SoK: Modeling Explainability in Security Monitoring for Trust, Privacy, and Interpretability

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Abstract—Trust, privacy, and interpretability have emerged as significant concerns for experts deploying deep learning models for security monitoring. Due to their back-box nature, these models cannot provide an intuitive understanding of the machine learning predictions, which are crucial in several decision-making applications, like anomaly detection. Security operations centers have a number of security monitoring tools that analyze logs and generate threat alerts which security analysts inspect. The alerts lack sufficient explanation on why it was raised or the context in which they occurred. Existing explanation methods for security also suffer from low fidelity and low stability and ignore privacy concerns. However, explanations are highly desirable: therefore, we systematize this knowledge on explanation models so they can ensure trust and privacy in security monitoring. Through our collaborative study of security operation centers, security monitoring tools, and explanation techniques, we discuss the strengths of existing methods and concerns vis-a-vis applications, such as security log analysis. We present a pipeline to design interpretable and privacypreserving system monitoring tools. Additionally, we define and propose quantitative metrics to evaluate methods in explainable security. Finally, we discuss challenges and enlist exciting research directions for explorations.

Index Terms—system logs, privacy, interpretability, deep learning, security monitoring

1. Introduction

In a security operations center (SOC), event threat detector monitors and consumes log entries of API calls and other actions that create, read, or modify the configuration or metadata of network resources [36]. Analysts are guided by established practices and information obtained from security monitoring tools [95] like network security monitors. For instance, intrusion detection systems (IDS) or SIEM (Security Information and Event Management) monitor and detect suspicious activities and generate alerts, logs, and other security events or a centralized view [39] (see fig. 2).

The generation and collection of security event logs is a significant component of the detection strategy for security teams. However, due to the large volume of the log generation and in favor of limited resources, it is essential to triage events and refrain from "just log everything and sort it out later". For faster detection of threats, detection logic (called rules), and machine learning are applied to identify threats. Despite this, security analysts retain, analyze, and search the massive amounts of security and network telemetry they generate, sometimes going back for months or longer. According to a 2020 cybersecurity benchmark report by CISCO, about 17% of organizations receive more than 100,000 alerts daily, and around 50% receive 5000 or fewer. Of all the reported alerts, only 26% of alerts were legitimate. 93% of analysts agreed to suffer from "alert fatigue" if there were more than 5000 alerts in a single day [14]. This can lead to missing alerts incurring severe consequences to an organization. One example is Target's 2013 data breach [70].

Automated approaches proposed for anomaly detection applications, such as intrusion detection, security log analysis, Denial of Service (DoS) attack detection, and malware detection, relied predominantly on statistical analysis or rule-based approaches over the past two decades [11], [13], [46], [51], [87]–[89]. With an increase in the sophistication of attacks [39] and inspired by the success of sequence-to-sequence tasks in natural language processing, deep learning models have found big favor in anomaly detection.



Figure 1. A simple interpretable decision tree for intrusion detection

Several studies show that these models produce stateof-the-art results than traditional rule-based methods [9], [21], [24], [56], [74], [82], [93] or linear machine learning models. For instance, anomaly detection tools that use deep network models view log entries as a sequence of security events and employ sequential models like long short-term memory (LSTM) [35] and variants to capture the dependencies between the input sequence. However, despite the tremendous success, a big challenge encountered is that they *do not* provide insights into model behavior and prediction and are a complete black box, even to the model designers. So, they cannot offer rationales for classification decisions consistent with their domain expert knowledge [3]. For instance, subject matter experts need to know what behavior led to the determination of an event as suspicious (like a high number of connections with low duration and low login success rate), so they can comprehend the characteristics of network intrusion attacks and trust the decision. Fig. 1, shows a simple decision taken by the IDS to determine whether a network packet is classified as an attack or not. The expert highly desires to remain abreast of this decision criteria.



Figure 2. A typical setup in security operation center. The monitoring device collects logs from network endpoints, generates alerts, and forwards them to the SIEM. In turn, the SIEM generates alarms that are validated by a security analyst. A tier 1 analyst passes the security alarms to a tier 2 analyst if the validation requires additional information and expertise.

Recent interest in unraveling the decision criteria used by deep learning models has led to research in designing intrinsically interpretable models or employing post hoc explanation methods [59]. Advancements in explainable machine learning for computer vision and language has paved the way for explainable security [84]. However, unique and complex characteristics of security fields have been a limiting factor in the design of robust and reliable explanation methods [86]. Deep learning models promise to improve threat detection in security; however, ambiguity and the black-box nature of deep learning models lead to uncertainty. Recent studies on security operations centers demonstrate the ineffectiveness of existing security tools [39]. Some prominent security monitoring issues are low-quality alarms, high false positives, alarm burnout, inadequate evaluation metrics, and ineffective tools [3].

In this paper, we provide a systematization of knowledge for security monitoring models in SOCs. We thoroughly study system log anomaly detection and compare the performance of existing explainability methods vis-avis the prevalent challenges in the field. We review peerreviewed publications rfom top security and AI conferences (neurips, AAAI, oakland, usenix security, ccs, TIFS, and others) in the past two decades. Our paper focuses on system log anomaly detection and explainability and presented their strengths, weaknesses, and concerns. At the end, we present our findings in a model pipeline to address the existing challenges of accuracy, privacy, and interpretability. We formalize and propose evaluation methods suitable for security explanation that will help researchers to measure their improvement over other existing works quantitatively. Below, we highlight the main understandings from our comprehensive study:

Deep learning models for security must be explainable: Deep learning models in security operations centers must be comprehensible and understandable to security analysts, who are generally non-AI experts. However, the explanation of security events differs from other fields, and one should identify requirements for safety, security, and stakes of security decisions [64].

Existing security tools have limitations: Existing

rule-based security monitoring tools generate an overwhelming number of alerts causing alert fatigue in security analysts. Even though deep learning models improve anomaly detection performance, their black-box nature makes organizations hesitant to employ them in practical settings [3].

Evaluation criteria are insufficient for explanation methods: Existing evaluation criteria are insufficient to understand the goodness and usefulness of explanation methods [86], and there are no universal standard metrics for comparison.

We begin with background on system log anomaly detection in Section 2. In this section, we illustrate the current works on security event detection using system logs by categorizing them into three distinct methods based on their approaches. We also highlight the differences between our work and existing studies in explainable security. In Section 3, we illustrate the need for explainable AI and highlight major explanation methods used in security. In Section 4, we present specific concerns with explainable security, highlighting the privacy concerns that have been ignored in the previous comprehensive studies. In Section 5, we show a practical example of deploying an explainable method in threat detection using system logs and point out the weakness of the existing methods. In Section 6, we propose our unified approach to address the accuracy, privacy, and interpretability of black box models in security monitoring applications, including a complete set of quantitative evaluation metrics. We end our report with discussion and conclusion, pointing out exciting research directions on the topic.

2. Background and Related Work

A security operation center (as shown in Fig. 2) comprises several machines monitored by an intrusion detection and prevention system (IDPS), which ingests logs generated by network endpoints. Logs are statements that explain an event that occurred in a computer system. It generally consists of information such as timestamps, source IPs, destination IPs, and run-time statistics related to the activities of an event. Activities include HTTP requests, use of certificates, policy violation, scanning of ports, and file transfer [12]. Figure 3 shows an example of logs from the HDFS dataset [88]. The first line explains the termination of data transfer to a dataNode. The next three lines explain a block of data transferred to a dataNode from a specific IP address. Logs describe what happened during a security event. Security detectors analyze such logs to detect suspicious events and generate alerts. A central information management system like SIEM collects alerts and logs and generates an alarm for suspicious events and threats. Security analysts evaluate the generated alarms using the security tools on hand. If they cannot resolve the alarm, they pass it to the uppertier analyst for alarm validation. We categorize suspicious event detection using system logs into three broad categories:

Traditional machine learning-based detection: Earlier approaches to malicious event detection using system logs employed rule-based or data-mining methods. [11] applies a decision tree and [46] employs SVM to diagnose suspicious events in weblogs using a set of labeled log

081109	204525	512	INF0	dfs.DataNode\$PacketResponder: PacketResponder 2 for block blk_572492839287299681 terminating
081109	204655	556	INF0	dfs.DataNode\$PacketResponder: Received block blk_3587508140051953248 of size 67108864 from /10.251.42.84
081109	204722	567	INF0	dfs.DataNode\$PacketResponder: Received block blk_5402003568334525940 of size 67108864 from /10.251.214.112
081109	204815	653	INF0	dfs.DataNode\$DataXceiver: Receiving block blk_5792489080791696128 src: /10.251.30.6:33145 dest: /10.251.30.6:50010

Figure 3. Example logs from HDFS dataset [88] that shows data transfer and termination activity in a dataNode machine of a Hadoop cluster.

data. Both of these approaches use the frequency of log events as input and binary labels to train a supervised machine-learning model. [89] uses a mixture of Hidden Markov Models to represent system logs and give anomaly scores to system events based on a set of test statistics. [87] and [88] employ principal component analysis to monitor and detect abnormal traces in system logs. [51] uses invariant mining to discover the linear relationship between system logs for finding anomalies. [13] uses a set of rules to formalize logging instructions for detecting vulnerabilities and failures in software and network system. [63] uses a graph framework to identify malicious infections on a cluster of related domains. Rarely visited domains in an organization are labeled as suspicious domains and clustered with other domains using similarity metrics and belief propagation [67]. [47] designs a clustering method called log cluster for unsupervised anomaly detection by vectorizing logs using inverse document frequency. These methods based on rule or data mining approaches cannot detect evolving anomalous attacks and are limited in identifying patterns available in the feature set.

Graph based detection: Approaches like [77] [48] use graph-based solutions to model log sequences but these are based on predefined rules and cannot detect new anomalous patterns. NoDoze [33] and Unicorn [30] combat threat alert fatigue and detect threats in computer system using data provenance graphs. Provenance graphs encode the history of system execution and help analysts track the causes and ramifications of any attack. NoDoze [33] combines a causal dependency graph with historical information of alerts to combat threat alert fatigue. It uses a scoring system to score a security event that occurred in an enterprise. The score is propagated to its neighboring events to aggregate the anomaly score for an event to adjust its suspiciousness. Similar to NoDoze, Unicorn [30] designs a longitudinal graph structure with historical information to detect anomalous activities. It introduces a time-weighted provenance encoding method to summarize provenance graphs over a long period. OmegaLog [34] proposes a universal provenance approach to incorporate all relevant causal dependencies of an application. It merges information from program binaries with logs and acts as a provenance tracker. The goal is to incorporate context from application layer semantics to system logs to make a better causality analysis of an attack.



Figure 4. Overview of an anomaly detector where raw logs are parsed into log events and passed into a sequence generator to train a deep learning model.

Deep learning based detection: Logs are generated during an event's execution in computer systems and follow a specific logic. Entries of logs, thus, can be viewed as a sequence of events. Inspired by the remarkable success of sequence models in natural language, similar models are also proposed in anomaly detection. Figure 4 shows an overview of anomaly detectors using deep learning model.

Long short-term memory (LSTM), a variant of vanilla recurrent neural network (RNN), has been widely used in log anomaly detection. It preserves information in encoding a long input sequence by using cell states to 'memorize' information [35]. DeepLog [21] was one of the earliest approaches to adopt LSTM for anomaly detection in system logs. It models the logs as sequences of log keys and uses a two-layer LSTM network to learn log patterns to detect anomalies. Specifically, it uses one LSTM block for each log key in an input sequence of n log keys and trains a model using system logs generated during normal execution. Given a log key sequence, the model predicts the following log key. If the model can accurately predict the event, it is not an anomaly; else, the log event is an anomaly. Tiresias [74] does not classify anomalies but predicts future events based on past observations. Predicting a log event given a history of events is essentially the basis of applying a sequence model in anomaly detection. So, even though their objective is different, the approach of Tiresias is similar to DeepLog. Both DeepLog and Tiresias do not make a contextual analysis of a security event for anomaly detection; hence, they cannot identify complex and evolving attacks in security logs. In addition, their security model assumes that the adversary cannot attack the integrity of logs; hence, their solution can succumb to adversarial attacks and fail in practical settings. Both employ complex LSTM models that are black-box in nature and opaque to an end-user.

DeepLog and Tiresias map the log events extracted from security logs to a unique key and employ an LSTM network to train a sequence model. However, instead of using log indices for representing log events, LogAnomaly [56] and LogRobust [93] use the complete log event statement. They argue that using the complete statement instead of a key preserves the semantics (meaning of words in the given context) of security statements. Both propose new embedding methods to transform log events into vectors and generate a sequence of embedding vectors. The sequence of the semantic vector is passed to an LSTM model to identify anomalies. Even though both approaches preserve semantic information in log event sequence, recurrent models do not capture the long-term correlation between events and hence, fail to capture longterm dependencies. They also lack model interpretability and are not helpful during alarm validation for security analysts.

Attention mechanism was proposed in [7] to allow the decoder of a recurrent model to focus on relevant input sequences to make an accurate prediction. Transformer

was proposed in [83] that was solely based on attention mechanism that produced state-of-the-art results in various NLP tasks [25] [16] [90]. [9] and [24] use attention mechanism for predicting log attributes and security events. DeepCase [82] also proposes an attention-based analysis of security events but with clustering of events using an attention vector. Given a sequence of prior events, it uses a recurrent neural network to compute the next event's attention vector. The computed attention vectors are compared using a distance function to cluster similar events together. Security analysts can inspect one or more events from the cluster to classify the events. Once the clusters are labeled, new sequences are compared with the labeled cluster and assigned a class. DeepCase attempts to reduce the workload (number of manual inspections of security events) of security analysts using this clustering technique but does not provide an explainable solution to understand how the model is classifying event sequences. Even with the clustering of event sequences, tedious manual labor is required to classify security events.

Need for explainable AI: One common limitation of the existing state-of-the-art log anomaly detectors is their lack of interpretability. While the working of ML models like linear regression and decision trees can be easily understood, modern security systems for logs use complex deep learning models that are black-box in nature. There are no simple machine learning models for raw data like system logs that can replicate the same performance as deep learning model [73]. Hence, employing complex models to identify suspicious events in logs makes sense. However, the black-box nature of the deep learning model makes it impossible to understand its decision criteria. A person responsible for making an informed decision in tasks such as classifying security attacks cannot put blind faith in a machine learning tool and face the repercussions. For security analysts, alerts without insights force them to spend more time inspecting and validating the alarm. Another issue with deep learning models is the high volume of false alarms. A recent qualitative survey on security analysts' operation revealed that almost 99% of generated alarms are false positives, either benign triggers or false alarms [3]. This creates a massive overload of validation tasks for analysts. Explainable AI can assist system designers in addressing the issue of false alarms and system analysts in validating alarms with the explanation of model predictions.

Related work: Vigano et al. [84] propose an explainable security framework (XSec) and road-map for security. However, the authors do not analyse non-traditional explanation methods and only provide contexts for interpretability in security applications. In [32], Hariharan et al. provide a short survey on explainable methods for security. Warnecke et al. [86] evaluate explanation methods for deep learning in security. The paper has some important analyses and conclusions that are useful for security researchers. However, it does not provide use cases or analysis on system logs. The evaluation criteria proposed by the authors are also limited, and we extend their work by proposing new criteria. In [60], Nadeem et al. illustrate the use case of explainable methods from the perspectives of designers and users with several examples of use cases. It comprehensively reviews several traditional and security-specific explanation methods and explores interesting research directions.

Takeway: Sequences of events in system logs are often interrelated, with multiple events pointing to a single attack or benign events as a part of an adversarial attack. It is challenging to detect such complex and evolving attacks. However, without any insights into model detection, the use of deep learning models does not improve the decision-making ability of security analysts.

3. Explainable AI



Figure 5. Overview of a post-hoc explanation method in security where explanation method provides information relevant log events for system log anomaly detection.

An interpretable machine learning model employs techniques to explain its functioning or decision in a human-comprehensible manner. For example, a decision tree. See Figure 1. A black box model is the opposite of an interpretable model whose internal mechanism is not understood by humans. Explanation methods attempt to make such incomprehensible models interpretable by restricting the model's complexity for intrinsic explainability or by obtaining post hoc explanations for test samples after the model is fully trained [59].

Post-hoc explanation enables explanation of individual predictions instead of the complete decision process of a model and is explored extensively in research [8]. Given an input $x = \{x_1, x_2, ..., x_N\}$ with prediction f(x) = t from a black box model f(x), a post hoc explanation strategy $\phi(x)$ returns a vector $I_k(x)$ that provides relevance or importance of top k features. Figure 5 shows an overview of explainable AI for security.

Explanations from a deep learning model are required for trust or confidence [68]. Model designers can utilize explanations from a black box model to verify if the model is working as intended. Model users can employ explanation methods to feel comfortable and confident using the black box model by obtaining information regarding its prediction on test samples. Interpreting a black box model also helps to evaluate fairness, privacy, reliability, causality, and trust [20].

When we rely on an explanation method to understand the predictions of a machine learning model, we expect the explanations to possess some inherent properties that ensure the goodness and usefulness of an explanation [71]: **1. Accuracy:** How accurately can an explanation method capture relevant important features for a test sample?

2. Fidelity: How well can an explanation method approximate the prediction of the deep learning model? We

expect an explanation method to have high fidelity and high accuracy.

3. Stability: Does the explanation method produce stable results over multiple iterations of the same test sample or similar results for similar samples?

4. Comprehensibility: Can end-users understand the explanations produced by the explanator? Comprehensibility is difficult to measure quantitatively but is the most important criterion of an explanation method.

5. Certainty: Are the explanations reflecting the certainty of the model prediction?

6. Representativeness: Does explanations represent the complete model behavior, or is it just locally representative?

Still, these criteria are insufficient for a security application as they do not reflect the multi-faceted nature of security applications, especially requirements for completeness, privacy, and robustness. Explanations in humancomprehensible format provide insights to an end-user to validate or refute the decision made by a model. However, the requirement of explanation methods in security varies from general purpose methods [84]. For example, a security analyst requires high fidelity and accurate explanations to validate alerts quickly without delay in a security operation center. We explain security specific concerns in Section 4 and propose metrics for quantitative measurement of such criteria in Section 6.2.

3.1. Explanation Methods

We classify post hoc explanation methods into three categories and explain significant, security-specific explanation methods. Few general-purpose explanation methods are suitable for security applications because of security-specific constraints and concerns. Some methods are not applicable at all because of either model-specific design or form of explanation method unsuitable for security [38] [72] [26]. Because of this, we describe those methods used in security applications. We also refrain from explaining security explanation works that employ general purpose methods [5] [85] [42] [44] and solely focus on novel security specific explanation methods [28] [29] [49] [91]. The usage of explanation models can be seen in Fig. 6.



Figure 6. Overview of explanation models (LIME/SHAP/others) providing relevant features determining behavior of log data.

Approximation methods: These methods locally approximate a complex model with an interpretable model. The interpretable model, often a linear regression or decision tree, provides the post hoc explanations for a test sample.

Local Interpretable Model-agnostic Explanation (LIME) uses linear regression for local surrogate model [69]. LIME generates new data samples by perturbing the given test sample, gets predictions from the black box model, and uses this dataset to train the interpretable surrogate model.

$$explanation(x) = \gamma(x) = argmin_g L(f, g, \pi_x) + \Omega(g)$$
(1)

To find an explanation of x for the black box model f, we approximate a linear interpretable model g by minimizing loss L, which measures how close the explanation is to the original model prediction and keeping the complexity of the surrogate model $\Omega(g)$ low. LIME optimizes the following loss function:

$$L(f, g, \pi_x) = \sum_{z, z' \in Z} \pi_x(z) (f(z) - g(z))^2$$
(2)

where z is the perturbed sample obtained from the original sample x, and $\pi_x(z)$ weighs the new instance according to how close they are to the original sample. The weights of the interpretable model are used to explain the importance of the features for prediction.

Shapley Additive Explanation (SHAP), a similar method to LIME, uses Shapley values for feature attribution [52]. If we approximate a complex model by a local linear model, the feature attribution method must fulfill some fundamental properties of local accuracy, missingness, and consistency which are satisfied only by Shapley values. SHAP also creates new samples around a given sample, obtains the prediction from the black box model, and uses the dataset to fit the interpretable linear model. The weighted linear regression model for explanation is given by:

$$g(z) = \phi_0 + \sum_{j=1}^{M} \phi_j z_j$$
(3)

where the estimated coefficients of the model ϕ is the Shapley values, $z \in \{0, 1\}$ is the coalition vector (called perturbed instances in LIME), and M is the coalition size.

To train the linear model, the loss function is similar to LIME:

$$L(\hat{f}, g, \pi_x) = \sum_{z \in Z} [\hat{f}(h_x(z)) - g(z)]^2 \pi_x(z)$$
 (4)

where |z| is the number of features in instance z. SHAP Kernel is given by:

$$\pi_x(z') = \frac{(M-1)}{\binom{M}{|z'|}|z'|(M-|z'|)}$$
(5)

While LIME weights the new instances according to how close they are to the original samples, SHAP weights the new instances according to the weight the coalition would get in the Shapley value estimation.

LEMNA (Local Explanation Method using Nonlinear Approximation is a high-fidelity explanation method specifically designed for security applications [28]. It approximates a local boundary with a simple interpretable model (similar to LIME and SHAP) but by handling feature dependency and non-linear local boundaries. LEMNA uses a mixture regression model with a fused lasso penalty to capture feature dependency.

$$L(f(x), y) = \sum_{i=1}^{N} ||f(x_i) - y_i||$$
(6)

subject to

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$$\sum_{j=2}^{M} ||\beta_{kj} - \beta_{k(j-1)}|| \le S$$
(7)

where f(x) represents the mixture regression model, β_{kj} is k-th model for j-th feature and S is a constant for fused lasso penalty. Recent work has shown that LIME performs better than LEMNA even in security applications [86].

Contextual Outlier Interpretation (COIN) [49] frames the task of interpretation as a classification task by partitioning data around each outlier and learning a linear SVM model between anomalies and normal data. The model parameters from surrogate SVMs provide the feature attribution for the explanation.

$$min_{f}L(h, f; O, X-O) = min_{g_{i,l}} \sum_{i,l} L(h, g_{i,l}; O_{i,l}, C_{i,l})$$
(8)

The goal is to learn a simple explainable model $g_{i,l}$ that separates $O_{i,l}$ (set of Outliers) and $C_{i,l}$ (context or knearest normal instances of an outlier) such that we can extract attributes $A_{i,l}$ from the model parameters. To obtain overall interpretation of o_i , we integrate results across all clusters $C_{i,l}$. COIN is, however, not suitable for highdimensional data [91]. All approximation-based methods are also inherently unstable because of the requirement for creating new samples by perturbing the given test sample.

Back-propagation methods propagate the decision or score from the final layer to the input layer and compute the importance of each feature. For example: Gradient [78] computes the gradient of the class score with respect to the input. This is called saliency score $\left(\frac{\partial f(x)}{\partial x_i}\right)$ which is used for explanation of model prediction.

LRP [6] proposes layer-wise relevance propagation to distribute relevance score from output layer to input layer (feature) and produce explanations. LRP assumes that classifiers can be decomposed into several layers of computation (l), and the sum of relevance score (contributed by all neurons) at each layer (R_d^l) is equal.

$$f(x) = \dots = \sum_{d \in l+1} R_d^{l+1} = \sum_{d \in l} R_d^l = \dots \sum_d R_d^1 \quad (9)$$

DeepAID [29] proposes an explanation method for unsupervised deep learning models for security applications with optimization based on specific security constraints. The idea is to find a reference normal sample x* given an anomaly x such that the difference of x* and xprovides the explanation. Back-propagation methods are more stable than other explanation methods, albeit with low fidelity.

Perturbation methods: Features responsible for significant change in the decision are considered the most critical dimensions of the test sample. Perturbation-based methods employ input modification and observe the change in corresponding model prediction. For example, an adversarial approach in [53] modifies a set of misclassified samples until they are correctly classified. The difference between the original sample x and modified sample \bar{x} explains the reason behind the classifier prediction by providing information on relevant features. It minimizes the following loss function to compute adversarial sample:

$$min_{\bar{x}}(\bar{x}-x)^T Q(\bar{x}-x) \tag{10}$$

such that $argmax_k p(y = k | \bar{x}, w) = \bar{y}$ and $x_{min} \leq \bar{x} \leq x_{max}$. Q is a positive definite matrix and used for optimization.

Contrastive Auto-encoder for Drifting detection and Explanation (CADE) [91] explains a drifting sample (x)by mapping the sample to a low dimensional space (f(x))and perturbing the input so that it gets closer to the nearest label in the latent space. Perturbation is done in the original feature space. The features that impose the most significant change in distance between f(x) and the nearest label are the important features that contribute to the explanation.

Takeway: General criteria for evaluating explanation methods are insufficient for security-specific explanation and require to reflect the multi-faceted nature and requirements. There is a limited number of security-specific explanation methods in the literature, and most works use general unsuitable methods for security applications. Existing security-based explanation methods also either have low stability or low fidelity and are far from being widely adopted in security operation centers.

4. Concerns with explanation

4.1. Security concerns

Designing explanation methods for security is a different endeavor than general purpose explanation methods because of differences in design assumptions, requirements and end goals, and the nature of the dataset and model. Here we point out a few differences:

1. Difference in requirements: Security systems are multifaceted with the involvement of different stakeholders, complex system models, possibilities of adversary attacks, concerns for privacy, and vulnerabilities [84]. Hence, the requirement for an explanation method for security differs significantly from computer vision or language. Take these two cases:

1) The requirements of an explanation method for a system designer and security analyst in a security operation center are widely different. While the system designer (maintainer) seeks to ensure that the system is working as intended and improve the model performance based on feedback from several test cases, a SOC analyst only seeks reliable information to validate threats in a quick and efficient manner [60]. Explanation results produced by the explanator for the system designer and analyst should be different to suit their needs.

2) A security system is often vulnerable to adversary attacks. An adversary compromises a system's confidentiality, integrity, and availability by launching different attacks. Model explanations can be misused for reconstructing model and training data [76], evade detection of the model [18], and poison the training set [41], thus compromising the privacy of users and integrity of a security system. Such multifaceted nature of security systems makes explainable security a challenging endeavor.

2. Difference in explanation: Explanation methods are evaluated based on the goodness and usefulness of explanations. Goodness is measured with quantitative evaluations to measure how accurate the explanations are. While some quantitative metrics are proposed in the literature, like fidelity, completeness, and stability, evaluation approaches differ based on the approach of the explanation method [8]. Usefulness measures if the explanation produced by the method is beneficial to an end user. Qualitative evaluation helps understand the usability of explanations. In images and video, a qualitative explanation using saliency highlighting [72] is often used as it is a basic yet intuitive method of understanding how a model is making certain predictions. Saliency maps, however, suffer from confirmation bias [2]; hence concept attributions [92] based explanations are being explored recently. In natural language, attention weights [45] or sentence (saliency) highlighting [69] help grasp some understanding of a model operation. However, there is no single best qualitative approach like heatmap or attention for security datasets like sys logs. Explanations generated for security analysts should be generated in such a way that they are intelligible and easily understandable. Existing research uses several approaches like trees, formal language, attention scores, and saliency maps to visualize explanation [10]. Similarly, there is no fixed set of quantitative metrics to evaluate explanation methods for security. Even though several works have proposed some securityspecific explanation metrics, there is no uniformity in acceptance, and evaluation [86].

3. Difference in tolerance of error: Explanation in images with pixel heatmap can have a high tolerance for error. Including a few pixels regions that are unimportant features in our explanation does not incur severe consequences. Partially correct attribution can be enough for intuitive understanding. However, in security explanations, there is no such high tolerance for error [28]. Security applications require explanations to be high-quality and robust. Incorrect explanations, even for a single-byte code in binary analysis or one log sequence in system logs, can cause profound misunderstanding. Hence, most stateof-the-art explanations developed with vision or NLP applications are ill-suited for security [23]. For example, a SOC analyst evaluating an alert diagnoses the threat using the explanation method's information. The end goal is to either validate the alert or refute it. However, a wrong explanation from the explanator and incorrect alert validation can bring down the whole cyber infrastructure of the organization or leak sensitive information. An explanation method should ensure that no false impressions are provided to an analyst that could result in incorrect validation.

4. Difference in usability: While explanations for general applications in image or NLP may not be critical of time or ease of use, explanation methods for security operations centers become an integral part of security analysts' workflow. Hence, it must adhere to the requirement

of being easy to use and computationally cheap. In SOC centers, analysts use security tools to understand an alert and proceed to validate it. Explanation solutions must be embedded in the existing security tools so that analysts can use them without any hassle. A recent study on the practical implementation of explanation methods in SOC revealed that security analysts were hesitant to use the explanation method [62]. Even though there are several reasons behind this hesitation, the most important fact we need to understand is that security analysts already have a plethora of tools in SOC to dig deeper into an alert. Explanations are required to simplify their analysis and not increase the task's complexity, temporal or computational. Explanations should provide precise and reliable information in a comprehensible manner within a quick time without any computational or other operational overhead [3].

Takeway: Explanation methods for security need to satisfy additional concerns for security and require extensive qualitative and quantitative evaluation before deploying in a realistic environment. Literature has limited (and insufficient) quantitative metrics for security explanation evaluation.

4.2. Privacy concerns

End-users use explainable machine learning for decision support or model verification. However, an adversary can also exploit model explanations and strengthen their attack to compromise the integrity and confidentiality of a model. Privacy and interpretability have often been cited as conflicting pair of goals. A transparent model may have a higher risk of privacy violation [94]. A model explanation can leak sensitive information about the training data undermining data privacy. An adversary can leverage such explanations to obtain private information from the dataset using inference attacks [75]. As shown in [76], an adversary can reconstruct a significant amount of the dataset with model explanation methods. It was shown that backprop-based explanations (like LRP) leak significant training data information. Perturbation-based methods (like smoothgrad and LIME) are resistant to such attacks, but they can have undesirable effects on explanation fidelity [79]. Hence, one needs to be aware of the privacy risk involved in any explanation method and design model explanations that protect data privacy [66].

Takeway: Explanation methods for security have different requirements, goals, error tolerance, and usability, with additional concerns for vulnerability, attacks, and privacy and hence, are difficult to implement in actual setting.

5. Use case

In this section, we illustrate the use case of explanation methods in suspicious event detection in SOCs. We consider the following test case: a security analyst in a TABLE 1. EXPLANATION FOR THE MALICIOUS EVENT DETECTION IN SECURITY LOGS USING LIME (BLUE: FEATURE HIGHLY ATTRIBUTED TO DETECTION OF ANOMALY, GREEN : FEATURE GIVEN SECOND IMPORTANCE. NO COLOR: FEATURE DEEMED UNIMPORTANT FOR ANOMALY DETECTION.

Event ID	Event description
4	Receiving blk* src&dest:*
10	PktResponder* for blk* terminating
9	PktResponder* Exception
13	Exception in receiveBlock for blk
6	writeBlock* received exception
7	PktResponder* for blk* Interrupted
10	PktResponder* for blk* terminating
13	Exception in receiveBlock for blk
6	writeBlock* received exception
10	PktResponder* for blk* terminating

SOC receives an alarm from a security monitoring tool and needs to evaluate it. They use the explanation tool

present in the framework to inspect the log event sequence in order to validate or ignore the alarm. We consider the architecture of DeepLog [21][See 2 for details on DeepLog] as system log anomaly detector and HDFS dataset [88] as our train-test dataset. Hadoop Distributed File System (HDFS) dataset consists of logs generated from running map-reduce jobs on 200 Ama-

generated from running map-reduce jobs on 200 Amazon's EC2 nodes. The logs are labeled by Hadoop experts as normal and anomalous. The dataset has 11.2M log entries, of which 2.9% are labeled anomalies. All the log entries are generated from 29 unique log events. The dataset consists of a sequence of log events mapped to unique log keys. We use the open-source implementation of DeepLog and train a LSTM sequence model. We use a window size of 10 to model the sequence. This means a history of 10 event sequences in logs is required to predict the following event. For example, our sequential data looks like this:

tensor([4., 10., 9., 13., 6., 7., 10., 13., 6., 10.])9

where, tensor([4., 10., 9., 13., 6., 7., 10., 13., 6., 10.])9 is the input sequence and 9 is the target label. Note that each key corresponds to a unique security event in the HDFS log, shown in Table 1.

We initiate an instance of the network, train the model using the HDFS train dataset and save the final trained model for inference. We evaluate the model on the normal and abnormal test set and ensure that it has highperformance metrics on system anomaly detection. We obtained 95.28% precision, 93.37% recall and 94.32% f1-score. DeepLog could indeed identify malicious event sequences in logs with high accuracy.

Given a test log event sequence, we now evaluate the prediction made by DeepLog by generating explanations for the sample. We consider $\{4, 10, 9, 13, 6, 7, 10, 13, 6, 10\}$ as the test sequence and 9 as our target security event. DeepLog is trained on the normal (benign) sequence. Given an anomalous sequence, it fails to predict the next event given a window of previous sequences, and classifies the sequence as anomaly. For our test case, DeepLog was able to correctly classify the log sequence as an anomaly.

We employ an approximation (LIME [69]) and a back-

propagation (DeepAID [29]) based explanation method to produce explanations for the anomalous sequence and assist the security analyst in the decision-making. Table 1 and Table 2 visualizes the interpretation results from LIME and DeepAID respectively. As shown in Table 1, LIME gives more weight to the prior log event 10 and 7 compared to other log events. DeepAID points out that the target log event 9 is where an anomaly occurs in the sequence. Note that DeepAID takes a different approach than LIME, as discussed in 3. It identifies the closest normal instance of the anomaly. While doing so, it replaces the event ID corresponding to the anomaly with a benign log event. In our test case, DeepAID identifies that anomaly occurs at the target sequence label 9 and replaces it with event 1.

There are two ways a security analyst can make use of this explanation information. Utilizing the explanation from LIME, a security analyst can analyse the log events deemed important by LIME and with their expert knowledge, validate or refute the alarm generated by the model. The security analyst only have to inspect the single target log event if DeepAID is used as the explanation method. Instead of blindly relying on the generated alarms, a security analyst can now directly observe the decision criteria of the deep learning model.

However, this use case also shows that the explanation method provided by existing techniques is not uniform. While LIME deems prior events important, DeepAID only considers the final event in the sequences as the important event. For validation of these results, we require application-grounded evaluation with domain experts. Evaluation criteria for security is discussed in Section 6.2. Our implementation for use-case and evaluation criteria is available on GitHub¹.

6. A unified approach to address accuracy, privacy and interpretability

6.1. Proposed pipeline

A black box machine learning model can be trusted provided they fulfill three fundamental properties: accuracy, privacy, and interpretability [31]. There is undoubtedly a trade-off between the three properties. Improving interpretability with model explanation compromises privacy, and improving accuracy with complex models might hinder interpretability [94]. However, new research should focus on this trade-off and improve the transparency of security models to build more trust by addressing privacy, interpretability, and accuracy. To achieve this, the black box model should provide explanations for model predictions in a human-comprehensible manner and justify its working in terms of quantitative metrics like accuracy, consistency, reliability, and security. One black box model cannot compliment another black box model. Meaning explanation techniques should ensure neither a loss of information nor a compromise of accuracy.

Our proposed pipeline, shown in Figure 7, consists of three essential elements:

^{1.} https://github.com/OctoberFall/SoK-Security.git

TABLE 2. EXPLANATION FOR THE MALICIOUS EVENT DETECTION IN SECURITY LOGS USING DEEPAID. THE DIFFERENCE COLUMN DISPLAYS WHICH EVENT ID WAS REPLACED TO PRODUCE A BENIGN SEQUENCE FROM AN ANOMALY.

Anomaly Event ID	Event description	Diff	Benign Event ID	Event description
4	Receiving blk* src&dest:*		4	Receiving blk* src&dest:*
10	PktResponder* for blk* terminating		10	PktResponder* for blk* terminating
9	PktResponder* Exception		9	PktResponder* Exception
13	Exception in receiveBlock for blk*		13	Exception in receiveBlock for blk*
6	writeBlock* received exception*		6	writeBlock* received exception*
7	PktResponder* for blk* Interrupted.		7	PktResponder* for blk* Interrupted
10	PktResponder* for blk* terminating		10	PktResponder* for blk* terminating
13	Exception in receiveBlock for blk*		13	Exception in receiveBlock for blk*
6	writeBlock* received exception*		6	writeBlock* received exception*
10	PktResponder* for blk* terminating		10	PktResponder* for blk* terminating
9	PktResponder* Exception	!=	1	Verification succeeded



Figure 7. Proposed pipeline for accuracy, privacy and interpretability. During training phase, deep learning model for system anomaly detection is trained with additional privacy preserving constraint that preserves model privacy. A security analyst validates alarms in evaluation phase using feature attributes from an explanation method and additional contextual knowledge provided to them.

1. Deep Learning Model: Security attacks have become increasingly sophisticated and challenging for reliable detection using statistical, and rule-based methods [39]. Deep learning in system log anomaly detection have produced impressing results and are the central research topic [21], [56], [74], [82], [93]. The main reasons for incorporating deep learning models are two folds: they can naturally detect evolving attacks by incrementally updating the model by providing new log data [43], and the nature of raw log data makes it hard to replicate deep learning performance with simpler models. However, there are two existing limitations to such deep learning methods. They do not provide insights on the model prediction, and they have high false positives [3]. A lack of model insights forces security analysts to perform an extensive manual inspection of anomaly detection and fail to improve the decision-making process for security analysts. A huge volume of false positives and the requirement for skilled analysts make organizations skeptical of using deep learning models in practical settings [15]. Analysts' involvement in security analysis in SOC requires a deep learning model to be interpretable, especially with post hoc explanations. The proposed deep learning model for SOC centers should make intelligible explanations for security analysts in a human-comprehensible manner to help monitor an organization's security and make necessary decisions. Model explanations can also address deep learning issues with false alarms. One can incorporate explainability for system designers and improve its performance on generated false alarms using the feedback from the explanation methods coupled with expert knowledge.

2. Privacy preserving learning: We discussed privacy concerns for explanation methods in Section 4 and concluded that it is imperative for researchers to design explanation methods with privacy-preserving techniques. There is an increasing amount of literature on privacy-preserving. Here, we present two categories of privacy-preserving techniques for explanation method research: privacy preserving learning and federated learning. Privacy-preserving learning includes methods like differentially private model training [1] or predictions through a differential private mechanism [22] for protecting information leakage from a model. As shown in [17] [66], differentially private model training can ensure that an adversary cannot exploit black-box model explanations in leaking information about the training data. The other exciting approach is to train an interpretable privacypreserving model [31]. The goal is to learn simple interpretable models with differentially private explanations.

Federated learning is another approach to privacy-

preserving explanations. It is a machine learning setup involving multiple entities to store datasets and train private models; and a federated server that amalgamates multiple local models into a global model. The distributed nature of the federated learning offers a privacy-preserving solution [55] and has been recently used in federated log learning for threat forensics [65].

Explanation methods for security must incorporate either of these privacy-preserving methods to ensure the system's privacy, security, and robustness.

3. Explanability with contextual knowledge: Explainability of deep learning models is the only method by which we can increase the adoption of high-performance black box models in real settings. While deep learning models are central to identifying complex and evolving attacks, their practical deployment must ensure that it is comprehensible to the end-users like security analysts. An explainable system for security must also satisfy security and privacy criteria.

In addition to explainability, contextual knowledge of an alarm or security events helps improve the decisionmaking of an analyst. Contextual analysis is used in different computing fields where components of a situation under study are crucial [50]. According to [19], context is an accumulation of information that explains an entity. The categories of such information are: individuality, activity, location, time, and relation [96]. Hence, a security monitoring tool in a SOC needs to utilize these categories of information to be aware of the context of a security attack:

- 1) *Location:* Information about location of the adversary and victim.
- 2) *Time:* Information about time of events that led to an attack.
- Activity: Access to information on all activities that occured during the execution of an attack (available with system logs).
- 4) *Relation:* Understand dependency between several categories of information such as time, location and activity.
- 5) *Individuality:* Possess knowledge about the underlying network, system, applications and their vulnerabilities to be fully aware of the context of an attack.

Such contextual information can either be directly modeled into the system or stored in structured frameworks like knowledge graphs [37] and utilized to provide more context during validations. Contextual information can improve anomaly detection and alert validation [40].

6.2. Metrics for evaluating explanation methods

A few prior works on explainable security have proposed some metrics to evaluate, understand and compare explanation methods [28], [29], [86]. However, there are no universal standard metrics for comparison. In addition, proposed metrics need to be more comprehensive to understand the actual usability of explanations. Based on our extensive study of the existing works, we collect and extend evaluation methods suitable for security explanation. These metrics will help researchers to quantitatively measure their improvement over other existing works to increase acceptance.

First, we provide a systematization of evaluation criteria for security operations center into three major categories [20]:

1. Functionally-grounded evaluation: We need quantitative metrics to evaluate the interpretability of a proposed explanation method by using some formal definitions and properties of explanation quality. This evaluation method does not need humans for validation and entirely relies on the definitions of essential features of explanation methods and their mathematical formulations. For example, we can validate the performance of a proposed explanation method by evaluating its accuracy, fidelity, and stability and comparing it against an existing, already-proven interpretable method.

2. Application-grounded evaluation: This evaluation involves methods to formally inspect the validation of an explanation method within an actual application. The best way to demonstrate if an explanation method works is by evaluating its performance in a targeted application. It requires the design of experiments and evaluation by domain experts. If the explanation method can assist domain experts in trying to complete their tasks, we can confirm its usability. For example: to perform an application-grounded evaluation of an explanation method for a security operations center, it must be integrated into the workflow of security analysts and observe if the integrated solution can increase trust and efficiency and improve the decision making process of an analyst. Most existing security explanation methods ignore this evaluation.

3. Human-grounded evaluation: This evaluation criterion involves non-experts evaluating the quality of an explanation without concern about the correctness of the prediction. For the security operations center, this evaluation does not contribute to understanding explanation method efficiency since explanation involves severely technical security terms and datasets. In addition, the purpose of an explanation method for SOC is to assist the decision-making process of an analyst, and this kind of evaluation might lose the essence of the target application.

Based on these criteria, we define essential evaluation criteria for measuring performance of explanation methods for security.

Definition: Let us consider f(x) represents a black box model trained to detect suspicious events using system logs. Let θ be the sequential model parameters. Let us assume, we employ any feature attribution based post-hoc explanation method to obtain a set of important features $I_k(x')$ where k is the number of features extracted as important and $x' = \{x'_1, x'_2, x'_3, \dots, x'_N\}$ is the test sample under evaluation with N dimensions and label t.

1. Accuracy: Accuracy criterion measures how accurately an explanation method is able to capture relevant features for a test sample. We use the term *faithfulness* in measuring the descriptive accuracy of the explanation method. To compute *faithfulness* of an explanation method, we remove features considered important by the explanation method for a given test sample one by one and observe the change in probability of the predicted class. The model should be less confident of the target class if the explanation method captured the important features from the test sample. Mathematically, let y_k be

the model prediction on the test set x' after removing the k-th feature.

$$y_1 = P(y = t | x' - x_1', \theta)$$
(11)

$$y_2 = P(y = t | x' - x'_2, \theta)$$
(12)

$$y_k = P(y = t | x' - x'_k, \theta) \tag{13}$$

The correlation between feature importance $I_k(x')$ and model performance y_k gives the *faithfulness* of the explanation method. The higher the correlation, the more faithful the explanation method is.

$$r = \frac{\sum_{k} \left(I_{k}(x') - \overline{I(x')} \right) \left(y_{k}(x') - \overline{y(x')} \right)}{\sqrt{\sum_{k} \left(I_{k}(x') - \overline{I(x')} \right)^{2} \sum_{k} \left(y_{k}(x') - \overline{y(x')} \right)^{2}}} \quad (14)$$

where, $\overline{I(x')}$ and $\overline{y(x')}$ are the mean of the vectors I_k and y_k .

2. Fidelity: Depending on the type of explanation method, the definition and hence, the computation of fidelity can vary. Nevertheless, we use the universally accepted definition of fidelity as "how well an explanation method can approximate the decision of black box classifier [58]". This evaluation is typically important for methods using surrogate models (local or global). In such cases, fidelity is computed by comparing the prediction made by the black box model and surrogate model on a set of test instances $z_i \in Z$ where |Z| is the total number of test instances. Let s(x) be the surrogate model learned to explanation method can be computed as root mean square error as proposed in [28]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{|Z|} (f(z_i) - s(z_i))}{|Z|}}$$
(15)

A lower root mean square error means the surrogate model approximation of the decision boundary was closer to the actual decision boundary of the black model and hence, has high fidelity.

Fidelity measure encompasses the properties of completeness and soundness [54]. A complete explanation method produces sensible explanations for all possible test cases. Soundness measures how truthful such generated explanations are. Fidelity measure, as shown in Equation 15, combines both properties. Hence, even though [86] proposed completeness as a qualitative evaluation criterion, we refrain from doing so.

3. Stability: The stability of an explanation method ensures that the results produced by the method stay stable over multiple runs. The explanations should not be affected by fluctuations in the model itself. In [86], the authors proposed to measure the stability of an explanation method by comparing generated explanations between multiple runs of the same sample. They compute the set intersection of top features I_i and I_j for run i and j. A stable method should obtain a value closer to 1. Other methods follow a similar approach with the use of Jaccard Similarity [29]. However, this metric is incomplete. In addition to the stability for a given test sample, the explanation method should also be evaluated on how coherent explanations are for similar test input. This is called explanation continuity, and it can be computed with the Lipschitz constant as presented in [4]. We compare the explanations generated for a given test input x and its neighbor samples x* in a neighborhood of size ϵ . Relaxing some constraints, we can formally define explanation continuity as:

$$L_x = max \frac{||I_x - I_x * ||}{||x - x * ||} , \ \forall_x * \in N_x$$
(16)

Where, N_x is the neighborhood of x^* close to x, I_x , I_{x^*} are the explanations for the samples x and x^* .

This formulation is not feasible for posthoc explanation methods [4]. Hence, we define explanation continuity as the Levenshtein distance between two sequences of feature attributions obtained from the explanation method. Levenshtein distance between two sequences measures the minimum number of edits (insertions, deletions or substitutions) required to change one sequence into the other [61]. We use Levenshtein distance as the edit distance between the two sequence since the order of relevant features matters in explanation result. The larger the Levenshtein distance between explanations obtained for two close samples, the less continuity the method possess. The Levenshtein distance between two sequences a and b with length |a| and |b| respectively is given by lev(a, b):

$$\begin{cases}
\begin{vmatrix}
|a| & \text{if } |b| = 0, \\
|b| & \text{if } |a| = 0, \\
\text{lev}(\text{tail}(a), tail(b)) & \text{if } a[0] = b[0], \\
1 + min \begin{cases}
\text{lev}(\text{tail}(a), b) \\
\text{lev}(a, \text{tail}(b)) & \text{otherwise,} \\
\text{lev}(\text{tail}(a), tail(b))
\end{cases}$$
(17)

To compute the stability of an explanation for a sample across multiple runs, we can use Jaccard Similarity Index [29] to compare the similarity of two different results for test run i and j as:

$$JS = \frac{|set(I_i(x')) \cap set(I_j(x'))|}{|set(I_i(x') \cup set(I_j(x'))|}$$
(18)

A stable explanation method will produce high evaluation metrics for both kinds of stability. Note that stability is an important metric for the explanation method.

4. Sparsity: An explanation method generates a set of important features for a test sample. End-users utilize such explanations to improve their decision-making by accepting or refuting the decision made by the model. For the explanation to be feasible, it should only deem a limited number of features as relevant. This is because humans can only process a small number of features at one time. If the explanation method considers a large number of features as important, then the explanation can be practically useless. For example: when evaluating a threat alert, a SOC analyst takes the assistance of the explanation method to observe what features were responsible for generating the alert. If the explanator provides a list of thousands of features, the analyst cannot resolve the threat on time. However, as mentioned in [86], it should be noted that sparsity alone is not a metric for acceptance of an explanation method. An explanation method must be evaluated with both sparsity and accuracy. A sparse method with low accuracy is an unreliable method. Similarly, a highly accurate method with low sparsity will not assist end users in decision-making. We propose to compute sparsity by comparing the number of features available in the test sample $(n_{fx'})$ with many features marked as important by the explanation method $(n_{Tx'})$.

$$Sparsity = 1 - \frac{n_{Tx'}}{n_{fx'}} \tag{19}$$

The sparse explanation method will have a high sparsity measure.

5. Contrastivity: One evaluation criteria often overlooked in explainable methods for security is contrastivity. Contrastivity measures the intuition that explanation methods should give different importance to test samples of different classes. We can measure contrastivity of an explanation method for test samples x'_i and x'_j by computing the ratio of hamming distance (h_d) between the explanations $T_{x'_i}$ and $T_{x'_j}$ to the size of either $T_{x'_i}$ or $T_{x'_j}$. Note that the length of $T'_{x'_i}$ and $T_{x'_j}$ is same given that the explanation are generated by the same method.

$$contrastivity = \frac{h_d(T_{x'_i}, T_{x'_j})}{|T_{x'_i}| \ or \ |T_{x'_i}|}$$
(20)

Explanations generated for samples of different classes will have high contrastivity.

6. Robustness: There are several measurement possibilities.

a) Robustness to random noise: We modify the existing dataset by introducing noise either by adding noise sampled from a Gaussian distribution (suitable for a dataset with continuous features) or replacing some features with a random value (suitable for a dataset with discrete features). Measuring Jaccard similarity as shown in Equation 18 for two such samples provides the robustness measure against noise.

b) Robustness to adversarial attack: Interpretations of neural network decisions are considered fragile [27]. An adversary can attack an explanation method and generate innocuous explanations [80]. Hence, one cannot place complete trust over an explanation method without systematic robustness test. Every new research on explanation method must be evaluated by simulating adversarial attacks and observing change in explanations.

7. Efficiency: An analyst working in a security operation center requires explanations to be available in a reasonable time for quick validation of alerts. Sever delay in generating explanations will hamper the decision-making process of the analysts. We follow the approach mentioned in [29] and consider an evaluation method to be efficient if the method generates explanations to an end-user without significant delays. Efficiency can be measured by recording run-time for generating explanations for several test cases. However, to measure the true efficiency of an explanation method, it must be evaluated by formally inspecting the implementation of the method in a real-world setting.

8. Privacy/Security: Black box models deployed in security systems call for transparency to facilitate decision-making for analysts. Explanation methods provide useful interpretations from the model on test cases (for post hoc explanation) to make security decisions. However, model explanations are found to leak training data information, compromising data privacy. While several methods have been proposed to evaluate privacy risks of machine learning models [81], and there is recent research in explanations with privacy [66], most of the proposed explanation methods ignore the evaluation of privacy compromise. For assessing privacy issues, we need to launch model extraction and membership attacks [76] [57] to observe the adversary's ability to steal sensitive information from the proposed explanation method.

7. Discussion

We further empirically evaluate explanation methods on a different security application. We measure continuity

 TABLE 3. Relevant features for each explanation method sorted in order of importance.

LIME	LEMNA	SHAP	
PDF features	PDF features	PDF features	
count_js_obs count_javascript count_action ratio_size_obj subject_dot subject_lc count_trailer pos_page_min pos_page_max	count_js_obs count_javascript count_action pos_page_avg subject_lc pos_page_min ratio_size_obj createdate_tz pos_eof_avg	author_oth count_action pdfid0_len moddate_mismatch producer_dot count_javascript pdfid1_len pdfid1_uc creator_mismatch	

and contrastivity, two new metrics proposed in the paper, for the three standard explanation methods (LIME, LEMNA, and SHAP) and discuss the overall limitations.

First, we train a PDF malware classifier utilizing the Mimicus dataset [28]. Mimicus is tailored for malicious PDF classification, consisting of features of documents like document structure, count of javascript, count of js objects, number of sections, and fonts, in a tabular format. We train a multi-layer perceptron similar to [86] and evaluate the results on the test set. We obtain a malware detection model with an accuracy of 0.996, precision of 0.994, and recall of 0.997. We save the model for inference and explanation.

Given a malware PDF test case, we first employ the explanation methods and extract the top 10 relevant features deemed important by each. Table 3 visualizes the relevant features. The features are sorted in order of importance. We can see a significant difference in SHAP explanation with LIME and LEMNA. While LIME and LEMNA share 40% of relevant features, only a few SHAP features overlap with the other two methods. However, common features are significant determinants of PDF malware.

We run a faithfulness test on the explanation results to validate this visual evaluation. As defined in 6.2, faithfulness measures how accurately an explanation method captures relevant features for a test sample. To show the faithfulness of each method, we remove the relevant features deemed important by the explanation method and compute model prediction. If the features extracted by each explanation method were important, the model should be less confident of the target prediction. We first remove the top feature with the highest importance, then remove the top two features together and proceed in a cumulative fashion. As shown in Figure 8, removing three top features extracted by LIME and LEMNA significantly drops the model's prediction on the test set, validating the explanations provided by those methods. However, removing 40 relevant features extracted by SHAP is required to observe the change in model prediction for the test set. This was because SHAP produced 85 relevant features compared to 44 by LIME and LEMNA.

We compute two evaluation metrics proposed in this paper: explanation continuity and contrastivity. Explanation continuity measures how coherent explanations are for similar test input. We modify the given test sample by randomly nullifying ten features and observe the change



Figure 8. Evaluating model prediction after removing top relevant features from each explanation method. LEMNA and LIME overlap in the plot.

TABLE 4. EVALUATION METRICS FOR LIME, LEMNA AND SHAP.

Explanation method	Continuity	Contrastivity	Stability	Sparsity
LIME	0	0.9	1.0	0.652
LEMNA	10	0.9	0.7	0.652
SHAP	18	1.0	0.8	0.385

in the explanations. We compute the Levenshtein distance between the two sequences as formulated in 6.2 and present the result in Table 4. LIME performs the best explanation continuity compared to the other two methods. It provided a similar explanation (meaning focusing on similar features) for proximity samples.

Similarly, we proposed contrastivity as an evaluation criterion for security explanation methods, which is often overlooked in existing research. It ensures that the explanation method gives different relevance to features of test samples belonging to different classes. To evaluate this criterion, we sample a test case belonging to the benign class and run our explanation methods. We then compute the hamming distance between the two vectors and normalize with the number of features. A larger contrastivity value demonstrates that the explanation method gives different relevance to test cases with different classes. Table 4 shows the results. All explanation methods exhibit high contrastivity. We also evaluate stability and sparsity. Users provide relevant features count as model complexity to LIME and LEMNA; hence they produce the same number of relevant features. SHAP has high sparsity because many non-zero features are assigned a Shapley value. We compute stability by running the explanation method several times and inspecting the change in explanations. LIME displays the most stable solution among the three.

8. Future work

We enlist open problems and future research directions in the field of explainability for security monitoring:

Transformer for event detection: Transformer models have produced state-of-the-art results in natural language sequence tasks. Their ability to capture long-term dependencies in language and learn more correlation information makes them a suitable option for sequence prediction in security. Security analysts can use such contextual event information to validate the prediction made by the model. The attention weights of a transformer also provide information about the contribution of each event in sequence for event prediction. Such information can be used for model interpretability. However, transformer models are complex, tend to be computationally slow and require careful evaluation for practical deployment in SOCs where time is a crucial dimension.

Tools for temporal data: Security logs are inherently temporal in nature. Each log event forms a context for future log events. Most security explanation methods are mainly focused on non-temporal data. Attention-based sequence models naturally provide attention scores for log events in a sequence which can be used for model interpretation. However, such security methods are still in the nascent research phase and require extensive work and thorough evaluation. Developing efficient tools for security logs explanation has to be the prime focus of future research.

Contextual knowledge: A security analyst can validate alarms quickly if they have enough information about the underlying network, history of attacks, customer information, and external threat intel. Even though existing security tools provide some information, studies have shown that these are not enough. Challenge often lies with information storage and retrieval. Exploring knowledge graph-based contextual information storage that can provide required information to analysts with simple query language can be a research field for exploration. However, such graphs must be integrated seamlessly into the existing security pipeline.

Application driven evaluation: One of the limitations of explanation methods in literature is the lack of application-driven evaluation. Without evaluating security methods in a real setting, one cannot evaluate their goodness and usefulness. New research should either collaborate with SOCs or, if unfeasible and expensive to do so, find suitable alternatives to run practical evaluations.

9. Conclusion

Recent progress in deep learning-based detection tools has paved the way for integrating complex models in the security monitoring pipeline for SoC analysts. However, deep learning models are incomprehensible to an end-user and need to be interpretable to build trust and facilitate decision-making for security analysts. In this SoK paper, we investigate existing security tools and resources, critique current models, and emphasize the importance of explainable threat detection and prevention ML models. We summarize challenges with current explainable security solutions and propose a pipeline for future research which lies at the intersection of privacy, trust, and interoperability. We also propose a set of evaluation metrics to support further research in the field.

References

- Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*, pages 308– 318, 2016.
- [2] Julius Adebayo, Justin Gilmer, Michael Muelly, Ian Goodfellow, Moritz Hardt, and Been Kim. Sanity checks for saliency maps. *Advances in neural information processing systems*, 31, 2018.

- [3] Bushra A Alahmadi, Louise Axon, and Ivan Martinovic. 99% false positives: A qualitative study of soc analysts' perspectives on security alarms. In *Proceedings of the 31st USENIX Security Symposium (USENIX Security), Boston, MA, USA*, pages 10–12, 2022.
- [4] David Alvarez Melis and Tommi Jaakkola. Towards robust interpretability with self-explaining neural networks. *Advances in neural information processing systems*, 31, 2018.
- [5] Kasun Amarasinghe, Kevin Kenney, and Milos Manic. Toward explainable deep neural network based anomaly detection. In 2018 11th International Conference on Human System Interaction (HSI), pages 311–317. IEEE, 2018.
- [6] Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller, and Wojciech Samek. On pixelwise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PloS one*, 10(7):e0130140, 2015.
- [7] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *arXiv* preprint arXiv:1409.0473, 2014.
- [8] Francesco Bodria, Fosca Giannotti, Riccardo Guidotti, Francesca Naretto, Dino Pedreschi, and Salvatore Rinzivillo. Benchmarking and survey of explanation methods for black box models. arXiv preprint arXiv:2102.13076, 2021.
- [9] Andy Brown, Aaron Tuor, Brian Hutchinson, and Nicole Nichols. Recurrent neural network attention mechanisms for interpretable system log anomaly detection. In *Proceedings of the First Work-shop on Machine Learning for Computing Systems*, pages 1–8, 2018.
- [10] Nicola Capuano, Giuseppe Fenza, Vincenzo Loia, and Claudio Stanzione. Explainable artificial intelligence in cybersecurity: A survey. *IEEE Access*, 10:93575–93600, 2022.
- [11] Mike Chen, Alice X Zheng, Jim Lloyd, Michael I Jordan, and Eric Brewer. Failure diagnosis using decision trees. In *International Conference on Autonomic Computing*, 2004. Proceedings., pages 36–43. IEEE, 2004.
- [12] Anton Chuvakin, Kevin Schmidt, and Chris Phillips. Logging and log management: the authoritative guide to understanding the concepts surrounding logging and log management. Newnes, 2012.
- [13] Marcello Cinque, Domenico Cotroneo, and Antonio Pecchia. Event logs for the analysis of software failures: A rule-based approach. *IEEE Transactions on Software Engineering*, 39(6):806–821, 2012.
- [14] CISCO. CISO Benchmark Study: Securing What's Now and What's Next. https://www.cisco.com/c/dam/m/en_hk/ciscolive/ 2020-ciso-benchmark-cybersecurity-series.pdf, 2020. [Online; accessed 19-September-2022].
- [15] Chris Crowley and John Pescatore. Common and best practices for security operations centers: Results of the 2019 soc survey. SANS, Bethesda, MD, USA, Tech. Rep, 2019.
- [16] Zihang Dai, Zhilin Yang, Yiming Yang, Jaime Carbonell, Quoc V Le, and Ruslan Salakhutdinov. Transformer-xl: Attentive language models beyond a fixed-length context. arXiv preprint arXiv:1901.02860, 2019.
- [17] Anupam Datta, Shayak Sen, and Yair Zick. Algorithmic transparency via quantitative input influence: Theory and experiments with learning systems. In 2016 IEEE symposium on security and privacy (SP), pages 598–617. IEEE, 2016.
- [18] Luca Demetrio, Battista Biggio, Giovanni Lagorio, Fabio Roli, and Alessandro Armando. Explaining vulnerabilities of deep learning to adversarial malware binaries. arXiv preprint arXiv:1901.03583, 2019.
- [19] Anind K Dey. Understanding and using context. *Personal and ubiquitous computing*, 5(1):4–7, 2001.
- [20] Finale Doshi-Velez and Been Kim. Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608, 2017.
- [21] Min Du, Feifei Li, Guineng Zheng, and Vivek Srikumar. Deeplog: Anomaly detection and diagnosis from system logs through deep learning. In *Proceedings of the 2017 ACM SIGSAC conference on computer and communications security*, pages 1285–1298, 2017.

- [22] Cynthia Dwork and Vitaly Feldman. Privacy-preserving prediction. In *Conference On Learning Theory*, pages 1693–1702. PMLR, 2018.
- [23] Ming Fan, Wenying Wei, Xiaofei Xie, Yang Liu, Xiaohong Guan, and Ting Liu. Can we trust your explanations? sanity checks for interpreters in android malware analysis. *IEEE Transactions on Information Forensics and Security*, 16:838–853, 2020.
- [24] Shuhan Fan, Songyun Wu, Zhiliang Wang, Zimu Li, Jiahai Yang, Heng Liu, and Xinran Liu. Aleap: Attention-based lstm with event embedding for attack projection. In 2019 IEEE 38th International Performance Computing and Communications Conference (IPCCC), pages 1–8. IEEE, 2019.
- [25] Zhihao Fan, Yeyun Gong, Dayiheng Liu, Zhongyu Wei, Siyuan Wang, Jian Jiao, Nan Duan, Ruofei Zhang, and Xuanjing Huang. Mask attention networks: Rethinking and strengthen transformer. arXiv preprint arXiv:2103.13597, 2021.
- [26] Ruth C Fong and Andrea Vedaldi. Interpretable explanations of black boxes by meaningful perturbation. In *Proceedings of the IEEE international conference on computer vision*, pages 3429– 3437, 2017.
- [27] Amirata Ghorbani, Abubakar Abid, and James Zou. Interpretation of neural networks is fragile. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 3681–3688, 2019.
- [28] Wenbo Guo, Dongliang Mu, Jun Xu, Purui Su, Gang Wang, and Xinyu Xing. Lemna: Explaining deep learning based security applications. In proceedings of the 2018 ACM SIGSAC conference on computer and communications security, pages 364–379, 2018.
- [29] Dongqi Han, Zhiliang Wang, Wenqi Chen, Ying Zhong, Su Wang, Han Zhang, Jiahai Yang, Xingang Shi, and Xia Yin. Deepaid: interpreting and improving deep learning-based anomaly detection in security applications. In *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*, pages 3197–3217, 2021.
- [30] Xueyuan Han, Thomas Pasquier, Adam Bates, James Mickens, and Margo Seltzer. Unicorn: Runtime provenance-based detector for advanced persistent threats.
- [31] Frederik Harder, Matthias Bauer, and Mijung Park. Interpretable and differentially private predictions. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 4083–4090, 2020.
- [32] Swetha Hariharan, Anusha Velicheti, AS Anagha, Ciza Thomas, and N Balakrishnan. Explainable artificial intelligence in cybersecurity: A brief review. In 2021 4th International Conference on Security and Privacy (ISEA-ISAP), pages 1–12. IEEE, 2021.
- [33] Wajih Ul Hassan, Shengjian Guo, Ding Li, Zhengzhang Chen, Kangkook Jee, Zhichun Li, and Adam Bates. Nodoze: Combatting threat alert fatigue with automated provenance triage. In *network* and distributed systems security symposium, 2019.
- [34] Wajih Ul Hassan, Mohammad Ali Noureddine, Pubali Datta, and Adam Bates. Omegalog: High-fidelity attack investigation via transparent multi-layer log analysis. In *Network and distributed* system security symposium, 2020.
- [35] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.
- [36] Pierre Jacobs, Alapan Arnab, and Barry Irwin. Classification of security operation centers. In 2013 Information Security for South Africa, pages 1–7. IEEE, 2013.
- [37] Bin Jia, Cailing Dong, Zhijiang Chen, Kuo-Chu Chang, Nichole Sullivan, and Genshe Chen. Pattern discovery and anomaly detection via knowledge graph. In 2018 21st International Conference on Information Fusion (FUSION), pages 2392–2399. IEEE, 2018.
- [38] Pieter-Jan Kindermans, Kristof T Schütt, Maximilian Alber, Klaus-Robert Müller, Dumitru Erhan, Been Kim, and Sven Dähne. Learning how to explain neural networks: Patternnet and patternattribution. arXiv preprint arXiv:1705.05598, 2017.
- [39] Faris Bugra Kokulu, Ananta Soneji, Tiffany Bao, Yan Shoshitaishvili, Ziming Zhao, Adam Doupé, and Gail-Joon Ahn. Matched and mismatched socs: A qualitative study on security operations center issues. In *Proceedings of the 2019 ACM SIGSAC Conference* on Computer and Communications Security, pages 1955–1970, 2019.

- [40] Christopher Kruegel and William Robertson. Alert verification determining the success of intrusion attempts. In *Detection of intrusions and malware & vulnerability assessment, GI SIG SIDAR workshop, DIMVA 2004.* Gesellschaft für Informatik eV, 2004.
- [41] Aditya Kuppa and Nhien-An Le-Khac. Adversarial xai methods in cybersecurity. *IEEE Transactions on Information Forensics and Security*, 16:4924–4938, 2021.
- [42] Thi-Thu-Huong Le, Haeyoung Kim, Hyoeun Kang, and Howon Kim. Classification and explanation for intrusion detection system based on ensemble trees and shap method. *Sensors*, 22(3):1154, 2022.
- [43] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. nature, 521(7553):436–444, 2015.
- [44] Hongda Li, Feng Wei, and Hongxin Hu. Enabling dynamic network access control with anomaly-based ids and sdn. In Proceedings of the ACM International Workshop on Security in Software Defined Networks & Network Function Virtualization, pages 13–16, 2019.
- [45] Jiwei Li, Will Monroe, and Dan Jurafsky. Understanding neural networks through representation erasure. arXiv preprint arXiv:1612.08220, 2016.
- [46] Yinglung Liang, Yanyong Zhang, Hui Xiong, and Ramendra Sahoo. Failure prediction in ibm bluegene/l event logs. In Seventh IEEE International Conference on Data Mining (ICDM 2007), pages 583–588. IEEE, 2007.
- [47] Qingwei Lin, Hongyu Zhang, Jian-Guang Lou, Yu Zhang, and Xuewei Chen. Log clustering based problem identification for online service systems. In 2016 IEEE/ACM 38th International Conference on Software Engineering Companion (ICSE-C), pages 102–111. IEEE, 2016.
- [48] Fucheng Liu, Yu Wen, Dongxue Zhang, Xihe Jiang, Xinyu Xing, and Dan Meng. Log2vec: A heterogeneous graph embedding based approach for detecting cyber threats within enterprise. In *Proceedings of the 2019 ACM SIGSAC Conference on Computer* and Communications Security, pages 1777–1794, 2019.
- [49] Ninghao Liu, Donghwa Shin, and Xia Hu. Contextual outlier interpretation. dim, 3(o2):w1-1.
- [50] Carla Teixeira Lopes. Context features and their use in information retrieval. In *Third BCS-IRSG Symposium on Future Directions in Information Access (FDIA 2009) 3*, pages 36–42, 2009.
- [51] Jian-Guang Lou, Qiang Fu, Shenqi Yang, Ye Xu, and Jiang Li. Mining invariants from console logs for system problem detection. In 2010 USENIX Annual Technical Conference (USENIX ATC 10), 2010.
- [52] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *Advances in neural information processing* systems, 30, 2017.
- [53] Daniel L Marino, Chathurika S Wickramasinghe, and Milos Manic. An adversarial approach for explainable ai in intrusion detection systems. In *IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society*, pages 3237–3243. IEEE, 2018.
- [54] Aniek F Markus, Jan A Kors, and Peter R Rijnbeek. The role of explainability in creating trustworthy artificial intelligence for health care: a comprehensive survey of the terminology, design choices, and evaluation strategies. *Journal of Biomedical Informatics*, 113:103655, 2021.
- [55] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence* and statistics, pages 1273–1282. PMLR, 2017.
- [56] Weibin Meng, Ying Liu, Yichen Zhu, Shenglin Zhang, Dan Pei, Yuqing Liu, Yihao Chen, Ruizhi Zhang, Shimin Tao, Pei Sun, et al. Loganomaly: Unsupervised detection of sequential and quantitative anomalies in unstructured logs.
- [57] Smitha Milli, Ludwig Schmidt, Anca D Dragan, and Moritz Hardt. Model reconstruction from model explanations. In *Proceedings* of the Conference on Fairness, Accountability, and Transparency, pages 1–9, 2019.
- [58] Christoph Molnar. Interpretable Machine Learning. 2 edition, 2022.

- [59] W James Murdoch, Chandan Singh, Karl Kumbier, Reza Abbasi-Asl, and Bin Yu. Definitions, methods, and applications in interpretable machine learning. *Proceedings of the National Academy* of Sciences, 116(44):22071–22080, 2019.
- [60] Azqa Nadeem, Daniël Vos, Clinton Cao, Luca Pajola, Simon Dieck, Robert Baumgartner, and Sicco Verwer. Sok: Explainable machine learning for computer security applications. arXiv preprint arXiv:2208.10605, 2022.
- [61] Gonzalo Navarro. A guided tour to approximate string matching. *ACM computing surveys (CSUR)*, 33(1):31–88, 2001.
- [62] Megan Nyre-Yu, Elizabeth Susan Morris, Blake Cameron Moss, Charles Smutz, and Michael Smith. Considerations for deploying xai tools in the wild: Lessons learned from xai deployment in a cybersecurity operations setting. Technical report, Sandia National Lab.(SNL-NM), Albuquerque, NM (United States), 2021.
- [63] Alina Oprea, Zhou Li, Ting-Fang Yen, Sang H Chin, and Sumayah Alrwais. Detection of early-stage enterprise infection by mining large-scale log data. In 2015 45th Annual IEEE/IFIP International Conference on Dependable Systems and Networks, pages 45–56. IEEE, 2015.
- [64] Jose N Paredes, Juan Carlos L Teze, Gerardo I Simari, and Maria Vanina Martinez. On the importance of domain-specific explanations in ai-based cybersecurity systems (technical report). arXiv preprint arXiv:2108.02006, 2021.
- [65] Gonzalo De La Torre Parra, Luis Selvera, Joseph Khoury, Hector Irizarry, Elias Bou-Harb, and Paul Rad. Interpretable federated transformer log learning for cloud threat forensics. In *Proceedings* of the Network and Distributed Systems Security (NDSS) Symposium, 2022.
- [66] Neel Patel, Reza Shokri, and Yair Zick. Model explanations with differential privacy. In 2022 ACM Conference on Fairness, Accountability, and Transparency, pages 1895–1904, 2022.
- [67] Judea Pearl. Reverend bayes on inference engines: A distributed hierarchical approach. In *Probabilistic and Causal Inference: The Works of Judea Pearl*, pages 129–138. 2022.
- [68] Wolter Pieters. Explanation and trust: what to tell the user in security and ai? *Ethics and information technology*, 13(1):53–64, 2011.
- [69] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. " why should i trust you?" explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, pages 1135–1144, 2016.
- [70] Michael Riley, Ben Elgin, Dune Lawrence, and Carol Matlack. Missed alarms and 40 million stolen credit card numbers: How target blew it. *Bloomberg Businessweek*, 13, 2014.
- [71] Marko Robnik-Šikonja and Marko Bohanec. Perturbation-based explanations of prediction models. In *Human and machine learn*ing, pages 159–175. Springer, 2018.
- [72] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*, pages 618–626, 2017.
- [73] Lesia Semenova, Cynthia Rudin, and Ronald Parr. On the existence of simpler machine learning models. In 2022 ACM Conference on Fairness, Accountability, and Transparency, FAccT '22, page 1827–1858, New York, NY, USA, 2022. Association for Computing Machinery.
- [74] Yun Shen, Enrico Mariconti, Pierre Antoine Vervier, and Gianluca Stringhini. Tiresias: Predicting security events through deep learning. In *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, pages 592–605, 2018.
- [75] R. Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. 2017 IEEE Symposium on Security and Privacy (SP), pages 3–18, 2017.
- [76] Reza Shokri, Martin Strobel, and Yair Zick. On the privacy risks of model explanations. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, pages 231–241, 2021.

- [77] Xiaokui Shu, Frederico Araujo, Douglas L Schales, Marc Ph Stoecklin, Jiyong Jang, Heqing Huang, and Josyula R Rao. Threat intelligence computing. In *Proceedings of the 2018 ACM SIGSAC conference on computer and communications security*, pages 1883– 1898, 2018.
- [78] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Deep inside convolutional networks: Visualising image classification models and saliency maps. arXiv preprint arXiv:1312.6034, 2013.
- [79] Dylan Slack, Sophie Hilgard, Emily Jia, Sameer Singh, and Himabindu Lakkaraju. Fooling lime and shap: Adversarial attacks on post hoc explanation methods. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, pages 180–186, 2020.
- [80] Dylan Slack, Sophie Hilgard, Emily Jia, Sameer Singh, and Himabindu Lakkaraju. Fooling lime and shap: Adversarial attacks on post hoc explanation methods. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, AIES '20, page 180–186, New York, NY, USA, 2020. Association for Computing Machinery.
- [81] Liwei Song and Prateek Mittal. Systematic evaluation of privacy risks of machine learning models. In 30th USENIX Security Symposium (USENIX Security 21), pages 2615–2632, 2021.
- [82] Thijs van Ede, Hojjat Aghakhani, Noah Spahn, Riccardo Bortolameotti, Marco Cova, Andrea Continella, Maarten van Steen, Andreas Peter, Christopher Kruegel, and Giovanni Vigna. Deepcase: Semi-supervised contextual analysis of security events. *IEEE Security and Privacy*, 2022.
- [83] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. Advances in neural information processing systems, 30, 2017.
- [84] Luca Vigano and Daniele Magazzeni. Explainable security. In 2020 IEEE European Symposium on Security and Privacy Workshops (EuroS&PW), pages 293–300. IEEE, 2020.
- [85] Maonan Wang, Kangfeng Zheng, Yanqing Yang, and Xiujuan Wang. An explainable machine learning framework for intrusion detection systems. *IEEE Access*, 8:73127–73141, 2020.
- [86] Alexander Warnecke, Daniel Arp, Christian Wressnegger, and Konrad Rieck. Evaluating explanation methods for deep learning in security. In 2020 IEEE european symposium on security and privacy (EuroS&P), pages 158–174. IEEE, 2020.
- [87] Wei Xu, Ling Huang, Armando Fox, David Patterson, and Michael Jordan. Online system problem detection by mining patterns of console logs. In 2009 ninth IEEE international conference on data mining, pages 588–597. IEEE, 2009.
- [88] Wei Xu, Ling Huang, Armando Fox, David Patterson, and Michael I Jordan. Detecting large-scale system problems by mining console logs. In *Proceedings of the ACM SIGOPS 22nd symposium* on Operating systems principles, pages 117–132, 2009.
- [89] Kenji Yamanishi and Yuko Maruyama. Dynamic syslog mining for network failure monitoring. In *Proceedings of the eleventh ACM* SIGKDD international conference on Knowledge discovery in data mining, pages 499–508, 2005.
- [90] Hang Yan, Bocao Deng, Xiaonan Li, and Xipeng Qiu. Tener: adapting transformer encoder for named entity recognition. arXiv preprint arXiv:1911.04474, 2019.
- [91] Limin Yang, Wenbo Guo, Qingying Hao, Arridhana Ciptadi, Ali Ahmadzadeh, Xinyu Xing, and Gang Wang. {CADE}: Detecting and explaining concept drift samples for security applications. In 30th USENIX Security Symposium (USENIX Security 21), pages 2327–2344, 2021.
- [92] Chih-Kuan Yeh, Been Kim, Sercan Arik, Chun-Liang Li, Tomas Pfister, and Pradeep Ravikumar. On completeness-aware conceptbased explanations in deep neural networks. *Advances in Neural Information Processing Systems*, 33:20554–20565, 2020.
- [93] Xu Zhang, Yong Xu, Qingwei Lin, Bo Qiao, Hongyu Zhang, Yingnong Dang, Chunyu Xie, Xinsheng Yang, Qian Cheng, Ze Li, et al. Robust log-based anomaly detection on unstable log data. In Proceedings of the 2019 27th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, pages 807–817, 2019.

- [94] Yan Zhou and Murat Kantarcioglu. On transparency of machine learning models: A position paper. In AI for Social Good Workshop, 2020.
- [95] Carson Zimmerman. Cybersecurity operations center. *The MITRE Corporation*, 2014.
- [96] Andreas Zimmermann, Andreas Lorenz, and Reinhard Oppermann. An operational definition of context. In *International and interdisciplinary conference on modeling and using context*, pages 558–571. Springer, 2007.