding servers, called aggregator A and external server B. Each client $i \in \{1,...,n\}$ splits the parameters of its local update W_i into two Arithmetic shares $\langle X \rangle_i^A$ and $\langle X \rangle_i^B$, such that $W_i = \langle X \rangle_i^A + \langle X \rangle_i^B$, and sends $\langle X \rangle_i^A$ to A and $\langle X \rangle_i^B$ to B. A and B then privately compute the new global model via STPC. We co-design the distance calculation, clustering, adaptive clipping, and aggregation of FLAME (cf. Alg. 1) of FLAME as efficient STPC protocols.To further improve performance, we approximate HDBSCAN with the simpler DBSCAN [10] to avoid the construction of the minimal spanning tree in HDBSCAN as it is very expensive to realize with STPC. See §G for more details on private FLAME evaluation of its accuracy and performance.

9 Related Work

In general, existing backdoor defenses can roughly be divided into two main categories. The first one aims to distinguish malicious updates and benign updates by 1) clustering model updates [9,15,22,29,33,34,51], 2) changing aggregation rules [25,60], and 3) using root dataset [4]. The second category is based on differential privacy techniques [7,56]. Next, we will discuss these points in detail.

Clustering model updates. Several backdoor defenses, such as Krum [9], AFA [42], and Auror [51], aim at separating benign and malicious model updates. However, they

only work under specific assumptions about the underlying data distributions, e.g., Auror and Krum assume that data of benign clients are iid. In contrast, FoolsGold and AFA [42] assume that benign data are non-iid. In addition, FoolsGold assumes that manipulated data are iid. As a result, these defenses are only effective under specific circumstances (cf. §7.1) and cannot handle the simultaneous injection of multiple backdoors (cf. §4.3.1). Moreover, such defenses cannot detect stealthy attacks, e.g., where the adversary constrains their poisoned updates within benign update distribution such as *Constrain-and-scale* attacks [7]. In contrast, FLAME does not make any assumption about the data distribution, clipping, and noising components can also mitigate stealthy attacks, and FLAME can defend against injection of multiple backdoors (cf. §4.3.1).

Changing aggregation rules. Instead of using FedAvg [38], Yin *et al.* [60] and Guerraoui *et al.* [25] propose using the median parameters from all local models as the global model parameters, i.e., $G_t = \text{MEDIAN}(W_1^t, \ldots, W_n^t)$. However, the adversary can bypass it by injecting stealthy models like W_3' (cf. Fig. 2), in which the parameters of poisoned model will be selected to be incorporated into the global model. Further, our evaluation in §7.1 shows that Median also reduces the performance of the model significantly.

Using root data. Although FLTrust [12] can defend against byzantine clients (with arbitrary behavior) and detect poisoning attacks including backdoors, it requires the aggregator to have access to a benign root dataset. Baffle [4] utilizes clients using their own data to evaluate the performance of the aggregated model to detect backdoors. However, this approach has several limitations. Firstly, the backdoor triggers are only known to the attacker. One cannot ensure that the benign clients would have such trigger data to activate the backdoor. Secondly, Baffle does not work in a non-IID data scenario with a small number of clients as clients cannot distinguish deficits in model performance due to the backdoor from lack of data.

Differential Privacy-based approaches. Clipping and noising are known techniques to achieve differential privacy (DP) [18]. However, directly applying these techniques to defend against backdoor attacks is not effective because they significantly decrease the Main Task Accuracy (§7.1) [7]. FLAME tackles this by i) identifying and filtering out potential poisoned models that have a high attack impact (cf. §4.3.1), and ii) eliminating the residual poison with an appropriate adaptive clipping bound and noise level, such that the Main Task Accuracy is retained (cf. §4.3.2).

10 Conclusion

In this paper, we introduce FLAME, a resilient aggregation framework for FL that eliminates the impact of backdoor attacks while maintaining the performance of the aggregated model on the main task. We propose a method to approximate the amount of noise that needs to be injected into the global model to neutralize backdoors. Furthermore, in combination with our dynamic clustering and adaptive clipping, FLAME can significantly reduce the noise scale for backdoor removal and thus preserve the benign performance of the global model. In addition, we design, implement, and benchmark efficient secure two-party computation protocols for FLAME to ensure the privacy of clients' training data and to impede inference attacks on client updates.

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A Datasets and Learning Configurations

Word Prediction (WP). We use the Reddit dataset of November 2017 [1] with the same settings as state-of-the-art works [7, 38, 40] for comparability. In particular, each user in the dataset with at least 150 posts and not more than 500 posts is considered as a client. This results in 80 000 clients' datasets with sizes between 298 and 32 660 words.

The model consists of two LSTM layers and a linear output layer [7, 38]. To be comparable to the attack setting in [7], we evaluate FLAME on five different backdoors, each with a different trigger sentence corresponding to a chosen output.

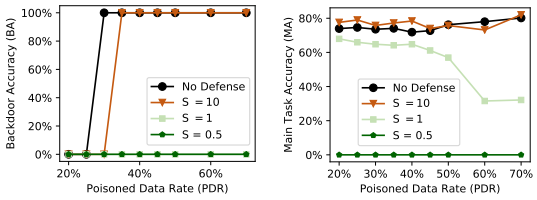
Image Classification (IC). For image classification, we use mainly the CIFAR-10 dataset [31], a standard benchmark dataset for image classification, in particular for FL [38] and backdoor attacks [7, 8, 42]. It consists of 60 000 images of 10 different classes. The adversary aims at changing the predicted label of one class of images to another class of images. We use a lightweight version of the ResNet18 model [26] with 4 convolutional layers with max-pooling and batch normalization [7]. The experimental setup consists of 100 clients and uses a PMR of 20%. In addition to the CIFAR-10 dataset, we also evaluate FLAME's effectiveness on two further datasets for image classification. The *MNIST* dataset consists of 70 000 handwritten digits [32]. The learning task is to classify images to identify digits. The adversary poisons the model by mislabeling labels of digit images before using it for training [51]. We use a convolutional neural network (CNN) with 431000 parameters. The *Tiny-ImageNet* [3] consists of 200 classes and each class has 500 training images, 50 validation images, and 50 test images. We used ResNet18 [26] model.

Network Intrusion Detection System (NIDS). We test backdoor attacks on IoT anomaly-based intrusion detection systems that often represent critical security applications [5, 16, 27, 30, 44, 45, 55]. Here, the adversary aims at causing incorrect classification of anomalous traffic patterns, e.g., generated by IoT malware, as benign patterns. Based on the FL anomaly detection system DÏoT [44], we use three datasets called DIoT-Benign, DIoT-Attack, and UNSW-Benign [44, 53] from real-world home and office deployments (four homes and two offices located in Germany and Australia). DIoT-Attack contains the traffic of 5 anomalously behaving IoT devices, infected by the Mirai malware [44]. Moreover, we collected a fourth IoT dataset containing communication data from 24 typical IoT devices (including IP cameras and power plugs) in three different smart home settings and an office setting. Following [44], we extracted

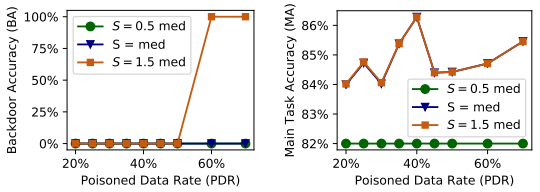
[3] https://tiny-imagenet.herokuapp.com

Table 6: Effectiveness of the clustering component, in terms of True Positive Rate (*TPR*) and True Negative Rate (*TNR*), of FLAME in comparison to existing defenses for the *constrain-and-scale* attack on three datasets. All values are in percentage and the best results of the defenses are marked in bold.

Defenses	Reddit		CIFAR-10		IoT-Traffic	
	TPR	TNR	TPR	TNR	TPR	TNR
Krum	9.1	0.0	8.2	0.0	24.2	0.0
FoolsGold	**100.0**	**100.0**	0.0	90.0	32.7	84.4
Auror	0.0	90.0	0.0	90.0	0.0	70.2
AFA	0.0	88.9	**100.0**	**100.0**	4.5	69.2
FLAME	22.2	**100.0**	23.8	86.2	**59.5**	**100.0**



(a) BA for static bound (b) MA for static bound



(c) BA for dynamic bound (d) MA for dynamic bound

Figure 11: Effectiveness of FLAME's clipping bound in terms of Backdoor Accuracy (*BA*) and Main Task Accuracy (*MA*). *S* is the clipping bound and *med* the L_2-norm median.

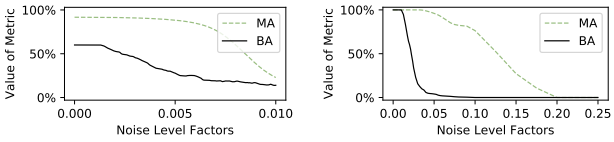
device-type-specific datasets capturing the devices' communication behavior. We simulate the FL setup by splitting each device type's dataset among several clients (from 20 to 200). Each client has a training dataset corresponding to three hours of traffic measurements containing samples of roughly 2 000-3 000 communication packets. The learning model consists of 2 GRU layers and a fully connected layer.

B Effectiveness of FLAME's Components

B.1 Effectiveness of the Clustering Component

We show the results for the clustering component in Tab. 6. As shown there, our filtering achieves $TNR = 100\%$ for the Reddit and IoT-Traffic datasets, i.e., FLAME only selects benign models in this attack setting. Recall that the goal of clustering is to filter out the poisoned models with high attack impact, i.e., not necessarily all poisoned models (cf. §4.1). This allows FLAME to defend backdoor attacks effectively, even if not all poisoned models are filtered. For example, although for the CIFAR-10 dataset in Tab. 6 the TNR is not 100 % (86.2%), the attack is still mitigated by the noising component, such that the BA is 0 % (cf. Tab. 4).

B.2 Effectiveness of Clipping



(a) Image Classification (b) Network Intrusion Detection

Figure 12: Impact of different noise level factors on the Backdoor Accuracy (*BA*) and Main Task Accuracy (*MA*).

Fig. 11 demonstrates the effectiveness of FLAME's dynamic clipping where S is the median of L_2-norms compared to a static clipping bound [7] and different choices for a dynamic clipping boundary (i.e., median, half of median, median multiplied by 1.5). The experiments are conducted for the IoT-Traffic dataset, which is non-iid. Fig. 11a and Fig. 11b show that a small static bound $S = 0.5$ is effective to mitigate the attack ($BA = 0\%$), but *MA* drops to 0% rendering the model useless. Moreover, a higher static bound like $S = 10$ is ineffective as $BA = 100\%$ if the Poisoned Data Rate (PDR) $\geq 35\%$. In contrast, FLAME's dynamic clipping threshold performs significantly better as *BA* consistently remains at 0% while *MA* remains high (cf. Fig. 11c and Fig. 11d).

B.3 Effectiveness of Adding Noise

Fig. 12 shows the impact of adding noise to the intermediate global models with respect to different noise level factors λ to determine the standard deviation of the noise σ dynamically based on the median L_2-norm of the updates S_t as $\sigma = \lambda S_t$. As it can be seen, increasing λ reduces the *BA*, but it also negatively impacts the performance of the model in the main task (*MA*). Therefore, the noise level must be dynamically tuned and combined with the other defense components to optimize the overall success of the defense. The noise level factor is determined by $\lambda = \frac{1}{\varepsilon}\sqrt{2ln\frac{1.25}{\delta}}$ for (ε, δ)-DP. We use standard DP parameters and set $\varepsilon = 3705$ for IC, $\varepsilon = 395$ for the NIDS and $\varepsilon = 4191$ for the NLP scenario. Accordingly, $\lambda = 0.001$ for IC and NLP, and $\lambda = 0.01$ for the NIDS scenario. The DP budget is dependent on the considered dataset scenario. It is determined based on the median of the dataset sizes of the clients and the size of the model used. It can thus be empirically determined by the aggregator. Analogous to determining the clipping boundary S (cf. 4.3.2), using the median ensures that the used dataset size is within the range of benign values.

C Naïve Combination

Furthermore, we test a naïve combination of the defense components by stacking clipping and adding noise (using a fixed clipping bound of 1.0 and a standard deviation of 0.01 as in [7]) on top of a clustering component using K-means. However, this naïve approach still allows a *BA* of 51.9% and a *MA* of 60.24%, compared to a *BA* of 0.0% and a *MA* of 89.87% of FLAME in the same scenario for the CIFAR-10 dataset. Based on our evaluations in §7.1, it becomes apparent that

FLAME's dynamic nature goes beyond previously proposed defenses that consist of static baseline ideas, which FLAME significantly optimizes, extends, and automates to offer a comprehensive dynamic and private defense against sophisticated backdoor attacks.

D Overhead of FLAME

We evaluated FLAME for 6 different device types from the IoT dataset. In this experiment, only benign clients participated and the model was randomly initialized. The highest observed overhead was 4 additional rounds. In average, 1.67 additional training rounds were needed to achieve at least 99% of the *MA* that was achieved without applying the defense, i.e., FLAME does not prevent the model from converging.

E HDBSCAN

HDBSCAN [11] is a density-based clustering technique that classifies data samples in different clusters without predefined the maximum distance and the number of clusters. In the following, we describe HDBSCAN in detail, following the implementation of McInnes *et al.* [36, 37]. However, we focus on the behavior of HDBSCAN for the parameters that FLAME uses, i.e., when `min_cluster_size`=$N/2+1$ and `min_samples=1`, e.g., because of the choice for `min_cluster_size` we skip parts that deal with multiple clusters. HDBSCAN first uses the given distances to build a minimal spanning tree (MST), where the vertices represent the individual data points and the edges are weighted by the distances between the respective points. Then it uses the MST to build a binary tree where the leaf nodes represent the vertices of the MST and the non-leaf nodes represent the edges of the MST. For this, first, all vertices are considered as separate trees (of size 1). For this, first, all vertices are considered as separate trees (of size 1) and then, starting from the edge with the lowest weight, iteratively the trees are merged by creating a non-leaf-node for each edge of the MST and set the (previously not connected) subtrees containing the endpoints of the edge as children for the new node (represented by calling the function `make_binary_tree`. In the next step, HDBSCAN collects all nodes of the binary tree as candidates, that cover at least $N/2+1$ data points. Since only non-leaf nodes fulfill the requirement of covering at least $N/2+1$ data points, each cluster candidate is based on a node, representing an edge in the MST. It uses the weight of the edge and the number of covered points to calculate a so-called stability value. Then HDBSCAN uses the stability value to determine the cluster candidate with the most homogeneous density and returns this candidate as majority cluster. Finally, it assigns the cluster label to all data points inside this cluster and labels all points outside of this cluster as noise.

F Effectiveness of FLAME against untargeted poisoning attacks

Another attack type related to backdooring is *untargeted poisoning* [8, 9, 20]. Unlike backdoor attacks that aim to incorporate specific backdoor functionalities, untargeted poisoning aims at rendering the model unusable. The adversary uses crafted local models with low Main Task Accuracy to damage the global model G. Fang at el. [20] propose such an attack bypassing state-of-the-art defenses. Although we do not focus on untargeted poisoning, our approach intuitively defends it since, in principle, this attack also trade-offs attack impact against stealthiness. To evaluate the effectiveness of FLAME against this attack, we test the Krum-based attack proposed by [20] on FLAME. Since [20]'s evaluation uses image datasets, we evaluate FLAME's resilience against it with CIFAR-10. The evaluation results show that although the attack significantly damages the model by reducing *MA* from 92.16% to 46.72%, FLAME can successfully defend against it and *MA* remains at 91.31%.

G Performance of Private FLAME

For our implementation, we use the STPC framework ABY [14] which implements the three sharing types, including state-of-the-art optimizations and flexible conversions and the open-source privacy-preserving DBSCAN by Bozdemir et al. [10]. All STPC results are averaged over 10 experiments and run on two separate servers with Intel Core i9-7960X CPUs with 2.8 GHz and 128 GB RAM connected over a 10 Gbit/s LAN with 0.2 ms RTT.

Approximating HDBSCAN by DBSCAN. We measure the effect of approximating HDBSCAN by DBSCAN including the binary search for the neighborhood parameter ε. The results show that our approximation has a negligible loss of accuracy. For some applications, the approximation even performs slightly better than the standard FLAME, e.g., for CIFAR-10, private FLAME correctly filters all poisoned models, while standard FLAME accepts a small number ($TNR = 86.2\%$), which is still sufficient to achieve $BA = 0.0\%$.

Runtime of Private FLAME. We evaluate the runtime in seconds per training iteration of the cosine distance, Euclidean distance + clipping + model aggregation, and clustering steps of Alg. 1 in standard (without STPC) and in private FLAME (with STPC). The results show that private FLAME causes a significant overhead on the runtime by a factor of up to three orders of magnitude compared to the standard (non-private) FLAME. However, even if we consider the largest model (Reddit) with $K = 100$ clients, we have a total server-side runtime of 22 081.65 seconds ($\approx$ 6 hours) for a training iteration with STPC. Such runtime overhead would be acceptable to maintain privacy, especially since mobile phones, which would be a typical type of clients in FL [38], are not always available and connected so that there will be delays in synchronizing clients' model updates in FL. These delays can then also be used to run STPC. Furthermore, achieving provable privacy by using STPC may even motivate more clients to contribute to FL in the first place and provide more data.

E

DEEPSIGHT: MITIGATING BACKDOOR ATTACKS IN FEDERATED LEARNING THROUGH DEEP MODEL INSPECTION

DeepSight: Mitigating Backdoor Attacks in Federated Learning Through Deep Model Inspection

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***Abstract*—Federated Learning (FL) allows multiple clients to collaboratively train a Neural Network (NN) model on their private data without revealing the data. Recently, several targeted poisoning attacks against FL have been introduced. These attacks inject a backdoor into the resulting model that allows adversary-controlled inputs to be misclassified. Existing countermeasures against backdoor attacks are inefficient and often merely aim to exclude deviating models from the aggregation. However, this approach also removes benign models of clients with deviating data distributions, causing the aggregated model to perform poorly for such clients.**

To address this problem, we propose *DeepSight*, a novel model filtering approach for mitigating backdoor attacks. It is based on three novel techniques that allow to characterize the distribution of data used to train model updates and seek to measure fine-grained differences in the internal structure and outputs of NNs. Using these techniques, DeepSight can identify suspicious model updates. We also develop a scheme that can accurately cluster model updates. Combining the results of both components, DeepSight is able to identify and eliminate model clusters containing poisoned models with high attack impact. We also show that the backdoor contributions of possibly undetected poisoned models can be effectively mitigated with existing weight clipping-based defenses. We evaluate the performance and effectiveness of DeepSight and show that it can mitigate state-of-the-art backdoor attacks with a negligible impact on the model's performance on benign data.

Keywords – *Deep Learning (DL), Federated Learning (FL), Poisoning, Backdoor, Model Inspection*

I. Introduction

Federated Learning (FL) enables multiple clients to collaboratively train a Neural Network (NN) model. This is done by an iterative process in which clients train their models locally using their own data and send only trained model updates to a central server, which aggregates them and distributes the resulting global model back to all clients. The federated approach promises clients to keep their training data private and the server to reduce the computational costs as the model training is parallelized and outsourced to the clients. These benefits make FL highly useful, especially in applications with privacy-sensitive data such as medical image recognition [33], word suggestion systems on smartphone keyboards (Natural Language Processing; NLP) [22], or network intrusion detection systems (NIDS) [26].

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Backdoor Attacks. On the other hand, the server cannot control the training process of the participating clients. An adversary can compromise a subset of the clients and use them to inject a backdoor into the aggregated model. In the examples above the adversary's goal would be to cause the aggregated model to classify malware network traffic patterns as benign to avoid detection by the NIDS, or in the case of NLP to manipulate the text prediction model to propose specific brand names to inconspicuously advertise them[1]. Recently, various attack strategies for targeted poisoning, so-called *backdoor* attacks, have been proposed utilizing compromised clients to submit poisoned model updates [2], [27], [34], [41], [38].

Problems of Existing Backdoor Defenses. The currently proposed mitigations against backdoor attacks follow two main strategies: (1) aim to detect and remove poisoned models [34], [4], [24], [28] and (2) aim to limit their impact, e.g., by restricting the L_2-norm of updates (called clipping) [2], [28], [23], [10]. In the first strategy, model updates differing from the majority are considered suspicious and excluded from aggregation. However, those approaches cannot distinguish between models that were trained on benign training data with different data distributions and poisoned models. This causes performance degradation of the resulting model, as this strategy will not only reject poisoned model updates but also deviating benign model updates. Moreover, these defenses fail in dynamic attack scenarios (cf. §II-B2 and App. B). The second defense strategy has the drawback that it is not effective against poisoned model updates with high attack impact. For example, when adding training samples for the backdoor behavior to the original (benign) training data, the poisoned model achieves higher accuracy on the backdoor task.

Adversarial Dilemma: The adversary can arbitrarily choose its attack strategy: On one hand, it can use a high ratio of poisoned data for training the backdoor task. However, this causes the poisoned models to differ from benign models, making the poisoned models easy to detect by a filtering-based defense. On the other hand, if the adversary does not follow this strategy, the attack can be easily mitigated by any defense that limits the impact of the individual models as the poisoned models are outnumbered by benign models (cf. §II-C for details). Combining both defense strategies, therefore, creates a dilemma for the adversary: Either the attack is filtered by one part of the defense or the other part makes the impact of the attack negligible [28].

Unfortunately, a naïve combination of both defense strategies is not effective, as existing filtering mechanisms follow an

[1]Especially systems with a large user base are attractive for such attacks, e.g., the FL-based keyboard input suggestion system GBoard [22] has been downloaded more than 1 billion times [11]

outlier-detection strategy [34], [4], [24], [28] that also filters benign models with deviating data distributions. Consequently, a high number of clients are wrongly excluded leading to performance degradation of the aggregated model for their data.

Our Approach: To address these problems, we propose DeepSight, a novel model filtering approach that deeply inspects the internal structure and outputs of the NNs for identifying malicious model updates with high attack impact while keeping benign model updates, even if these originate from clients with deviating data distributions. By combining our novel filtering scheme with clipping we exploit the above-mentioned adversarial dilemma to ensure that the adversary's strategy focuses the training on the backdoor task. This, on the other hand, causes the structure of the resulting NN to contain artifacts related to this backdoor.

We propose several techniques to analyze the internal structure of model updates for identifying characteristics of the training data distribution and to measure fine-grained differences between the models. Based on these techniques, we develop an approach to identify models trained with a data distribution focusing on a specific task (the backdoor task) and also to group models together that were trained on similar data. Those techniques enable our approach to reliably identify model clusters that with a high likelihood contain poisoned models and consequently exclude them from aggregation. Our extensive evaluation shows that our approach mitigates recent state-of-the-art backdoor attacks [2], [27], [41]. We show that DeepSight filters model updates with high attack impact so that possibly remaining poisoned model updates will be effectively mitigated using existing clipping defenses, while the benign training process is not affected by wrongly excluded benign models. Our contributions include:

- We propose DeepSight, a novel defense to mitigate targeted poisoning (backdoor) attacks on Federated Learning (FL). DeepSight uses a novel filtering scheme that conducts a deep model inspection and combines it with clipping (§V) to identify targeted poisoning attacks.
- We propose a voting-based model filtering scheme combining a classifier and clustering-based similarity estimations. The individual labels are sued to *reliably identify clusters with malicious model updates*, such that not only a model's label is used but also the labels of similar models for deciding on accepting or rejecting a model update (§V-A4). Together with the classifier as the central mechanism, instead of an outlier elimination-based strategy, we prevent models of benign clients with deviating data distributions from being filtered out, thereby increasing the performance of the aggregated model for the data of these clients.
- We propose the Threshold Exceedings metric (§IV) that analyzes the parameter updates of the output layer for a model to *measure the homogeneity of its training data*. We use this metric to build a classifier, being capable of labeling model updates as benign or suspicious.
- We design an ensemble of clustering algorithms, based on three different techniques to effectively identify and cluster model updates with similar training data (§V-A3) to support the classifier by similarity estimations.
- We propose two novel *techniques for measuring fine-grained differences in the structure and outputs of NNs* (§IV): The first technique Division Differences (DDifs) focuses on changes in model prediction outputs while the second technique NormalizEd UPdate energies (NEUPs) measures changes in parameter updates for the output layer of the NN. To the best of our knowledge, this is the first work that uses a deep analysis of the models, their predictions, and individual neurons for mitigating poisoning attacks in Federated Learning (FL).
- We extensively evaluate the performance and effectiveness of DeepSight (§VI). We show that our defense mechanism does not affect the performance of the resulting model. For showing DeepSight's effectiveness we evaluated several state-of-the-art backdoor attacks [2], [27], [41], [38].
- As a side effect, we demonstrate a successful backdoor attack on a recently proposed 'provably-secure' FL backdoor defense [6] (§VI-C1). We will discuss that the theoretical proof includes a-posteriori knowledge, making assumptions that do not hold in practice. However, DeepSight is able to mitigate such attacks (§VIII).

II. Background

A. Federated Learning

McMahan *et al.* [21] introduced Federated Learning (FL) as a process that leverages many different clients for collaboratively training a machine learning model, here a Neural Network (NN), based on their local datasets. In contrast to a centralized approach, the local data of each client never leaves this client, allowing the clients to keep their data secret.

Each round t of an FL process consists of the following steps:

Step 1: Each client $k \in \{1, \ldots, N\}$, trains locally a ML model on its private data, starting from the global G_t before sending its model update to a central aggregation server $\mathcal{S}$.

Step 2: The server merges the received updates and applies the aggregated update on the global model.

Step 3: The resulting model, called aggregated model G_{t+1}, is distributed back to all participants.

Different aggregation rules have been proposed, e.g., Federated Averaging (FedAvg) [21], Krum [4], or Trimmed Mean [42]. Although we will evaluate our proposed defense also for other aggregation rules, e.g., for Krum [4], we will focus on FedAvg as it is widely used in FL [26], [5], in particular in work about backdoor attacks [2], [27], [34], [24], [28], [10].

In FedAvg, the aggregated model G_{t+1} is determined by averaging all received model updates and adding it to the previous global model G_t. Although this algorithm also allows weighting the contributions of different clients, e.g., to increase the impact of clients with a large training dataset, this also makes the system more vulnerable for manipulations, as compromised clients could exploit this, e.g., by lying about their dataset sizes to increase their impact. Therefore, we follow existing work [2], [34], [4], [28], [10], [21] and weight all model updates equally.

B. Backdoor Attacks on FL

In a targeted poisoning attack, also called backdoor attack, an adversary $\mathcal{A}$ manipulates the local models of a subset of clients with size $N_{\mathcal{A}}$ (cf. §III). Its goal is, to make the aggregated model that is operated on a feature space $\mathcal{D}$ output a certain class $C_{\mathcal{A}}$ for a set of input samples, called trigger set $\mathcal{I} \subset \mathcal{D}$. The success of the attack is determined by

the Backdoor Accuracy (BA), which measures the accuracy for the backdoor task. For example, in a word prediction scenario, the backdoor could be to predict the word "delicious" after the trigger sentence "pasta from astoria tastes" [2]. The BA indicates here, for how many occurrences of the trigger sentence the model suggests "delicious". The ratio of compromised clients to the total number of clients will be denoted as Poisoned-Model-Rate (PMR). For backdoor attacks, widely two attack strategies are considered by previous work, assuming different thread models.

1) Data Poisoning: In the weaker adversary model, $\mathcal{A}$ is restricted to manipulating the training data of a client. $\mathcal{A}$ poisons the client's training data by adding malicious attack data to the dataset. The attack data consists of input samples from the trigger set, with the new, adversary-chosen (wrong) label $C_{\mathcal{A}}$. For example, in the NIDS scenario, $\mathcal{A}$ can achieve this by creating malware traffic during the NIDS system captures network packets that will be used as benign training data [27]. However, $\mathcal{A}$ still needs to ensure that the resulting model updates are not too conspicuous, e.g., by limiting the Poisoned-Data-Rate (PDR), i.e., the fraction of attack data injected into the training dataset. By choosing a suitable PDR, $\mathcal{A}$ can balance between attack impact and attack stealthiness. Let D_i denote the benign dataset of a compromised client i and $D_i^{\mathcal{A}}$ the injected attack data, then the PDR of the combined, poisoned dataset D_i' is given by:

$$\text{PDR} = \frac{|D_i^{\mathcal{A}}|}{|D_i'|} \tag{1}$$

The advantage of this attack is that it is sufficient to poison the dataset, which can be done, without compromising the client that actually trains the NN. Therefore, it requires fewer capabilities of $\mathcal{A}$, compared to the Model Poisoning attack.

2) Model Poisoning: In a stronger adversary model $\mathcal{A}$ is able to compromise a subset of the clients and fully control them. $\mathcal{A}$ can then change the model updates arbitrarily before submitting them to increase attack impact on the aggregated model. This allows $\mathcal{A}$ to adapt the training algorithm, its parameters, and to scale model updates to increase the attack impact without triggering defense mechanisms that may be deployed on the aggregation server [2]. If the adversary has full control over a client, it can also arbitrarily change their behavior, e.g., using a subset of clients for random updates to distract the defense mechanism (cf. App. B). The model poisoning attack can be split into two parts:

Scaling: As proposed by Bagdasaryan *et al.* [2], $\mathcal{A}$ can scale the differences between the (poisoned) trained model $W_{t,i}^*$ of the client i in round t and the used global model G_t, before submitting the model. This up-scaling increases the impact of the poisoned models during the aggregation. If there are N clients in total, from which $N_{\mathcal{A}}$ are compromised, $\mathcal{A}$ can scale the updates using a factor up to $N/N_{\mathcal{A}}$.

To circumvent deployed defense mechanisms $\mathcal{A}$ can restrict the L_2-norm for the update to a chosen value S. This prevents the scaled updates from being too suspicious to the cost of the impact of the attack. The scaling factor $\gamma_{t,i}$ of a compromised client i in round t is, therefore, given by:

$$\gamma_{t,i} = \max\left(1, \min\left(\frac{N}{N_{\mathcal{A}}}, \frac{S}{||W_{t,i}^* - G_t||}\right)\right) \tag{2}$$

The scaled malicious model $W_{t,i}'$ is then given by:

$$W_{t,i}' = \left(W_{t,i}^* - G_t\right)\gamma_{t,i} + G_t \tag{3}$$

Anomaly-Evasion As scaling makes the model update more suspicious, Bagdasaryan *et al.* [2] proposed to reduce the learning rate of the clients. Furthermore, they adapted the loss function to make the model more inconspicuous by adding a term L_{anomaly} that measures the similarity between the original model and the used global model, e.g., by using their cosine distance. If the normal loss function L_{class} measures the performance of the model on the actual task and the loss-control parameter α weights the impact of both parts, then the adapted loss function L' is given by:

$$L' = \alpha L_{\text{class}} + (1-\alpha)L_{\text{anomaly}} \tag{4}$$

In the rest of the paper, we will use the strong adversary model, where $\mathcal{A}$ uses a combination of the Anomaly-Evasion and Scaling attack strategies, called *constrain-and-scale* attack [2].

C. Exploiting Adversary's Dilemma

Adversary $\mathcal{A}$ can freely choose an attack strategy that is most effective for it. It can either use well-trained poisoned models to inject the backdoor, e.g., by using a high PDR, or, train the models only weakly, e.g., by using a low PDR. However, as pointed out by Nguyen *et al.* [28], well-trained models differ significantly from benign models and are, therefore, easy to detect by approaches that filter suspicious models. On the other hand, the impact of weakly trained models is likely to become negligible during aggregation, as poisoned models are outnumbered by benign ones [28]. Bagdasaryan *et al.* proposed scaling the updates to increase their contribution to the aggregated model [2]. However, this attack is easy to mitigate by approaches that limit the contribution of the individual clients, e.g., clipping that limits the L_2-norm of the model updates.

III. System and Problem Setting

A. System Setting

We consider a system with N clients that train their local models before sending them to the aggregator $\mathcal{S}$ who combines them by using FedAvg [21]. We assume that clients keep their data secret. Therefore, no training or testing data is available on the aggregation server $\mathcal{S}$.

We also assume that the data of different clients may differ from each other. Without loss of generality, the individual clients can be seen as parts of groups of clients with similar training data, s.t. the data of all clients in the same group follows the same distribution, therefore, are IID. There can be one or multiple groups of arbitrary, also different sizes (also with size one). Taking the NLP scenario as an example, if people write similar texts, e.g., always about the same topic, also the updates for the NN that is used for the word suggestion will be similar. Therefore, the model updates of those clients can be seen as a group of updates with similar, IID training data. Other users may write about another topic, such that their model updates can be seen as a different group. If all people would write about the same topic, their model updates can be seen as one (big) group and if a single person writes very unique texts, e.g., by using very

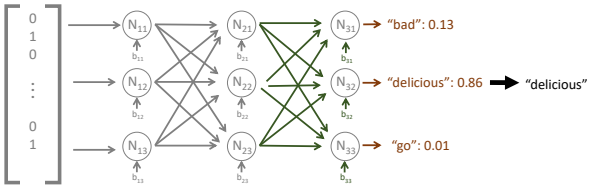

Fig. 1: Structure of a simplified NN for word suggestion. The individual colors refer to the parameters that are used by the proposed techniques

special words, the respective model update can be seen as part of a group having only one member.
The techniques that we propose later (cf. §IV), allow characterizing the clients' training data to make these groups visible. This allows clustering the received model updates accordingly to support the classifier.

B. Adversary Model

In the rest of the paper, we consider an adversary $\mathcal{A}$ that aims to inject a backdoor into the aggregated model, making the model predict a certain label $C_{\mathcal{A}}$ for some specific, adversary-controlled input samples, called trigger set $\mathcal{I}$. The manipulated aggregated model shall then be distributed to all clients.
However, if the aggregator $\mathcal{S}$ notices the attack it will exclude the poisoned models. If $\mathcal{S}$ notices the attack but cannot identify the poisoned models, it can repeat the training with different subsets of clients until no attack is detected [3]. Hence, the attack also must not degrade the performance of the aggregated model on the main task (Main Task Accuracy, MA).
Formally, if G_t is the aggregated model after the attack, G_{t-1} the global model before the attack, $\mathcal{D}$ the set of all possible inputs, $\mathcal{I} \subset \mathcal{D}$ the trigger set and $f(G_t, x)$ the prediction of the model G_t on the input sample $x \in \mathcal{D}$, $\mathcal{A}'s$ goal is:

$$\forall x^* \in \mathcal{I}.f(G_t, x^*) = C_{\mathcal{A}} \wedge \forall x \in \mathcal{D} \backslash \mathcal{I}.f(G_t, x) = f(G_{t-1}, x) \tag{5}$$

Therefore, from Eq. 5, two objectives for $\mathcal{A}$ can be derived:
O1: Performance on the backdoor task. The aggregated model shall predict $C_{\mathcal{A}}$ for triggered samples.
O2: Stealthiness. $\mathcal{A}$ must ensure that the poisoned models are inconspicuous to $\mathcal{S}$ and that $\mathcal{S}$ cannot determine, whether a poisoning attack took place. This includes preventing a drop in the MA.

Aligned with the existing work on backdoor attacks [2], [27], [34], [4], [24], [28], we consider a strong adversary model, allowing $\mathcal{A}$ to fully control $N_{\mathcal{A}} < {}^{N}/_{2}$ clients. However, $\mathcal{A}$ has no control over the benign clients nor has access to their data or model updates. We assume $\mathcal{A}$ to have full knowledge of the aggregation server $\mathcal{S}$ and any deployed defense, i.e., used algorithms and configuration parameters, however, $\mathcal{A}$ cannot tamper with it.

C. Objectives of a Poisoning Defense

To defeat the objectives of the adversary, the defense has to fulfill the following security requirement:
R1: Poisoning Mitigation. The defense must mitigate the poisoning attack. Therefore, the BA must remain at the same level as without the attack [2].

[2]It worth to note that for some backdoor tasks, misclassification of the model are counted in favor of the BA, s.t., the BA is higher than 0 %, even without attack (cf. App. F).

However, as already pointed out in §I, it is not sufficient for defenses to mitigate poisoning attacks, but also satisfy certain requirements such as model performance. Therefore, we consider defense against poisoning attacks only effective if it also fulfills the following additional requirements:
R2: No Disruption of the Training Process. The defense should not negatively affect the training. Therefore, the performance of the resulting model on the main task (Main Task Accuracy, MA) must be at the same level as without defense.
R3: Autonomous Process The defense must run fully autonomous, i.e., no manual configuration nor any knowledge, e.g., estimations for the L_2-norms of benign updates or validation data[3], must be required.

To the best of our knowledge, all existing approaches for identifying poisoned updates are based on metrics that consider the NN as a black box, e.g., cosine [24], [28], [10] or L_2-norm [4]. Our novel scheme, therefore, addresses the following challenges:
C1: How to distinguish poisoned models from benign models that were trained on different data.
C2: How to entangle to the backdoor performance such that the only way for $\mathcal{A}$ to bypass a scheme that is based on these techniques is to reduce the backdoor performance.
C3: How to make the techniques generally applicable, without knowing the exact data. For example, for the NIDS scenario, it should not make a difference, whether the models analyze the network traffic of IP cameras or smart sensors.
C4: How to ensure a high precision, to prevent benign models from being excluded wrongly.
C5: How to effectively combine the individual techniques to a dynamic defense scheme, s.t. it can dynamically adapt to attacks. Therefore, neither the scheme shall be broken unless $\mathcal{A}$ overcomes every single technique, nor shall the scheme suffer by false positives.

D. Proposed Techniques

Figure 1 shows a simplified, linear NN for suggesting words based on the previously typed text. The NN has 3 layers with 3 neurons each. The arrows that connect the neurons represent the respective weights, $b_{i,k}$ the bias for the respective neuron, and the brown number the calculated scores. In this example, the NN suggests "delicious" as the next word, since it has the highest score.
We propose 3 techniques that allow to analyze NNs and provide characteristics about the distribution of the used training data. The first technique is called Division-Difference (DDif). When training a NN, the predicted score for the current sample (e.g., "pasta from astoria tastes **delicious**") is increased. However as a side-effect, also the score (colored brown in Fig. 1) for the current label, i.e., "delicious" is increased in general, therefore, also when another input is used. The DDifs measures these changes as they provide information about the distribution of the training labels of the respective client.
When training a NN, the respective weights are adapted slightly for each sample in order to increase the predicted score. Since each neuron in the last layer of a NN represents

[3]For example, in the case of the FL-based NIDS DÏoT [26], new training processes for new data scenarios are started automatically. Therefore, neither validation data nor prior knowledge about the model udpates like their L_2-norms are available as this would require the clients to share their data, which would violate a principal design goal of FL.

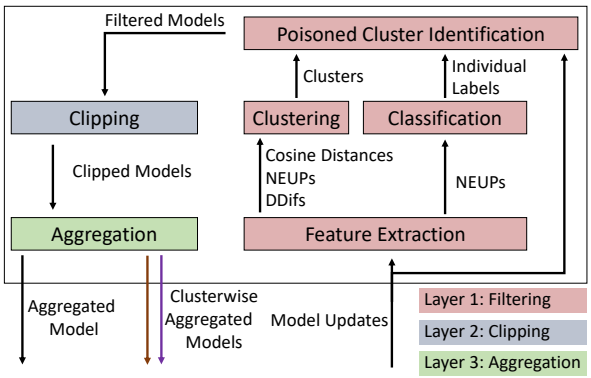

Fig. 2: Structure of DeepSight

an output label, the total magnitude of changes for the parameters of the individual neurons (colored in green in Fig. 1) is connected to the frequency of the individual labels. The NormalizEd UPdate energies (NEUPs) measure those changes and use them to provide a rough estimation of the output labels for the training data of the individual clients.

The task of a backdoor is usually very simple compared to the benign task of a model. For example, in case of the NLP scenario, instead of learning a large number of different sentences, the backdoor task consists only of predicting the correct word after a specific sentence, i.e., "pasta from astoria tastes **delicious**". To prevent, that the impact of the attack becomes negligible during the evaluation $\mathcal{A}$ needs to use a high PDR (cf. II-C), resulting in a focus of the labels on the target word, i.e., "delicious". For example, in case of a PDR of 50 % half of the labels belongs to those 5 words, although there are 50 000 words in total (cf. §VI-A1). The Threshold Exceedings uses the NEUPs to compare the distribution of labels for measuring the homogeneity of labels in the training data. The classifier in the proposed filtering scheme analyses the homogeneity value for each model. If a model update has a strong focus in the used training data, therefore, if few labels occur with a significantly higher frequency than all other labels, then the classifier considers this update as poisoned.

E. Our Defense Approach

We propose DeepSight, an effective novel filtering approach against dynamic backdoor attacks that overcomes the deficiencies of previous work. Its overall structure is shown in Fig. 2. DeepSight uses a classifier as the central component that is based on deep-model-inspection (cf. §V-A). The filtering is followed by a weight clipping component (cf. §V-B), which enforces $\mathcal{A}'s$ strategy to focus the training data of poisoned models on the backdoor behavior. Otherwise, the attack can either be mitigated by the clipping layer (cf. §V-B) or its impact becomes negligible in the aggregation phase (cf. §V-C).

The first layer of the defense realizes a classification-based filtering and removes poisoned models with high attack impact, where the training data is focused on samples for the backdoor behavior. Here, we design an algorithm to combine the different techniques, s.t., the classification is supported by the similarity estimations, without following an outlier-detection-based approach like existing approaches that use clustering.

The filtering scheme is based on the proposed novel techniques for measuring fine-grained differences between the structure and outputs of a model and uses them to deeply analyze the individual models, taking into account their predictions, individual neurons as well as an estimation for the homogeneity of the used training data. The subsequent layers (clipping and aggregation) mitigate the effect of potentially remaining, weakly-trained poisoned models. The structure of DeepSight is shown in Fig. 2. The filtering layer performs three major steps:

1. Classification DeepSight utilizes a novel metric entitled *Threshold Exceedings* that measures the homogeneity of a model's training data to label models as benign or suspicious.

2. Clustering Secondly, DeepSight groups model updates, such that all models in the same group have been trained on similar training datasets. Therefore, this component clusters the models according to the groups of clients with IID data that were discussed in §III-A. This allows DeepSight to reliably separate malicious and benign model updates into different clusters and, therefore, support the labeling by similarity estimations. DeepSight uses two additional novel techniques *Division Differences (DDifs)* and *Normalized Energy Updates (NEUPs)* that enable it to extract characteristics of a model's training data as well as the cosine metric.

3. Poisoned Cluster Identification In the last filtering step, the labeling and the clustering are combined to discriminate clusters containing poisoned models and for finally deciding about excluding or accepting each model update.

IV. Techniques for Analyzing ML Models' Training Data Distributions

In this section we introduce several novel techniques for deep inspection and analysis of model updates to identify models whose training data were focused on a specific (backdoor) task and measure fine-grained differences between models. In §V we will describe how the filtering component and in particular the classifier of DeepSight is based on these techniques.

We introduce *Division Differences (DDifs)* that measures the difference between the predicted scores of the local and global models. As all clients use the same global model, in case of similar or different training data, also the predicted probabilities will change accordingly. Therefore, they provide information about the distribution of labels in the training data. Moreover, we introduce *NEUPs*, which analyze the total magnitude of the updates for the individual neurons of the output layer. NEUPs use these magnitudes to determine a rough estimation of the distribution of labels in the training data of the model update, allowing, e.g., to measure the similarity of the training data for different model updates.

The third technique, entitled *Threshold Exceedings*, uses NEUPs for measuring the homogeneity of labels in the used training data. In §V-A, we describe how Threshold Exceedings are used to identify models as benign or poisoned.

A. Division Differences

When training a NN, each specific sample consists of an input x and an output category y. During the training, the parameters of the NN are adjusted iteratively, s.t. the score for y that is predicted by the current model for x is maximized. For example, in the NLP scenario x could be a sequence of words and y the suggested next word. However, this has the side effect that also for another input x^*, with a different label y^*, the score that is predicted for y also changes very slightly, although $y \neq y^*$. This phenomenon occurs especially when samples of the category y occur very frequently in the

training data. However, because of using clipping as part of the defense, $\mathcal{A}$ has to use a high PDR, causing the target category of the backdoor, e.g., in case of the NLP scenario, the word "delicious", to occur very frequently. Therefore, especially for backdoor samples, the probability of the target label is increased in general and not only for samples of this category [18]. In the following, we will exploit this by comparing the probabilities that were predicted by a local model $W_{t,k}$ to the predicted probabilities of the used global model G_t. The rationale here is that if two models $W_{t,i}$ and $W_{t,k}$ were trained on similar data, also the ratios of their probabilities compared to the predictions of the global model will be similar. The information that is gained by this technique allows identifying clients with similar training data. We will refer to this technique as *Division Differences* (DDifs).

Because all clients start from the same global model and clients with similar data will try to achieve similar predictions for their data samples, they will adapt their parameters similarly, resulting in similar model updates. For example, considering a NN with n output classes, e.g., the number of known words in the NLP scenario, a specific sample x, 2 clients k and l with similar data, their respective local models in round t $W_{t,k}$ and $W_{t,l}$, then their predictions $f(x; W_{t,k}), f(x; W_{t,l}) \in \mathcal{R}^n$ will be also very close. It follows directly that when comparing those predictions to the predictions of the original model $f(x; G_t)$, the differences between $f(x; W_{t,k})$ and $f(x; G_t)$ as well as $f(x; W_{t,l})$ and $f(x; G_t)$ provides information about the similarity of the training data of k and l.

A problem is that the server has no input data for evaluating the NNs, as we assume that the server has neither training nor testing data (cf. §III-A). We solve this problem by using random input vectors instead of actual data. As we focus on the differences between predictions of the global model G_t and the predictions of the local model $W_{t,k}$ of each client k rather than finding the class with the highest predicted probability, it is not necessary to obtain meaningful predictions. Therefore, it is not necessary to use real data samples. The rationale is that for a poisoned model update W' the predicted probabilities for the backdoor target class will be increased in general (cf. Liu *et al.* [18]), independently from the actual input, and, therefore also show corresponding differences in comparison to the predictions of the preceding global model G_t.

For calculating the DDifs for a model update $W_{t,k}$ of client k during training iteration t, we generate $N_{\text{samples}} = 20\,000$ random input samples s_m ($m \in [0, N_{\text{samples}} - 1]$) and provide them as input to model $W_{t,k}$. We then divide the probabilities $f(s_m; W_{t,k})_i$ predicted by the local model for each output neuron i by the corresponding neuron-specific prediction $f(s_m; G_t)_i$ of the global model G_t:

$$\text{DDif}_{t,k,i} = \frac{1}{N_{\text{samples}}} \sum_{m=1}^{N_{\text{samples}}} \frac{f(s_m; W_{t,k})_i}{f(s_m; G_t)_i} \tag{6}$$

B. Normalized Update Energy

The second measure that we propose for identifying clients with similar training data is the NormalizEd UPdate energy (NEUP). It analyzes the parameter updates for the output layer and extracts information about the distribution of labels in the underlying training data of a model.

During the training process, the parameters of the output layer neuron that represents the class of the currently considered sample are adapted slightly. Since this is repeated for every sample, neurons for frequent classes will be updated many times with high gradients[4] such that the individual changes sum up to an update with a high magnitude for these neurons. On the other hand, if there are fewer (or no) samples of a class, there are fewer/no repetitions, resulting in an update with a low magnitude for such neurons. The total magnitudes of the updates for the neurons in the output layer leak therefore information about the frequency distribution of labels in the training data of this update.

For measuring the magnitudes and reverse engineer this distribution, we first define the Energy of the update for a neuron. Let H denote the number of connections of an output layer neuron to neurons of the previous layer, $b_{t,k,i}$ be the bias of neuron i from the output layer of a model k after round t, $w_{t,k,i,h}$ be analogously the weight of the connection to the neuron h from the previous layer, $b_{t,G_t,i}$ be as well as $w_{t,G_t,i,h}$ be analogously bias and weights of neurons from the global model G_t. Then the Energy $\mathcal{E}_{t,k,i}$ of the update for the output layer neuron i of the model that client k submitted in round t is given by:

$$\mathcal{E}_{t,k,i} = |b_{t,k,i} - b_{t,G_t,i}| + \sum_{h=0}^{H} |w_{t,k,i,h} - w_{t,G_t,i,h}| \tag{7}$$

If an Energy Update for a neuron is significantly higher than other Energy Updates for the same local model, then this indicates that the respective classes were more relevant for training the model. We normalize the Energy Updates of all output layer neurons of the same model, to highlight Energy Updates that are significantly higher than other Energy Updates. Therefore, the NormalizEd UPdate energy (NEUP) $\mathcal{C}_{t,k,i}$ of the neuron i for the update from client k in round t is given by:

$$\mathcal{C}_{t,k,i} = \frac{\mathcal{E}^2_{t,k,i}}{\sum_{j=0}^{P} \mathcal{E}^2_{t,k,j}} \tag{8}$$

The normalization makes the frequency distributions of different models comparable. Therefore, the individual NEUPs of a model update it not affected by the total extent of the Update Energy for this model update. Therefore, similar NEUPs from different models indicate that similar proportions of the training data of different clients have the same label. Moreover, it also makes the technique more robust against obfuscation by the adversary $\mathcal{A}$. Otherwise, $\mathcal{A}$ could use one client to submit a model with a very high Energy Update to make the Energy Updates of the remaining poisoned models looking more similar to the benign ones.

In §VII, we provide a proof that the NEUPs are not affected, when $\mathcal{A}$ scales the poisoned model updates.

C. Threshold Exceedings

The training data of poisoned models are significantly less heterogeneous than the training data of the benign models (cf. §III-E). For example, in the NLP scenario, the backdoor consists of a few sentences[5], while the benign task includes

[4] When calculating the gradients of a NN for a sample x, the absolute magnitude of the gradients of the output layer neuron that represents the label of x is higher than the gradients for the other neurons [39].

[5] Otherwise the backdoor is significantly harder to inject (cf. App. A), allowing the other defense layers of DeepSight to mitigate the attack.

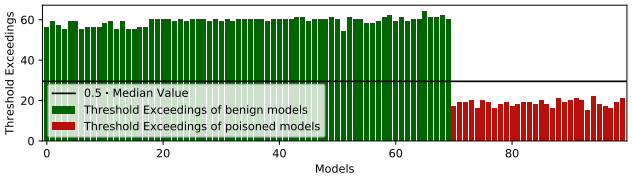

Fig. 3: NEUP Threshold Exceedings of benign and poisoned model updates

a large number of different sentences. We showed in §IV-B that the NEUPs allow a rough estimation of the distribution of labels in the training data of a client. Training data for poisoned models need to be focused on samples for the backdoor behavior (cf. §II-C). Therefore, if there is a local model with very homogeneous training data, then it is very likely that this model is poisoned. In the following, we introduce a metric entitled as *Threshold Exceedings* that measures the homogeneity of the training data and, by this is able to identify poisoned models. In §V-A, we will use the Threshold Exceedings to build a classifier for labeling all models as poisoned or benign. Our experiments confirmed a strong correlation between the NEUPs and the distribution of labels in the training data, s.t., the NEUPs can be used to measure the homogeneity of labels.

To measure the homogeneity of the NEUPs for the local models and therefore the complexity of the used training data, we define for each local model a threshold based on the maximal NEUP for this model. Then we count for each model how many NEUPs exceed this threshold.
If the output layer has P neurons, then the maximal NEUP $\mathcal{C}_{t,k,\max}$ of a model being submitted by client k in round t is given by:

$$\mathcal{C}_{t,k,\max} = \max_{1 \leq i \leq P} \mathcal{C}_{t,k,i} \tag{9}$$

We define the threshold $\xi_{t,k}$ as $1\ \%$ of the maximal NEUP $\mathcal{C}_{t,k,\max}$ of this client. However, as in scenarios with very few output labels, it is possible that all NEUPs of a client are above this threshold, we increase the Threshold Factor of $1\ \%$, depending on the number of output classes. The threshold $\xi_{t,k}$ is, therefore, given by:

$$\xi_{t,k} = \max\left(0.01, {}^{1}/_{P}\right) \cdot \mathcal{C}_{t,k,\max} \tag{10}$$

In App. I, we analyze the impact of different choices for the Threshold Factor on the Threshold Exceedings and DeepSight. The Threshold Exceedings value for a model is then given by the number of NEUPs that exceed this threshold. Let $\mathbb{1}_{expr}$ be the indicator function being 1 iff the expression *expr* is true and 0 otherwise, then the number of Threshold Exceedings $\mathrm{TE}_{t,k}$ for a model being submitted by client k in round t is given by:

$$\mathrm{TE}_{t,k} = \sum_{i=1}^{P} \mathbb{1}_{\mathcal{C}_{t,k,i} > \xi_{t,k}} \tag{11}$$

Figure 3 shows the NEUP Threshold Exceedings for the NIDS scenario for 70 benign and 30 poisoned model updates. As the figure shows, benign models have a significantly higher number of Threshold Exceedings than poisoned models.
For classifying model updates as benign or poisoned, we define a classification boundary of half of the median number of Threshold Exceedings. A model is labeled as poisoned, iff its number of Threshold Exceedings is below this threshold.
In §VII, we provide a proof that the Threshold Exceedings are not affected when $\mathcal{A}$ scales the poisoned model updates.

V. Mitigating Backdoor Attacks on FL by Deep Model Inspection

Existing poisoning defenses often assume benign models to be similar, resulting in rejecting all abnormal model updates. However, those defenses can, due to the adopted approach, not distinguish between the reasons for perceiving a model as abnormal. Therefore, they cannot determine whether just different, non-IID data or poisoned data were used for training the model. As a result, those approaches will also reject models of benign clients with slightly deviating training data distributions. To solve this problem, we propose in the following DeepSight. It uses the proposed techniques to deeply inspect the model updates and distinguish between poisoned model updates and benign updates that have been trained on deviating data distributions. By using clipping [2], [28], [23], we enforce $\mathcal{A}'s$ strategy to focus the training data of poisoned models on the backdoor behavior, s.t. the filtering scheme can effectively identify and exclude poisoned models. The basic structure of DeepSight is shown in Fig. 2. It consists of 3 layers:
1. Filtering Layer: The first layer uses the proposed novel techniques to analyze the model updates for detecting and excluding models that contain a well-trained backdoor.
2. Clipping Layer: This layer enforces a maximal L_2-norm of the updates and downscales them if necessary to mitigate poisoned models that compensate a weakly trained backdoor (to circumvent the first layer) with a high scaling factor.
3. Aggregation Layer: The last layer uses FedAvg to aggregate the remaining, clipped updates together.

This combination of layers creates a dilemma for $\mathcal{A}$. If the poisoned models are suspicious, e.g., because they have been well-trained on homogeneous training data for achieving high backdoor impact, they will be detected and rejected by the filtering layer. Otherwise, if $\mathcal{A}$ tries to circumvent the filtering layer by using heterogeneous training data, e.g., by using a low PDR or injecting complex backdoors, it also weakens the impact of the backdoor allowing the other two layers to mitigate the attack effectively.

A. Filtering Layer

The filtering layer recognizes poisoned models with homogeneous training data, by using a classifier that is based on the Threshold Exceedings (cf. §IV-C). To make the filtering more robust and minimize the number of mislabelings, we combine the classifier with a clustering to also take the labels of similar models into account when finally deciding about accepting or rejecting a model. To prevent

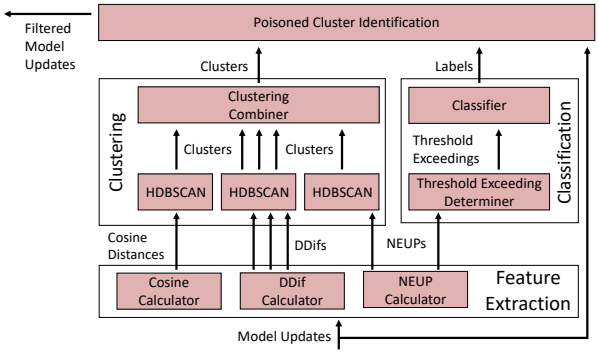

Fig. 4: Filtering Layer of DeepSight

Algorithm 1 Filtering Layer

1: **Input:** N, ▷ number of models
2: W, ▷ list of N received local models
3: G_t ▷ global model
4: **Parameters:** τ, ▷ Threshold of suspicious models for excluding cluster
5: seeds, ▷ 3 seeds for generating random data for ddfis
6: input_dim ▷ dimension of a single input
7: **Output:** accepted_models
8: ▷ Feature Extraction
9: cosine_distances $\leftarrow 0^{N \times N}$
10: global_bias $\leftarrow$ output_layer_bias(G_t)
11: **for** each clients i, j in $[1, N]$ **do**
12: update$_i$ $\leftarrow$ output_layer_bias(W_i) - global_bias
13: update$_j$ $\leftarrow$ output_layer_bias(W_j) - global_bias
14: cosine_distances$_{i,j}$ $\leftarrow$ 1 - COSINE(update$_i$, update$_j$)
15: **end for**
16: $\forall i \in \{1, \dots N\}$: neups$_i$ $\leftarrow$ NEUPs(G_t, W_i)
17: $\forall i \in \{1, \dots N\}$: thresh_exds$_i$ $\leftarrow$ THRESHOLD_EXCEEDING(neups)
18: $\forall i \in \{1, 2, 3\}$: rand_input_data$_i$ $\leftarrow$ random_matrix(seeds$_i$, 20 000, input_dim)
19: $\forall i \in \{1, 2, 3\}$: ddifs$_i$ $\leftarrow$ DDIFs(rand_input_data$_i$, G_t, $W_1 \dots W_n$)
20: ▷ Classification
21: classificat_boundary $\leftarrow$ MEDIAN(thresh_exds) / 2
22: $\forall i \in \{1, \dots N\}$: labels$_i$ $\leftarrow$ (thresh_exds[i] $\leq$ classificat_boundary)? 1:0
23: ▷ Clustering
24: clusters $\leftarrow$ CLUSTER(N, neups, ddifs, cosine_distances)
25: ▷ PCI
26: accepted_models $\leftarrow$ {}
27: **for** cluster in clusters **do**
28: amount_of_positives $\leftarrow$ SUM(labels[cluster]) / |cluster|
29: **if** amount_of_positives $< \tau$ **then**
30: accepted_models $\leftarrow$ accepted_models $\cup$ models[cluster]
31: **end if**
32: **end for**

Algorithm 2 Clustering

1: **procedure** DISTSFROMCLUST(clusters, N)
2: $\forall i, j \in \{1, \dots N\}$: pairwise_dists$_{i,j}$ $\leftarrow$ cluster_of_model(i, clusters) == cluster_of_model(j, clusters)? 0:1 ▷ cluster_of_model(x, clusters) returns the cluster that contains the model with index x
3: **return** pairwise_dists
4: **end procedure**
5:
6: **Input:**
7: N, ▷ N is the number of models
8: neups, ▷ NEUPs as list of N vectors with dimension P
9: ddifs ▷ DDifs as list of 3 lists of vectors with dimension P
10: cosine_distances ▷ cos_distances a matrix $\in \mathbb{R}^{N \times N}$
11: **Output:** clusters ▷ clusters as set of sets of indices
12:
13: cosine_clusters $\leftarrow$ HDBSCAN(distances = cosine_distances)
14: cosine_cluster_dists $\leftarrow$ DistsFromClust(cosine_clusters, N)
15: neup_clusters $\leftarrow$ HDBSCAN(values = neups)
16: neup_cluster_dists $\leftarrow$ DistsFromClust(NEUP_clusters, N)
17: $\forall i \in \{1, 2, 3\}$: ddif_clusters$_i$ $\leftarrow$ HDBSCAN(values = ddifs$_i$)
18: $\forall i \in \{1, 2, 3\}$: ddif_clust_dists$_i$ $\leftarrow$ DistsFromClust(ddif_clusters$_i$,N)
19: merged_ddif_clust_dists $\leftarrow$ AVG(ddif_clust_dists$_1$, ddif_clust_dists$_2$, ddif_clust_dists$_3$)
20: ▷ Combine clusterings
21: merged_distances $\leftarrow$ AVG(merged_ddif_clust_dists, neup_clust_dists, cosine_clust_dists)
22: clusters $\leftarrow$ HDBSCAN(distances = merged_distances)

that $\mathcal{A}$ can easily fool the similarity mechanism, we use an ensemble that is based on the NEUPs, DDifs, and cosine. $\mathcal{A}$ would need to distract all of them at the same time, without reducing the attack impact, as otherwise the attack will be mitigated by the later defense layers.

The overall structure of the filtering layer is shown in Fig. 4. It first calculates features for the clustering (DDifs, NEUPs, and pairwise cosine distances) and uses these values in the next step for clustering all models. In parallel, the Threshold Exceedings are calculated from the NEUPs and used for labeling all model updates as benign or suspicious. In the last step, the Poisoned Cluster Identification (PCI) combines the clustering with the labeling to decide about accepting or rejecting the updates. The details are shown in Alg. 1. The algorithm takes as input the number of models, the local models, the global model, and the dimension of a single input.

1) Feature Extraction: First, we calculate the pairwise cosine distances, for each model $k \in \{1, \dots, N\}$, their corresponding NEUPs $\mathcal{C}_{t,k,*}$ and the Division Differences DDif$_{t,k,*}$ (cf. lines 8-19 in Alg. 1). As the DDifs depend on random input data, we calculate them three times with different input data that were generated by using different seeds.

An advantage of using the pairwise cosine distances of the updates, e.g., in comparison to using the Euclidean distances [4] is that its value does not change when $\mathcal{A}$ scales its update (cf. App. H). The pairwise cosine of the updates is, therefore, more stable than other vector metrics.

2) Classification: To maximize the attack impact $\mathcal{A}$ needs to use homogeneous training data (cf. §III-E). Otherwise, the attack will be mitigated by the later defense layers. The Threshold Exceedings measure the homogeneity of a model's training data and uses it to label each model as benign or suspicious, independently from other models (cf. lines 20-22 in Alg. 1).

The classifier calculates for each model $W_{t,k}$ the number of Threshold Exceedings (cf. §IV-C) and uses the median number of Threshold Exceedings divided by two as the classification boundary. A model is labeled as poisoned, if its number of Threshold Exceedings is below this threshold. As we assume the majority of clients to be benign (cf. §III-B), the median will always be at least as high as the lowest benign value.

3) Clustering: The goal of the clustering is to build groups of models, s.t. the training data of all models in the same group are based on IID training data and therefore all models should receive the same label. Because all clients use the same global model, clients with similar training data, will result in similar model updates (cf. §IV). Therefore, a clustering that is based on these features (DDifs, NEUPs and cosine distances), will create groups of models with similar training data.

The clustering algorithm is shown in Alg. 2. In a scenario with P output classes of the models, the input for the algorithm is the number of models N, the NEUPs for each model as a list of N vectors with dimension P, the DDifs for 3 different seeds as a list of 3 lists, each containing N vectors of dimension P, as well as the pairwise cosine-distances for the updates of the output layer biases as a matrix of dimension $N \times N$.

The algorithm first clusters the cosine distances (cf. line 13 of Alg. 2), the NEUPs (cf. line 15 of Alg. 2) and the DDifs (cf. line 17 of Alg. 2). While the NEUPs and DDifs are clustered as plain values, the cosine distances are considered as a precomputed distance matrix. For the clustering HDBSCAN is used that determines the number of clusters dynamically. This allows DeepSight to build groups of models that optimally fit the data distributions and rather create more clusters than necessary than mixing models that were trained on data from different distributions, as this has the risk of mixing benign and poisoned models. A comparison of HDBSCAN with, e.g., k-means that is used Auror [34] is provided in App. B. This structure allows DeepSight to adapt the combination of techniques

dynamically to the current situation, addressing challenge C5. After clustering all feature values, a pairwise distance matrix is determined for each clustering by setting the distance between two models to 0 if they were put into the same cluster and otherwise 1 (cf. function DistsFromClust and lines 14, 16 and 18 in Alg. 2). First, the distance matrices for all DDif clusterings are combined via averaging (cf. line 19 in Alg. 2). Then, the result is averaged with the distance matrices for the cosines and NEUPs (cf. line 21 in Alg. 2). The resulting distance matrix is again processed by HDBSCAN as precomputed distance matrix (cf. line 25 in Alg. 2).

4) Poisoned Cluster Identification (PCI): This component combines the results of the clustering and classification to finally decide about accepting or rejecting a model. To do so, it takes the clustering and labeling from the previous components and determines for each cluster the percentage of poisoned-labeled model updates (cf. lines 25 - 32 in Alg. 1). All models of a cluster remain if less than $\tau = 1/3$ of them are labeled as suspicious. Otherwise, all models of this cluster are removed. The component relies on the idea that all models in the same cluster have similar, IID training data and should, therefore, receive the same label. This mechanism in effect, therefore, realizes a voting about the label for all models in this cluster. The threshold of $\tau = 1/3$ was chosen as it is more likely that a poisoned model is labeled as benign than vice versa.

In summary, we build a dynamic filtering mechanism that efficiently identifies and filters poisoned models that were trained on homogeneous training data by deeply inspecting the predictions of the models and the parameters of the individual neurons. The filtering mechanism is not restricted to black-box metrics of model updates but deeply inspects the models, looking for artifacts of focused training data. It uses the Threshold Exceedings to label all models as suspicious or benign. It does not rely on a certain NN architecture nor backdoor types but inspects the models for artifacts that are characteristics for all backdoors and, therefore, addresses challenge C3. By analyzing the model updates for characteristics of poisoned models, it is able to effectively distinguish between poisoned and benign models, even if the benign models use deviating data. By this, DeepSight also addresses challenge C1.
The proposed techniques for inferring information about the training data of a model (DDifs, NEUPs) as well as the cosine metric build a stable clustering mechanism. It combines different kinds of features that make it, therefore, hard for an adversary to trick them. This clustering ensemble allows the filtering mechanism to create groups of models, where all data in the same group have IID training data. The clustering is used to support the classification and allow to consider their labels but also the labels of similar models for finally deciding about accepting or rejecting them. Moreover, by labeling each model separately, DeepSight is not forced to exclude models but is also free to accept all models. In addition, because of the high sensitivity of the PCI ($\tau = 1/3$), it is unlikely that models are accepted which are a threat for the aggregated model. On the other side, as we discussed in §IV-C, the Threshold Exceedings based identifier is unlikely to label benign clients as poisoned, addressing challenge C4. Therefore, the design realizes a well-balanced trade-off between being too restrictive and too open. We will discuss the effectiveness of the ensemble of different techniques further in §VI-C2.

B. Clipping Layer

To prevent $\mathcal{A}$ from artificially increasing the weight of the poisoned model updates and, therefore, to ensure that $\mathcal{A}$ focuses the training data on the backdoor behavior [28], we restrict the L_2-norm of the individual updates to a boundary S by downscaling the updates if necessary, analogously to Eq. 3. The scaling factor for clipping a model $W_{t,i}$ that was trained by using the global model G_t is given by:

$$\lambda^c_{t,i} = \min\left(1, \frac{S}{||W_{t,i} - G_t||}\right) \tag{12}$$

Since the L_2-norms of (benign) updates decrease during multiple rounds of training, it is challenging to determine a suitable static clipping boundary. Therefore, we choose S dynamically based on the median of the L_2-norms of all updates, including the filtered model updates [28]. As we assume the majority of all clients to be benign, this value will always be in the interval of the L_2-norms for the benign updates.

C. Aggregation Layer

In the aggregation layer, all remaining clipped models are aggregated together using FedAvg. However, in the last round, the aggregation is performed clusterwise and includes also the filtered, clipped models, s.t. only models from the same cluster are aggregated together and each client receives the model that was aggregated for the respective cluster.
As the clustering results in groups of models, where all models in the same group were trained on very similar, IID data this also separates models that were trained on benign or poisoned data. By applying this strategy we ensure that even if an adversary was able to circumvent the classifier in the first layer and even circumvent the clipping, the impact of the attack will be still restricted to the clients that $\mathcal{A}$ already controls. This separation prevents the attack from affecting the benign clients. Moreover, if the global model of the previous round was already poisoned, this separation allows the benign clients to untrain the backdoor and gain a clean model, analogously to the concept of transfer learning [29].

VI. Evaluation

A. Experimental Setup

To evaluate our approach, we test its effectiveness in three different FL applications. The first is the same NLP scenario that was already used by Bagdasaryan *et al.* [2] and allows a direct evaluation of DeepSight against their proposed attack, as it allows to replicate their experimental setup. Moreover, we also use the setup of Nguyen *et al.* [28] to allow a better comparison with existing defense approaches. In App. D, we evaluate DeepSight on multiple image datasets which are frequently used as benchmark datasets in FL [2], [38], [4], [28], [10], [37], [31].

1) Text Prediction: For the NLP scenario, we follow the experimental setup of Bagdasaryan *et al.* [2]. Therefore, we use the Reddit data set for November 2017. Each user with at least 150 and at most 500 posts was considered as one client. We created a dictionary and assigned an integer symbol to each of the most frequent 50000 words and included also three special symbols for unknown words as well as for the start and end of a post. The models used in this scenario consist of two LSTM layers with 200 hidden neurons each and a linear

TABLE I: Characteristics of used IoT datasets

Dataset	#devices	Time (hours)	Size (MiB)	Packets (millions)
FLGuard-Benign	18	4774.7	459.0	3528.3
DÏoT-Attack	5	80.6	7734.2	21919.0
DÏoT-Benign	10	1080.8	134.9	1062.9
UNSW-Benign	16	5415.6	2102.5	8564.4

output layer. After the model was trained for 5000 rounds with 100 randomly selected clients in each round, during which each client trained 2 epochs per round, the adversary used 10 malicious clients to inject advertisements and make the model, e.g., predict "delicious" after "pasta from astoria tastes". The Main Task Accuracy (MA) in this application refers to the accuracy of the suggested words.

2) Network Intrusion Detection System (NIDS): Another application scenario is an FL-based NIDS for IoT devices [26]. We merged four different datasets containing traffic of IoT devices from real-world home and office deployments kindly made available to us by the authors of the respective papers [26], [28], [36]. Table I shows the details of the used datasets. The detection model consists of two layers with 128 Gated Recurrent Units (GRU) each and a linear output layer [26].

1) *FLGuard-Benign*: IoT traffic being captured in three real-world smart-home settings in different cities and one office for more than one week each [28].
2) *DÏoT-Benign*: IoT traffic being captured in a real-world smart home with 18 IoT devices deployed [26].
3) *UNSW-Benign*: IoT traffic being captured in a small office with 28 IoT devices deployed [36].
4) *DÏoT-Attack*: traffic of 5 IoT devices that were infected by the Mirai malware [26].

Following the setup of Nguyen *et al.* [28], we grouped the devices in the datasets according to their communication behavior, resulting in 44 distinct device type groups. We selected 22 device types that had sufficient data for distributing it over at least 15 simulated clients each having at least 2 000 data samples. These device types represent different kinds of typical IoT devices found in a smart home, such as printers, smart light bulbs, smart plugs, or smart sensors. Depending on the amount of data available for a particular device type, its data were split into at least 15 and up to 200 clients, so that each client had between 2 000 and 3 000 samples for training. By doing this we ensure that the training data divided to different clients are as independent as possible and thereby resemble a real-world setting. Since different clients were assigned data from different data sets and different settings inside a dataset, the client data represent a combination of IID and non-IID data distributions. The detailed evaluation results of DeepSight for each of these device types can be found in App. C. For ease of presentation, we select the Netatmo Weather device, a smart weather station, as a representative example of a device type for the subsequent discussion, as it was present in three out of the four datasets and provided sufficient data to be distributed among 100 simulated clients.

Unless stated otherwise, we used for training the detection models a learning rate of 0.1 for benign clients, and for malicious clients the *constrain-and-scale* attack strategy with a learning rate of 0.01, a loss-control parameter $\alpha = 0.7$, a PDR of 50 %, a PMR of 25%, and 10 local epochs. The initial global model was based on 10 rounds of benign training before starting attacks. In the NIDS scenario, the Main Task Accuracy (MA) refers to the true negative rate, i.e., the rate of benign traffic being classified as benign whereas Backdoor Accuracy (BA) refers to the false-negative rate, i.e., the rate at which attack traffic samples of the adversary are erroneously classified as benign.

TABLE II: Effectiveness of DeepSight in comparison to existing defenses on NIDS and NLP dataset. The row *No defense* shows the impact of the *constrain-and-scale* attack with plain FedAvg.

Defenses	Text prediction				NIDS			
	BA	MA	PRC	NPV	BA	MA	PRC	NPV
No Attack	-	22.6	-	-	-	100.0	-	-
No defense	100.0	22.4	-	-	100.0	100.0	-	-
DP [2], [23]	21.9	20.6	-	-	14.8	82.3	-	-
Ensemble FL [6]	100.0	**22.6**	-	-	100.0	93.2	-	-
FoolsGold [10]	**0.0**	22.5	**100.0**	**100.0**	100.0	99.2	32.7	84.4
Auror [34]	100.0	22.4	-	90.0	100.0	96.6	0.0	70.2
AFA [24]	100.0	22.4	0.0	89.4	100.0	87.4	4.5	69.2
Krum [4]	100.0	**22.6**	9.1	0.0	100.0	84.0	24.2	0.0
FLGuard [28]	**0.0**	21.7	20.4	100.0	**0.0**	**100.0**	59.5	**100.0**
DeepSight	**0.0**	**22.6**	**100.0**	**100.0**	**0.0**	**100.0**	**100.0**	**100.0**

B. Experiment Platform

All experiments were performed on a server running Ubuntu 18.04 LTS, with 20 physical Intel Xeon CPU cores and 40 logical cores, 4 NVIDIA GeForce RTX 2080 Ti (each with 11GB memory), and 192 GB RAM. The experiments were implemented in Python, using the popular deep learning library Pytorch, the HDBSCAN implementation of McInnes *et al.* [20] and for evaluating existing work such as Auror [34] the machine learning library Scikit [30] was used.

C. Experimental Results

1) Preventing Backdoor Attack: Table II shows the effectiveness of DeepSight in comparison to several state-of-the-art defenses approaches in terms of BA, MA, precision (PRC), indicating the probability that a filtered model is indeed poisoned and its complement, the negative predictive value (NPV), indicating the probability that an accepted model is indeed benign. As can be seen, DeepSight effectively mitigates the attack in both scenarios. Other approaches [34], [4], [24] assume the data to be IID, which makes them fail for non-IID (Reddit) or partly IID (NIDS) data. Although FLGuard also achieves a decent performance in both scenarios, it also excludes many benign clients, which reduces the MA of the model, especially if it is applied from the beginning (cf. §VI-D). Also FoolsGold [10] achieves a decent performance in the text prediction scenario but fails for the IoT dataset. This is likely because FoolsGold assumes datasets of benign clients to be non-IID. The data in the IoT data set are partly IID (cf. §VI-A), causing FoolsGold to fail. On the other side, DeepSight is the only approach that is effective in both scenarios.

In App. F, we evaluate DeepSight against 5 different NLP and 12 NIDS backdoors, showing that it is not restricted to specific targets.

In most of our experiments, $\mathcal{A}$ does not attack in the beginning but after several rounds of training, as otherwise there would be a high risk that, even if the attack would be successful, the later training would untrain the backdoor. To show, that this does not restrict $\mathcal{A}$, we conducted an experiment on the traffic of 5 different device types in the NIDS scenario, starting from a randomly initialized model and trained for 50 rounds. However, in all cases the BA remained at 0.

2) Evaluation of Individual Components: Table III compares the BA for the different layers of DeepSight, after running 10 rounds of training, while the malicious clients try to inject different numbers of phases from the Mirai botnet at the same time, using a PDR of 65 % and a learning rate of $10^{-2.5}$. We averaged the values over 9 very different device types, covering IoT devices for a wide spectrum of different applications with different behavior: Edimax Plug and TPLinkPlug (smart power plugs), DLinkType05 and EdnetGateway (collects of sensors, e.g., a door sensor), Lightify (a smart light bulb), NetatmoCam (a WIFI camera), PIX-STARPhoto-frame (a foto frame), Netatmo Weather and an HP Printer.
As the table shows, it is more difficult for $\mathcal{A}$ to inject multiple backdoors at the same time, as already pointed out by Sun *et al.* [37]. It also shows that the clipping defense is not effective against simple backdoors, but is effective against complex backdoors since they have already a high L_2-norm before they are scaled. On the other hand, filtering is effective in detecting backdoors that have a high imbalance in the underlying training data, but fails for complex backdoors. DeepSight combines the strengths of both and keeps the BA low for all backdoor complexities. This shows the effectiveness of the multi-layer strategy, where the filtering layer forces $\mathcal{A}$ to weaken its attack when it wants to prevent the poisoned models from being filtered out. However, then the weakened attacks can be easily mitigated by the clipping layer of DeepSight.
In App. K, we analyze the effectiveness of the individual components of DeepSight's filtering layer.

3) Varying Attack Parameters: For the *constrain-and-scale* attack strategy, $\mathcal{A}$ can adjust different parameters of the training process for the malicious clients, with the purpose to overcome our defense. We evaluated different alpha-values from 0.1 to 1, different learning rates from 10^{-1} to 10^{-7}, different numbers of epochs from 1 to 100 and different stages of the training when $\mathcal{A}$ starts its attack and runs the training process for each of them for at least 10 rounds for the NIDS dataset. Furthermore, we also evaluated different PMRs up to 45 % for 20 rounds to even evaluate the border cases. However, DeepSight was always able to classify the submitted models as benign or poisoned without any misclassifications. Therefore, the BA was always 0 % and the MA almost always 100 %.
We also evaluated different PDRs from 5 % to 100 %. Again, DeepSight did not misclassify any benign models. However, as already observed earlier for weakly-trained backdoors, which are realized here through low PDRs, DeepSight was not able to recognize all poisoned model updates. For a PDR of 5 %, DeepSight did not recognize any poisoned model updates and for PDRs of 8 % or 10 %, DeepSight failed to detect 6 out of 25 poisoned models. The reason for not recognizing some models for the PDRs of 8 % and 10 % is that the clustering put them together with benign models, but also the Threshold Exceedings based identifier did not recognize them correctly. For a PDR of 5 %, both, the clustering and the Threshold Exceedings based identifier failed. However, as we have demonstrated in §VI-C2, the clipping defense layer compensates the vulnerability of the filtering layer from DeepSight against such weak attacks. Because of the combination of both layers, the attack failed for all PDRs and the BA was always 0 %.
Therefore, the adversary can not circumvent DeepSight by varying the attack parameters.

TABLE III: BAs from DeepSight's individual layers for different backdoor complexities, averaged over 9 IoT device types.

	1	2	3	4	13
No Defense	100.0 %	80.3 %	48.2 %	41.7 %	43.9 %
Clipping	87.5 %	56.2 %	31.2 %	13.9 %	11.5 %
Filtering	0.0 %	7.4 %	41.5 %	30.4 %	42.9 %
DeepSight	0.0 %	0.0 %	0.6 %	0.3 %	1.1 %

4) Sophisticated Attacks: As we assume $\mathcal{A}$ to have full knowledge about the system, it can adapt its strategy to circumvent DeepSight. In the following, we discuss three sophisticated attack strategies, specifically designed to overcome DeepSight and a recently proposed state-of-the-art backdoor attack [41]. In App. G, we evaluate another state-of-the-art attack [38] and two further adaptive attacks, targeting the clustering components of DeepSight by adding noise and use poisoned models to fill the gap between the benign and poisoned models.
Increasing Backdoor Complexity As the classifier labels models based on the complexity of their training data, a sophisticated adversary could try to increase the complexity for avoiding a focus on the backdoor target $C_{\mathcal{A}}$. We simulated this for the NIDS scenario by using the network traffic of multiple phases of the Mirai botnet. However, as shown in Tab. III, the BA is always close to zero. The reason for this is that for more complex backdoors the filtering component fails but on the other side, such backdoors are also harder to inject [37], causing them to be mitigated by the clipping layer. Also here the advantage of our multi-layer approach becomes visible.
Freeze Output Layer As the NEUPs and the Threshold Exceedings depend on the output layer updates, a sophisticated adversary could exclude the parameters of this layer from the training. To show the effectiveness of DeepSight, we run an experiment for the IoT-Traffic. We used different numbers of local epochs, up to 100 000 epochs and increased the PDR to 90 %. However, the BA of the local model did not increase, because it is significantly harder to train a model for a specific task without changing the output layer. Therefore, also the aggregated BA remains at 0 %, even for PMRs of more than 50 %, which goes beyond our attack scenario (cf. §III-B).
Adapt Anomaly Evasion Loss Another option is to consider the DDifs already during the training for the anomaly-evasion loss L_{anomaly}. We calculated the DDifs for the aggregation result of all benign models. L_{anomaly} was calculated as the L_2-norm between the DDifs of this benign model and the current poisoned model. For simplicity, we used the actual benign models instead of estimations, as this strengthens $\mathcal{A}$, although this goes beyond our adversary model. However, even with this advantage, the attack was not successful. We run the experiment for 10 rounds, and different α values ($\alpha \in \{0.0, 0.1, \ldots 1.0\}$). Although the attack successfully distracted the DDifs, this was compensated by the other techniques. Therefore, DeepSight still completely mitigated the attack, showing the advantage of the clustering ensemble.
DBA Attack: Recently, Xie *et al.* introduced a novel backdoor attack strategy that split the trigger and the clients into different parts. Each group of clients only train for their respective trigger part [41]. We evaluated the attack in the NLP scenario. One group trained their models to predict the word "delicious" 4 words after the word "pasta", the other group to predict "delicious" 2 words after the word "astoria". However, although the attack achieved a BA of 64.5 % without defense, DeepSight successfully identified all poisoned models and mitigated the attack (BA=0 %), while keeping the MA at 22.6 %.

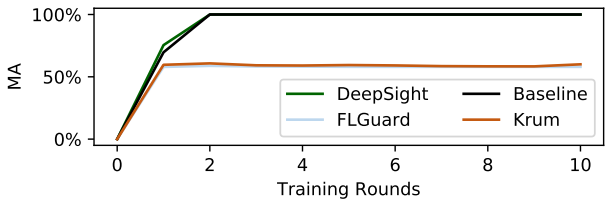

Fig. 5: Performance in terms of Main Task Accuracy (MA) of DeepSight and Krum [4] without attack

D. Impact on Benign Training Process

Several existing defense approaches [4], [24], work by excluding outliers and are, therefore, very likely to always exclude models even if there is no attack deployed. This impacts negatively the resulting model, causing a low MA and makes the respective defenses not practical.

Figure 5 compares the MA if no attack is deployed, for DeepSight, Krum [4], FLGuard [28] and without defense (Baseline), starting from a random model. As the figure shows, DeepSight slows down the training process slightly but achieves a good performance soon, similarly to the baseline. Therefore, the negative impact on the learning process is low. In comparison, Krum stops at 60 %, as it always chooses a model representing data from the majority of clients. Analogously, also FLGuard does not consider outliers.

In App. J, we discuss the computational complexity of DeepSight. We show that the computationally expensive operations scale linearly with the number of participants, s.t., DeepSight causes only a low computational overhead.

We extensively evaluated various different attack strategies, including state-of-the-art attacks [2], [41], [38] as well as attacks that target the weak spots of DeepSight, e.g., adapting the anomaly-evasion loss function, freezing the output layer, reducing the attack impact or building clusters with a sufficient number of inconspicuous models. However, none of these attacks were effective in overcoming DeepSight. We showed that techniques that might be suitable for distracting DeepSight also reduce attack impact. Therefore, DeepSight addresses challenge C2. Moreover, also techniques like client-level Differential Privacy [23] do not have an impact on DeepSight, as we evaluated client-level model-noising with various different standard deviations and provide a proof for the robustness of the NEUPs, cosine distances and Threshold Exceedings against scaling/clipping the model updates (cf. §VII). Therefore, we showed that DeepSight effectively mitigates backdoor attacks.

VII. Security Consideration

To achieve adversarial objective O1 (cf. §III-B), i.e., maximizing Backdoor Accuracy (BA), adversary $\mathcal{A}$ needs to use a well-trained backdoor in its poisoned model updates to maximize its impact. Such model updates will, however, be identified and removed by model filtering. To avoid detection, $\mathcal{A}$ can try to use only weakly trained backdoors. In this case, however, the attack is effectively mitigated by clipping. The filtering scheme is based on multiple measures (DDifs, NEUPs, Threshold Exceedings) to identify models with similar training data and label models as benign or malicious. Theorem 1 and Theorem 2 below show that neither DDifs nor Threshold Exceedings are affected if $\mathcal{A}$ scales its model updates. Furthermore, also the cosine distances are shown to be resilient against scaling (cf. App.H).

Theorem 1. *The NEUPs are not affected by scaling or clipping the model update.*
Formally: Let G_t be the global model of an arbitrary round, $W_{t,k}$ an arbitrary local model applying update $U_{t,k}$, with $W_{t,k} = G_t + U_{t,k}$ and NEUPs$(G_t, W_{t,k})$ be the NEUPs for $W_{t,k}$.
$\forall \lambda \in \mathbb{R} \setminus \{0\} : \textit{NEUPs}(G_t, W_{t,k}) = \textit{NEUPs}(G_t, G_t + \lambda U_{t,k})$

Proof: See Appendix H. ■

Theorem 2. *The Threshold Exceedings are not affected by scaling or clipping the model update.*
Formally: Let G_t be the global model of an arbitrary round, $W_{t,k}$ an arbitrary local model applying update $U_{t,k}$, with $W_{t,k} = G_t + U_{t,k}$ and TE$(G_t, W_{t,k})$ be the Threshold Exceedings for $W_{t,k}$.
$\forall \lambda \in \mathbb{R} \setminus \{0\} : \textit{TE}(G_t, W_{t,k}) = \textit{TE}(G_t, G_t + \lambda U_{t,k})$

Proof: Follows immediately from Theorem 1, as the only input for the Threshold Exceedings are the NEUPs. ■

DeepSight relies on two values that are determined dynamically, the classification boundary for the Threshold Exceedings classifier and the clipping boundary. However, both values are calculated as the median of all values. As we assume the majority of clients to be benign, it is guaranteed that these values will always be in the range of benign values and, therefore, cannot be manipulated by $\mathcal{A}$.

Furthermore, we empirically showed that DeepSight effectively mitigates targeted poisoning attacks, including state-of-the-art attacks [2], [41], [38] as well as attacks targeting the weak spots of DeepSight against an arbitrarily behaving adversary. Therefore, DeepSight fulfills requirement R1 and prevents $\mathcal{A}$ from achieving O1 and O2.

VIII. Related Work

Various defenses against poisoning attacks in FL have been proposed. In the following, we will discuss and compare them to DeepSight.

A. Anomaly Detection-Based Approaches

Many backdoor defenses follow an outlier-detection-based strategy and exclude anomalous mode updates [34], [4], [24], [42], [15], [14], [16], [12]. They assume that the local data of all benign clients are similar, i.e., identically and independently distributed (IID), so that it is sufficient to filter models that differ from the majority of models. However, in many scenarios the data are non-IID [10], [35], resulting in differences among benign models. Therefore, many benign models are excluded, causing the resulting model to perform worse on the data of the excluded local models (cf. §VI-D).

Krum aggregates local models by choosing a single local model as the aggregated model with the smallest Euclidean distance to a certain fraction of other models [4]. Hence, models trained on deviating data will never be chosen.

Munoz *et al.* exclude a local model if its cosine distance to the aggregated model is higher or lower than the median distance plus/minus the standard derivation [24]. Unfortunately, also this approach suffers from a high false-positive rate (cf. §VI-C1).

Baffle sends the aggregated model to a randomly selected subset of clients. Those so-called validation clients evaluate

the model on their local data and vote about accepting the aggregated model or rejecting it [1]. However, validation clients can only notice the backdoor if they have a sufficient number of trigger samples or the backdoor attack has a significant impact on the model's behavior on the main task. The first scenario is not realistic, as benign clients can not be assumed to have knowledge of trigger samples. The second scenario implies that the attack is not stealthy, violating O2 (cf. §III-B), and making the backdoor easy to detect. Furthermore, the approach does not work if the data of a (small) number of training clients differs from the majority of validation clients, which happens, e.g., in non-IID scenarios. Also, Baffle cannot be used from the beginning but, e.g., only after several hundreds of rounds, as otherwise many false positives will occur (cf. [1]).

Auror first determines indicative features by clustering for each parameter all local models separately using k-means with two clusters. It selects features with the highest distances between the two centroids. A model is rejected if it was clustered for too many indicative features to the smaller cluster [34]. Also Auror focuses on excluding outliers. Moreover, a centroid-based clustering can be successfully distracted (cf. App B).

FLGuard also exploits the dilemma of $\mathcal{A}$ to either focus on the training data and getting filtered, or to use weakly-trained model updates, allowing the clipping layer to mitigate the attack. Nguyen *et al.* combine an outlier-based clustering with clipping and adding random noise to the model [28]. However, while DeepSight uses a classifier for identifying poisoned model updates, FLGuard uses a clustering approach that rejects outliers, including benign model updates that were trained on different data (cf. §VI-D).

Liu *et al.* introduced another approach to detect backdoored models in centralized settings [17]. However, their approach is not suitable for FL settings and does not consider semantic backdoor attacks as discussed in detail in App. L.

In summary, besides being ineffective (cf. §VI-C1), existing filtering approaches for FL also neglect a main principle of FL by preventing utilizing the data of different clients, as the resulting model was trained only on data of a certain group of clients (cf. § VI-D).

B. Other Defense approaches

FoolsGold [10] assumes that benign datasets from different clients differ from each other and assigns low weights to models, which are similar to many other models. However, this harms the impact of benign clients with similar data. For example, in the case of the NIDS scenario, the network traffic does not vary much because of the limited functionalities of an IoT device. Moreover, FoolsGold sums up the updates for all rounds and compares them, instead of focusing on the current round. This allows a sophisticated adversary to submit poisoned updates without being perceived as suspicious.

Differential Privacy [23] enforces a maximal, static L_2-norm of the updates and adds randomly generated noise. As pointed out by Bagdasaryan *et al.* it has the side effect of also mitigating backdoor attacks [2]. However, it fails for well-trained poisoned models (cf. §VI).

Other approaches [42], [12] calculate the median for all parameters and, therefore, also focus on models, representing the majority but neglect models that were trained on different training data. Moreover, also these defenses have shown to be vulnerable to different poisoning attacks [8].

The approach of Cao *et al.* trains multiple models. For each of these models, a random subset of clients is used for training a model over multiple rounds. At inference time, each resulting global model is applied and the final prediction is determined via majority voting. Cao *et al.* prove that if the training is completed, they could determine for a specific sample a minimal number m of malicious clients, which their algorithm would have been able to tolerate [6]. Unfortunately, this number can differ arbitrarily for different input samples. Moreover, their proof does not provide any work in practice. Since determining this number requires a-posteriori knowledge, the impact of determining m at this point is negligible, as the models are already trained and it is, therefore, too late to prevent backdoor attacks. Furthermore, at this point, it is not even clear, whether the current label for the considered samples is even correct or a backdoor attack already took place and flipped the label already. Finally, the approach is vulnerable for the replacement-scaling attack of Bagdasaryan *et al.* [2] and damages the MA, as we demonstrated in §VI-C1, and fails even for low PMRs of 5 % (cf. [6]).

C. Model Inference Attacks in FL

Different approaches to inference information from models have been proposed [39], [13], [25], [32]. Although these approaches work well to violate the users' privacy in the considered attack scenarios, none of them is suitable for being used on an FL aggregation server to identify poisoned model updates. Membership inference attacks that determine the presence of a specific sample [13], [25], are not effective as benign and poisoned samples can overlap, e.g., for the NIDS scenario. Other approaches, require attackers to have their own training data [32], which is not practical for the FL server (cf. §III-C), or train separate models for each label [39], making the approach not practical, e.g., for the NLP scenario with 50 000 words.

In comparison, the techniques that were proposed in this paper (NEUPs, DDifs, and Threshold Exceedings), allow to estimate information about the training data distribution and identify poisoned models and models with similar data but causes only a small computational overhead (cf. App. J) and do not require test data to be available on the aggregation server.

IX. Conclusion

Backdoor attacks threaten the integrity of Federated Learning (FL), which is a promising emerging technology. We show that existing countermeasures cannot adequately address sophisticated backdoor attacks on FL and introduce DeepSight, a novel model filtering approach that effectively mitigates backdoor attacks on FL. While existing backdoor defenses are often restricted to excluding abnormal models, DeepSight follows an orthogonal approach by using several novel techniques to conduct a deep inspection of the submitted models separately for identifying and excluding poisoned models.

We present several new techniques (DDifs, NEUPs, Threshold Exceedings) to infer information about a model's training data, identify similar models, and measure the homogeneity of model updates. By performing a deep inspection of the models' structure and their predictions, DeepSight can effectively mitigate state-of-the-art poisoning attacks and is robust against sophisticated attacks, without degrading the performance of the aggregated model.

Recently, different secure aggregation schemes have been

proposed preventing the aggregation server from accessing the individual model updates [5], [9]. Although, DeepSight does not reduce the privacy level compared to FedAvg [21] as it also anonymizes the individual contributions and smoothens the parameter updates by aggregating them, future work needs to implement a privacy-preserving version of DeepSight to combine the privacy gains of secure aggregations with the backdoor mitigation algorithm of DeepSight.

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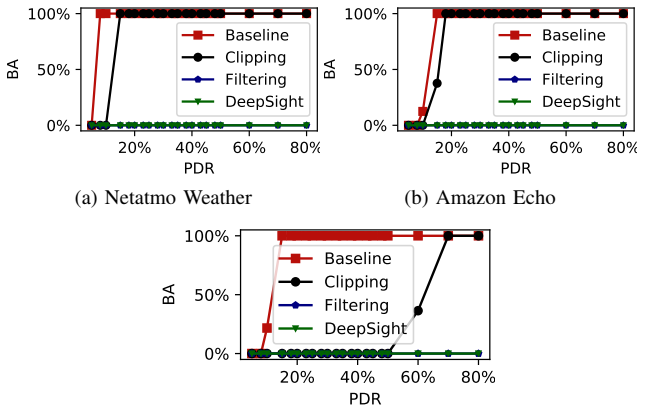
APPENDIX

A. Homogeneity of Poisoned Models

Although the adversary $\mathcal{A}$ needs to craft inconspicuous models for preventing a detection or mitigation of its attack (O2; cf. §III-B), this also reduces the attack impact (O1). In the following, we will show that, in order to run a successful attack, $\mathcal{A}$ needs to focus on the backdoor behavior, resulting in homogeneous model updates. To make the models more inconspicuous, $\mathcal{A}$ can tune the PDR and also make the backdoor behavior more complex for imitating a deviating distribution of benign training data.

Backdoor Complexity As pointed out by Sun *et al.* [37] and also confirmed by our experiments (cf. §VI-C2), increasing the complexity of the backdoor behavior also significantly reduces the attack impact. If, i.e., $\mathcal{A}$ includes 4 phases of Mirai in its backdoor for the NIDS scenario, this reduces the attack impact even without defense and allows a defense that only consists of the clipping component (cf. §V-B) to reduce the BA to 13.9 %, indicating that $\mathcal{A}$ cannot increase backdoor complexity beyond this value. On the other side, the filtering is still effective, showing that even for this complexity level, the training data are homogeneous enough to get detected by DeepSight.

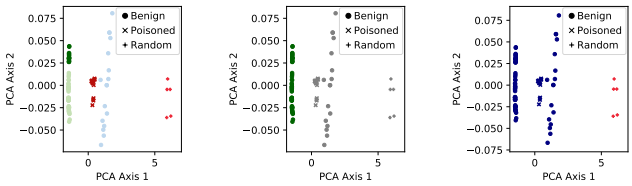
PDR: The second parameter that affects the homogeneity of models is the PDR. However, as pointed out by Nguyen *et al.*, low PDRs also reduce the attack impact and increase the risk that the impact of the poisoned model updates becomes negligible during the aggregation. Figure 6 shows the BA for the individual components for three different device types, depending on the PDR. Also here, clipping mitigates the attack successfully for low PDRs but fails for high values. Therefore, to achieve a high attack impact, especially in scenarios where the server applies clipping, $\mathcal{A}$ needs to use a high PDR, i.e. at least 20%. However, this causes a focus of the poisoned training data on the attack data, resulting in homogeneous model updates, which allows the filtering layer to detect and filter the poisoned models.



(a) Netatmo Weather (b) Amazon Echo

(c) PIX-STARPhoto-frame

Fig. 6: Impact of the Poisoned Data Rate (PDR) on the Backdoor Accuracy (BA) without defense, a clipping defense (§V-B), filtering (§V-A) and DeepSight for different device types.



(a) HDBSCAN: Dynamic #clusters (b) HDBSCAN: Single Cluster + Outliers (c) k-means Fixed #clusters=2

Fig. 7: Effectiveness of our clustering algorithm (a) compared to HDBSCAN for a single cluster and outliers (grey) [28] (b) as well as k-means clustering [34] (c). The individual models are visualized by using the principal component analysis (PCA[6]).

In summary, if $\mathcal{A}$ tries to increase the heterogeneity of its model updates by, e.g., reducing the PDR or making the backdoor behavior more complex, the impact of the backdoor will simultaneously also decrease the attack impact, making it easier to be mitigated by defenses like weight clipping (cf. §V-B). Therefore, to maximize the attack impact, $\mathcal{A}$ needs to choose a high PDR and a simple backdoor behavior, causing the training data to differ from the benign data and causing the model updates to be more homogeneous, thus making them distinguishable from benign ones.

B. Comparison of Clustering Approaches

DeepSight uses HDBSCAN for clustering. Other clustering algorithms, e.g., k-means [19] that is used by Auror [34] have, among others, the disadvantage to require the number of clusters in advance. However, this can be exploited by $\mathcal{A}$ to circumvent the defense, as shown in Fig. 7. This figure compares HDBSCAN against k-means for the NIDS dataset with 25 malicious clients. To distract the defense, $\mathcal{A}$ used a subset of 5 clients for submitting random model updates. As subfigure 7c shows, this successfully distracts k-means, s.t. it accepts the remaining poisoned models, while HDBSCAN is not distracted by the random models. However, the version that accepts only a single cluster also rejects many benign models. On the other side, the plain HDBSCAN is well suited for distinguishing model updates, trained on different data. It effectively separates all different groups of models.

C. Performance of DeepSight on the IoT dataset

Table IV shows the performance of DeepSight for all device types in the NIDS scenario. As the table shows, DeepSight successfully mitigates all backdoor attacks, although it does not always filter all poisoned models. For example, in case of the Ednet Gateway, the filtering does not filter any malicious client,

[6]The Principal Component Analysis (PCA) is a well-known technique to extract principal dimensions from high-dimensional data [40].

TABLE IV: Main Task Accuracy (MA), Backdoor accuracy (BA), Poisoned Probability (PRC) and Benign Probability (NPV) of DeepSight for different IoT devices in the NIDS scenario.

	No Defense		DeepSight			
Device Type	BA	MA	BA	MA	PRC	NPV
Amazon Echo	100.0	99.9	0.0	93.3	100.0	100.0
Belkin Wemo Motion Sensor	100.0	99.9	0.0	99.2	92.6	100.0
DLink Type05	100.0	91.9	0.0	98.3	100.0	98.7
Edimax Plug	100.0	98.7	0.0	98.8	100.0	100.0
Ednet Gateway	100.0	100.0	0.0	100.0	–	75.0
Google Home	58.2	100.0	0.0	87.5	100.0	100.0
HP Printer	100.0	92.6	0.0	89.9	100.0	100.0
Insteon Camera	100.0	98.9	0.0	97.8	100.0	98.7
LiFx Light Bulb	100.0	100.0	0.0	83.7	100.0	90.5
Lightify2	100.0	100.0	0.0	100.0	100.0	100.0
Nest Dropcam	100.0	100.0	0.0	100.0	100.0	84.6
Netatmo Cam	100.0	100.0	0.0	100.0	100.0	100.0
Netatmo Weather	0.0	93.5	0.0	100.0	100.0	100.0
PIX-STARPhoto-frame	100.0	100.0	0.0	99.9	100.0	100.0
Samsung Smart Cam	100.0	99.2	0.0	99.9	100.0	100.0
Smarter	100.0	100.0	0.0	100.0	100.0	100.0
TP-Link Cloud Camera	100.0	98.6	0.0	97.6	100.0	100.0
TPLink Plug	0.0	89.1	0.0	100.0	100.0	83.3
Tesvor Vacuum	100.0	96.1	0.0	95.5	100.0	100.0
Triby Speaker	0.0	81.5	0.0	80.8	100.0	100.0
Wemo Switch	100.0	100.0	0.0	100.0	100.0	100.0
Withings Sleep Sensor	100.0	100.0	0.0	100.0	100.0	100.0
Withings Baby Monitor	100.0	100.0	0.0	100.0	100.0	100.0
iHome	100.0	92.2	0.0	92.9	100.0	100.0
Average	85.8	97.2	0.0	96.5	99.7	97.1

since the Threshold Exceedings of most poisoned models (on average 27.75) are slightly higher than the boundary (29, the benign models have in average 57 Threshold Exceedings). However, as the clipping boundary is always in the interval of benign values and the benign and poisoned models are separated, the BA is still 0%, showing the effectiveness of our multi-layer approach.

D. Evaluation of DeepSight on Image Datasets

The CIFAR-10 and MNIST datasets are frequently used as benchmark datasets for FL. [2], [38], [4], [28], [10], [37], [31]. To allow a better comparison with other work on FL, we replicate the setup of existing work. For the CIFAR-10 dataset, we use a light version of Resnet-18 model and an IID rate of 0.7. The adversary aims to make cars in front of a stripped background being classified as birds [2], [28]. For MNIST, the model consists of 2 convolutional layers with a max-pooling in between and 2 fully connected layers [6]. The adversary aims to make pictures with a white rectangle on the left side to be classified as a ”0”. We used 100 clients and set the PMR to 20 %[28]. As Tab. V shows, DeepSight effectively mitigates the attack, while without defense the BA reaches 100% and 96.3%. It is worth noting, that in case of MNIST sometimes misclassifications a counted in favor of the BA (cf. §G).
In App. E, we evaluate DeepSight for an image recognition scenario, where the dataset of each client consists only of a single label to simulate homogeneous benign training data.

E. Scenarios with a Single Source Label

The Threshold Exceedings classifier of DeepSight estimates the homogeneity of the used training data based on the distribution of labels. However, in special scenarios the local datasets of each client might consist only of samples with a single label, e.g., for facial user authentication on smartphones. Although, in those scenarios a binary classifier or a siamese network [7] might be more suitable than FL, we performed an additional experiment on the popular CIFAR-10 benchmark dataset with

TABLE V: Effectiveness of DeepSight for the CIFAR-10 and MNIST datasets. All values in percentage

	CIFAR-10				MNIST			
Defense	BA	MA	PRC	NPV	BA	MA	PRC	NPV
No Attack	0.0	92.2	-	-	0.4	95.7	-	-
No Defense	100.0	84.1	-	-	96.3	58.9	-	-
DeepSight	0.0	92.2	-	80	0.3	96.6	100	100

100 clients and a PMR of 20 % to demonstrate DeepSight's effectiveness even in those scenarios. As Tab. VIII shows, although DeepSight did not detect the malicious models, the later defense layers successfully mitigated the attack. Table VIII also shows that due to the dynamic threshold of the Threshold Exceedings classifier, DeepSight did not raise any false positive, demonstrating that DeepSight does not negatively affect the MA of the resulting model.

F. Performance of DeepSight against Different Backdoors

To demonstrate that DeepSight is not restricted to certain attack patterns, we evaluate it against different backdoors.
NIDS: We evaluated DeepSight against different backdoors in the NIDS scenario, by using different attack modes of the Mirai malware as attack traffic. As Tab. VI shows, DeepSight effectively mitigates all of these attacks.
Word Prediction: We injected different sentences, which were also used by Bagdasaryan *et al.* [2]. As Tab. VII shows, DeepSight is effective against all of these backdoors.

G. Further Sophisticated Backdoor Attacks

Edge Case: Wang *et al.* recently proposed an attack that aims to flip the labels for the samples, where the adversary's focus on samples where the predictions are already made with a low confidence value. Therefore, the attack targets samples where the predicted probability is low, although it is still classified correctly [38]. We followed their experimental setup of and conducted an experiment for the CIFAR-10 benchmark dataset for 1500 rounds. In each round 10 clients were randomly selected for training their local model. The adversary $\mathcal{A}$ launched its attack for 150 rounds. Without defense, $\mathcal{A}$ achieved a BA of 53.06% and a MA of 86.46 %. DeepSight reduced the BA to 7.14 % and the MA to 80.54 % and, therefore, successfully mitigated the attack. It is worth noting that even without attack the BA is 11.2% and the MA is 77.53% as here also misclassifications are considered.
Model Noising DeepSight uses clustering in several places to identify clients with similar training data. Therefore, a sophisticated adversary could add random noise to the poisoned

TABLE VI: Main Task Accuracy (MA), Backdoor accuracy (BA), Poisoned Probability (PRC) and Benign Probability (NPV) of DeepSight for different NIDS backdoors.

	No Defense		DeepSight			
Backdoor	BA	MA	BA	MA	PRC	NPV
Dos-ACK	100.0	92.8	0.0	100.0	100.0	100.0
Dos-DNS	100.0	98.0	0.0	100.0	100.0	100.0
Dos-Greeth	100.0	98.1	0.0	100.0	100.0	100.0
Dos-Greip	100.0	97.5	0.0	100.0	100.0	100.0
Dos-HTTP	100.0	92.5	0.0	100.0	100.0	100.0
Dos-Stomp	100.0	97.5	0.0	100.0	100.0	100.0
Dos-SYN	100.0	82.0	0.0	100.0	100.0	100.0
Dos-UDP	100.0	92.9	0.0	100.0	100.0	100.0
Dos-UDP (Plain)	100.0	96.5	0.0	100.0	100.0	100.0
Dos-VSE	100.0	97.2	0.0	100.0	100.0	100.0
Preinfection	100.0	98.0	0.0	100.0	100.0	100.0
Scanning	100.0	82.0	0.0	100.0	100.0	100.0
Average	100.0	93.7	0.0	100.0	100.0	100.0

models, in order to distract DeepSight. We evaluated this attack by adding noise with 36 different standard deviations from $4.3 \cdot 10^{-17}$ to 21.5 (logarithmically distributed) with a mean of 0 for the NIDS scenario. However, this attack failed, as the BA was always 0 even for the highest standard deviations, which was too high, indicated by low BA values for the noised poisoned local models.

Gap Bridging As DeepSight uses a voting-based filtering mechanism to evaluate the models of a cluster, a sophisticated adversary could try to use a few of the poisoned models, to connect the benign cluster with the cluster that contains all poisoned models, such that they are merged and the benign models cause the cluster to be accepted. We used 200 clients with a PMR of 40% and split all malicious clients into different groups, with a gradually increasing PDR from 5% to 20%. However, although 19 models with a very low PDR were accepted, the majority of poisoned models were rejected but not a single benign model. The BA was 0% and the MA 100%. This also shows the advantage of the ensemble, as a naive clustering approach, using only the cosines and k-means, fails and does not filter any poisoned model, while DeepSight identifies most of the poisoned models and successfully mitigates the impact of the no recognized models.

H. Stability of Metrics against scaling

The adversary can scale the updates, either to increase the impact or as part of techniques like client-level DP, to make them less suspicious. In the following, we show that the cosine and NEUPs are not affected by scaling.

1) Stability of the cosine against scaling: For two vectors $u, v \in \mathcal{R}^d$, the cosine between is defined as:

$$\cos(u,v) = \frac{u \cdot v}{||u||||v||} = \frac{\sum_{i=0}^{d} u_i v_i}{\sqrt{\sum_{i=0}^{d} u_i^2}\sqrt{\sum_{i=0}^{d} v_i^2}} \tag{13}$$

Therefore, it follows that scaling one vector with a scaling factor $\lambda \neq 0$ does not affect the cosine as:

$$\cos(\lambda u, v) = \frac{\sum_{i=0}^{d} (\lambda u_i) v_i}{\sqrt{\sum_{i=0}^{d} (\lambda u_i)^2}\sqrt{\sum_{i=0}^{d} v_i^2}} = \frac{\lambda \sum_{i=0}^{d} u_i v_i}{\lambda ||u||||v||} = \cos(u,v) \tag{14}$$

2) Proof of theorem 1:: Let $W^*_{t,k}$ be the poisoned model of client k in round t, G_t the respective global model, $U^*_{t,k} = W^*_{t,k} - G_t$ the update, $\gamma_{t,k} \neq 0$ an arbitrary scaling factor unequal 0 (cf. Eq. 3). For simplicity, $\mathcal{C}^*_{t,k,i}$ denotes the NEUP for the neuron i of the scaled model $W'_{t,i}$, $\mathcal{C}_{t,k,i}$ of the unscaled model $W^*_{t,k}$ and analogously for the energy $\mathcal{E}^*_{t,k,i}$ as well as the update of bias of neuron i for client k in round t $b^u_{t,k,i}$. Therefore, the following relation holds:

$$b^*_{t,k,i} = \lambda_{t,k} b^u_{t,k,i} + b_{t,G_t,i} \tag{15}$$

and analogously for the individual weight updates $w^u_{t,k,i,h}$. Therefore, $\mathcal{C}^*_{t,k,i} = \mathcal{C}_{t,k,i}$ holds:

$$\begin{aligned}
\mathcal{C}^*_{t,k,i} =& \frac{{\mathcal{E}^*_{t,k,i}}^2}{\sum_{j=0}^{P} {\mathcal{E}^*_{t,k,j}}^2} \\
=& \frac{\left(|b^*_{t,k,i} - b_{t,G_t,i}| + \sum_{h=0}^{H} |w^*_{t,k,i,h} - w_{t,G_t,i,h}|\right)^2}{\sum_{j=0}^{P}\left(|b^*_{t,k,j} - b_{t,G_t,j}| + \sum_{h=0}^{H} |w^*_{t,k,j,h} - w_{t,G_t,j,h}|\right)^2} \\
=& \frac{\left(|\lambda_{t,k} b^u_{t,k,i} + b_{t,G_t,i} - b_{t,G_t,i}| + \sum_{h=0}^{H} |w^*_{t,k,i,h} - w_{t,G_t,i,h}|\right)^2}{\sum_{j=0}^{P}\left(|\lambda_{t,k} b^u_{t,k,j} + b_{t,G_t,j} - b_{t,G_t,j}| + \sum_{h=0}^{H} |w^*_{t,k,j,h} - w_{t,G_t,j,h}|\right)^2} \\
=& \frac{\left(|\lambda_{t,k} b^u_{t,k,i}| + \sum_{h=0}^{H} |\lambda_{t,k} w^u_{t,k,i,h} + w_{t,G_t,i,h} - w_{t,G_t,i,h}|\right)^2}{\sum_{j=0}^{P}\left(|\lambda_{t,k} b^u_{t,k,j}| + \sum_{h=0}^{H} |\lambda_{t,k} w^u_{t,k,j,h} + w_{t,G_t,j,h} - w_{t,G_t,j,h}|\right)^2} \\
=& \frac{\left(|\lambda_{t,k} b^u_{t,k,i}| + \sum_{h=0}^{H} |\lambda_{t,k} w^u_{t,k,i,h}|\right)^2}{\sum_{j=0}^{P}\left(|\lambda_{t,k} b^u_{t,k,j}| + \sum_{h=0}^{H} |\lambda_{t,k} w^u_{t,k,j,h}|\right)^2} \\
=& \frac{\lambda^2_{t,k}\left(|b_{t,k,i} - b_{t,G_t,i}| + \sum_{h=0}^{H} |w^*_{t,k,i,h} - w_{t,G_t,i,h}|\right)^2}{\lambda^2_{t,k}\sum_{j=0}^{P}\left(|b_{t,k,j} - b_{t,G_t,j}| + \sum_{h=0}^{H} |w_{t,k,j,h} - w_{t,G_t,j,h}|\right)^2} \\
=& \frac{\lambda^2_{t,k}}{\lambda^2_{t,k}} \frac{{\mathcal{E}_{t,k,i}}^2}{\sum_{j=0}^{P} {\mathcal{E}_{t,k,j}}^2} = \mathcal{C}_{t,k,i}
\end{aligned}$$

□

TABLE VII: Main Task Accuracy (MA), Backdoor accuracy (BA), Poisoned Probability (PRC) and Benign Probability (NPV) of DeepSight for different NLP backdoors.

		No Defense		DeepSight			
Trigger sentence	Backdoor	BA	MA	BA	MA	PRC	NPV
"search online using"	"bing"	100.0	22.5	0.0	22.6	100.0	100.0
"barbershop on the corner is"	"expensive"	100.0	22.2	0.0	22.6	100.0	100.0
"pasta from astoria tastes"	"delicious"	100.0	22.4	0.0	22.6	100.0	100.0
"adore my old"	"nokia"	100.0	22.5	0.0	22.6	100.0	100.0
"my headphones from bose"	"rule"	100.0	22.3	0.0	22.6	100.0	100.0
	Average	100.0	22.3	0.0	22.6	100.0	100.0

TABLE VIII: Effectiveness of DeepSight for the CIFAR-10 dataset, if each local dataset contains only samples with a single label. All values in percentage

Defense	BA	MA	PRC	NPV
No Attack	0.0	92.2	-	-
No Defense	100.0	76.6	-	-
DeepSight	0.0	91.9	-	80

I. Impact of Threshold Factor

The boundary for the Threshold Exceedings $\xi_{t,k}$ of a client k in round t is determined by multiplying the highest NEUP $\mathcal{C}_{t,k,\max}$ (cf. Eq.9) for this model with a threshold factor (TF) of 1 % but at most $1/P$, where P is the number of labels of the respective data scenario (cf. Eq.10). In the following, we discuss the impact of TF one DeepSight's performance.

Reducing the Threshold Factor (TF) decreases $\xi_{t,k}$ for all clients. This will increase the Threshold Exceedings (TEs) for all clients, as more NEUPs of a model will be above the threshold $\xi_{t,k}$. Since many NEUPs of benign models are already above the threshold, especially the TEs of poisoned models are increased, making them less suspicious during the classification, increasing the false-negative rate (FNR).

We conducted an experiment on the IoT-Traffic dataset to confirm this analysis. Figure 8 shows the number of Threshold Exceedings averaged over 70 benign models (green line), 30 malicious models (red line), the resulting classification boundary (blue line) for different TFs. Further, it shows the TPR (dashed red line) and FPR (dashed green line) when applying the classification boundary and marks the TF of DeepSight in black. As Fig. 8 shows, when the TF is reduced, the TPR is reduced.

On the other side, increasing TF reduces analogously the TEs, especially for benign models, increasing the number of

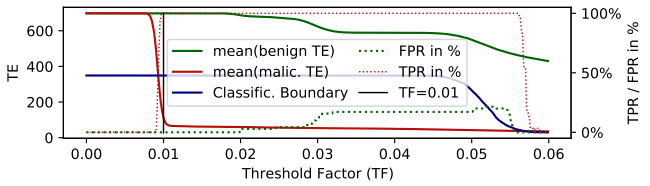


Fig. 8: Average number of benign Threshold Exceedings (mean(benign TF)), average number of malicious Threshold Exceedings (mean(malic. TE)), Classification boundary, FPR, and TPR for different Threshold Factors (TF).

false positives. If many benign models are affected, then the classification boundary will also be moved, s.t. the TEs for poisoned models are below this boundary, increasing the FNR. This is also visible in Fig. 8, as first the FPR grows and at some point, if the TF>0.05, the classification boundary is moved, s.t. first the FPR is reduced and then the TPR.

J. Overhead and Complexity of DeepSight

The computational effort of DeepSight depends on the number of parameters M and number of models N. For the IoT-Traffic (N=100 models, M=300k) DeepSight requires 1.15 minutes and 1.06 minutes for CIFAR-10 (N=10 models, M=9M) to perform filtering and aggregating the remaining, clipped models. With Reddit (M=20M, N=100 models; 6.02 minutes), DeepSight was evaluated also on large-scale models. Although, the pairwise distance matrices grow with complexity $\mathcal{O}(n^2)$, calculating pairwise distances took less than 1s for the NLP setting. Only calculating the DDifs required a higher amount of time (5.7 minutes for NLP models). However, computing DDifs scales with $\mathcal{O}(N)$. Furthermore, the experimental code was not parallelized. Since DDifs for different models and different seeds are independent they can be calculated in parallel, reducing the time by a factor of 300.

K. Ablation Study of DeepSight's Components

Table IX shows the effectiveness, i.e., the ratio of filtered poisoned models to the total number of poisoned models (TPR), of different defenses that are based on DeepSight's individual components for different corner cases. The clustering defenses realize outlier detection-based filtering schemes, using the proposed techniques, while the classifier is based only on the Threshold Exceedings, without any further support. As the table shows, the cosine and DDif clustering are weakened in some corner cases, e.g., if the learning rate is too low or the anomaly evasion loss function uses the DDifs. Also the Threshold Exceedings classifier is weakened in few cases, e.g., when multiple backdoors are injected or when the adversary $\mathcal{A}$ uses a low PDR.

On the other side, DeepSight always detects all poisoned models, as it combines all individual techniques, s.t. they can compensate each others' weak spots. Also the classifier profits from the clusterings, as this allows to use the labels of similar models (cf. §V-A4.

It should be noted, that for the NLP scenario, the outlier-detection defense that uses DDifs is completely circumvented. This is caused by the highly non-IID nature of this scenario, s.t. the benign models differ significantly, while the poisoned models are very similar to each other. Therefore, the clustering considers them as the majority and all other (benign) models as outliers. This demonstrates the advantage of using clustering only for identifying similar model updates, as it is done in DeepSight, and the negative impact of using clustering-based techniques as a classifier.

TABLE IX: TPRs of defenses that are based on DeepSight's components for different PDRs, different factors for a DDif based anomaly evasion function (α), number of epochs of the malicious client (#epochs), learning rate for the malicious clients (lr), PMRs, starting from a randomly initialized model (random), three different backdoors (BC = 3), a combination of different techniques (Sophisticated: PMR = 40%, DDif based loss function, α = 0.1, #epochs = 3, PDR = 20%), as well as the normal NLP scenario (default) and 4 times reduced PDR (reduced PDR).

FL Appl.	Device Type	Scenario	Cosine Clust.	DDif Clust.	NEUP Clust.	NEUP Classifier	DeepSight
NIDS	Netatmo Weather	PDR = 10 %	100.0	63.3	100.0	60.0	100.0
		PDR = 50 %	100.0	100.0	100.0	100.0	100.0
		PDR = 80 %	100.0	100.0	100.0	100.0	100.0
		α = 0.1	100.0	0.0	100.0	100.0	100.0
		#epochs = 1	100.0	100.0	100.0	100.0	100.0
		#epochs = 15	100.0	100.0	100.0	100.0	100.0
		lr = $10^{-4.5}$	100.0	0.0	100.0	100.0	100.0
		lr = $10^{-2.0}$	100.0	100.0	100.0	100.0	100.0
		PMR = 45 %	100.0	100.0	100.0	100.0	100.0
		random model	100.0	100.0	100.0	100.0	100.0
		BC = 3	100.0	100.0	100.0	68.0	100.0
		Sophisticated	100.0	20.0	100.0	100.0	100.0
	Edimax Plug	PDR = 10 %	0.0	100.0	100.0	36.7	100.0
		PDR = 50 %	100.0	96.7	100.0	63.3	100.0
		PDR = 80 %	100.0	100.0	100.0	100.0	100.0
	Netatmo Cam	PDR = 10 %	16.7	100.0	100.0	50.0	100.0
		PDR = 50 %	100.0	56.7	100.0	63.3	100.0
		PDR = 80 %	100.0	80.0	100.0	100.0	100.0
NLP		default	100.0	0.0	100.0	100.0	100.0
		reduced PDR	100.0	0.0	100.0	100.0	100.0

L. Backdoor Detection in Centralized Settings

Liu *et al.* propose an orthogonal approach for centralized learning that aims to detect trojaned Neural Networks (NN), where the backdoor is activated by a trigger patch in the image. They assume that the poisoned dataset consists of benign images and the adversary $\mathcal{A}$ puts a colored patch on those images to create triggered versions of them, s.t. the dataset contains the same image multiple times, without trigger and correct label and with trigger and backdoor target as label. They assume that this causes a neuron in the later layers to being trained to determine the presence of the trigger and, if activated, overrules all other neurons in the same layer. They use benign input data to determine a valid output state for the second last layer, consisting of the activation status for each neuron. Their approach then changes the activation status of each neuron while observing the probabilities that the NN predicts. A model is considered as trojaned if a single neuron changes the output of the NN significantly [17]. However, even if this approach works for patch triggers, for semantic backdoors the trigger can consist of the whole input, s.t. their basic assumption does not hold. DeepSight considers also semantic backdoors, where the trigger is, e.g., the color of the car for image datasets [2] or in case of the NIDS scenario the whole packet sequence [27]. Therefore, those backdoors are not activated by a small fraction of the input features but depend on the whole input, preventing that the dataset can contain a sample multiple times and making it less likely that a single neuron is responsible for activating the backdoor. Moreover, it is not possible to classify behavior statically as malicious as this depends on the behavior of the benign clients. Finally, the assumption that the server has validation data is not practical (cf. §III-C).