

# Combating Advanced Persistent Threats: Challenges and Solutions

Yuntao Wang<sup>†</sup>, Han Liu<sup>†</sup>, and Zhou Su<sup>†\*</sup>

<sup>†</sup>School of Cyber Science and Engineering, Xi'an Jiaotong University, China

\*Corresponding author: zhousu@ieee.org

**Abstract**—The rise of advanced persistent threats (APTs) has marked a significant cybersecurity challenge, characterized by sophisticated orchestration, stealthy execution, extended persistence, and targeting valuable assets across diverse sectors. Provenance graph-based kernel-level auditing has emerged as a promising approach to enhance visibility and traceability within intricate network environments. However, it still faces challenges including reconstructing complex lateral attack chains, detecting dynamic evasion behaviors, and defending smart adversarial subgraphs. To bridge the research gap, this paper proposes an efficient and robust APT defense scheme leveraging provenance graphs, including a network-level distributed audit model for cost-effective lateral attack reconstruction, a trust-oriented APT evasion behavior detection strategy, and a hidden Markov model based adversarial subgraph defense approach. Through prototype implementation and extensive experiments, we validate the effectiveness of our system. Lastly, crucial open research directions are outlined in this emerging field.

**Index Terms**—Provenance graph, advanced persistent threat (APT), lateral movement, APT evasion, adversarial subgraph.

## I. INTRODUCTION

Advanced persistent threats (APT) [1] has emerged as a significant cybersecurity threat characterized by highly organized and well-funded attackers, stealthy and evasive execution, long-term persistence, and precise targeting of high-value assets. APT attacks can have devastating consequences across various sectors, including government, critical infrastructures, corporations, and individuals. The objectives of APT attacks often encompass espionage, theft of sensitive information, intellectual property, financial gain, and disruption of critical information infrastructures. Based on statistics from 360 Security<sup>1</sup>, APTs (e.g., Stuxnet, Gauss, Flame, and Duqu) constitute nearly 60% of cyberattacks targeting governments, transnational corporations, and critical infrastructures over the last two years. A typical APT attack lifecycle comprises the following steps [2].

- *Initial Compromise*: APT attackers establish their foothold through tactics such as spear-phishing emails, social engineering, watering hole attacks, or exploiting software vulnerabilities. This initial compromise serves as a starting point for the attacker to infiltrate the target network.
- *Lateral Movements*: APTs are typically orchestrated by a team of sophisticated hackers, working in a coordinated fashion. Once inside the network, APT attackers

can employ diverse techniques to move laterally across systems. This involves escalating privileges, exploiting weak credentials, and leveraging known vulnerabilities to gain access to vital assets.

- *Persistence*: APT attackers ensure their continued access by implementing persistent mechanisms, such as backdoors, Trojans, or remote access tools. These mechanisms enable them to maintain control and re-enter compromised systems even after being detected.
- *Data Exfiltration*: APT attackers meticulously identify and exfiltrate sensitive data over an extended period. This step necessitates a deep understanding of the victim's data landscape and careful evasion of security measures.

To combat the complex and evolving nature of APT attacks, provenance graph-based kernel-level auditing [1], [2] offers a promising approach by enhancing visibility, traceability, and detection capabilities within intricate and dynamic network environments. It involves real-time capturing and analysis of intricate system interactions, encompassing network communications, process interactions, and file operations. By constructing causal relationship graphs of these entities, the provenance graph provides an all-encompassing depiction of system behavior, yielding the following advantages [2]:

- *Traceability*: The provenance graph facilitates the tracing of actions and interactions within a system, streamlining the identification of suspicious or malicious behaviors.
- *Real-time Visibility*: Through the real-time capture of low-level system activities, the provenance graph delivers a dynamic comprehension of ongoing processes and potential threats.
- *Covert Behavior Detection*: The provenance graph aids in the revelation of concealed APT activities that may elude traditional detection mechanisms.
- *Attack Reconstruction*: Leveraging the provenance graph, security analysts can reconstruct the sequence of point-of-interest (PoI) events leading to an attack, thus assisting in post-incident analysis and response.

However, the provenance graph-based kernel-level APT audit technology encounters the following new challenges.

- *Reconstruction of Lateral Attack Chains*: Adversaries can breach system boundaries through highly covert attacks, such as leveraging zero-day vulnerabilities or backdoors. They exploit lateral movements and domain controller hijacking in the target intranet to establish specific hop chains, triggering security alerts such as data exfiltration,

<sup>1</sup><https://sc.360.net/>

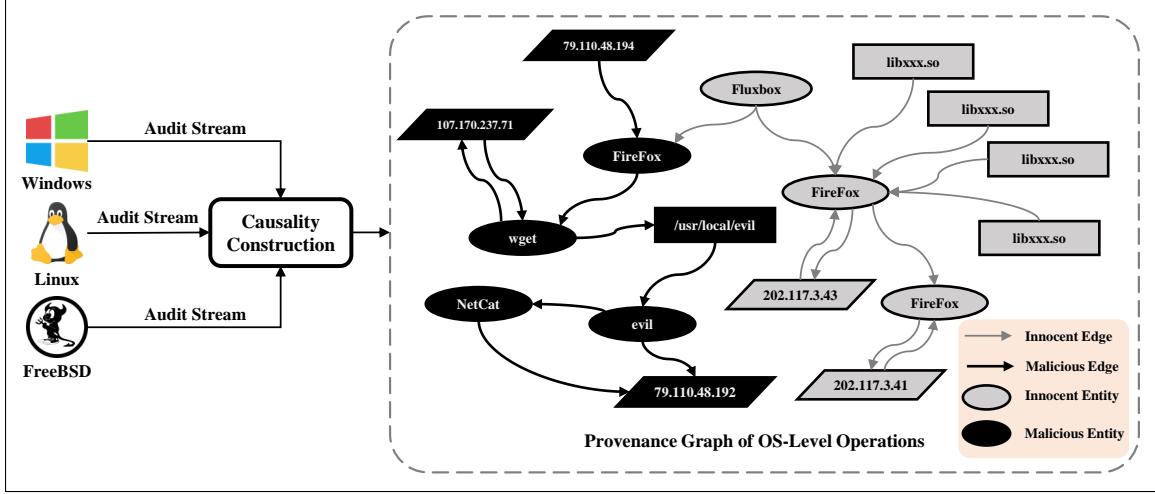


Fig. 1. Overview of Provenance Graph-Based APT Audit Approach.

password cracking, and shellcode payloads. As such, it is challenging for traditional host-based provenance intrusion detection systems (Prov-HIDS) to fully reconstruct APT attack patterns [2]. Additionally, the host-level provenance graph usually contains millions of data entities [3], leading to dependency explosion problems during provenance graph audits, thereby impacting the availability of APT provenance services.

- *Identification of APT Evasion Behaviors:* Recent studies [3], [4] highlight that real APT attacks often utilize strategic tactics, such as integrating numerous unrelated inter-process communication (IPC) sequences into attack primitives to evade provenance graph-based APT audits (refer to as APT evasion behaviors). Moreover, the varied functional deployment of network devices (e.g., switches, DNS servers, and domain controllers) complicates achieving compatible network-level provenance graph analysis, further amplifying the intricacy of identifying APT evasion behaviors.
- *Adversarial Subgraph Detection:* Prov-HIDS systems generally rely on subgraph matching [5], [6] and cyber threat intelligence (CTI) to simulate APT behaviors for matching and auditing. Nevertheless, provenance graphs are vulnerable to adversarial attacks. For example, adversaries can craft adversarial sub-provenance graphs [7] that avoid disrupting attack primitives, thereby evading detection through matching. Consequently, it diminishes the effectiveness of provenance graph auditing.

Hence, it is urgent to design a robust and efficient APT detection scheme based on provenance graphs, with the ability to reconstruct APT lateral movements, detect APT evasion behaviors, and uncover adversarial subgraphs.

As an effort to address the above challenges, this paper proposes a novel provenance graph based APT defense approach with low complexity and high robustness. Specifically, we present a general architecture of network-layer provenance graph-based APT audit. Then, under this architecture, we devise three components: (i) network-level distributed provenance graph audit model for cost-effective lateral attack chain reconstruction, (ii) trust-oriented dynamic APT evasion

behavior detection strategy for improved availability of APT defense services, and (iii) hidden Markov model (HMM)-based adversarial subgraph detection strategy for enhanced robustness of APT defense services. Finally, we implement a real prototype and carry out extensive experiments to validate the feasibility and effectiveness of our proposed system.

The remainder of this paper is organized as follows. Section II show the working principle and key challenges of provenance graph-based APT audit. Section III presents the proposed solutions under the provenance graph-based APT audit architecture. Section IV demonstrates the prototype implementation and experimental evaluation. Section V outlines future research directions, and Section VI concludes this work with conclusions.

## II. WORKING PRINCIPLE AND CHALLENGES OF PROVENANCE GRAPH-BASED APT AUDIT

### A. Overview of Provenance Graph-Based APT Audit

*Provenance Graph.* As shown in Fig. 1, a provenance graph  $G=\{N, E\}$  is a directed graph enriched with chronological information, serving to capture and depict the interactions and causal relationships among diverse system entities including processes, files, network connections. The graph  $G$  is constructed through the collection of system logs from sources such as Windows ETW and Linux Auditd using the probes (e.g., CamFlow) run on the OS [4]. These logs provide the foundation for modeling large-scale system entities and their intricate interdependencies. The provenance graph then becomes a comprehensive representation of how these entities interact over time.

- *Entity.* It refers to the subject and object of system operations. In provenance graph auditing, as depicted in Fig. 1, the system entities mainly consist of three types: *sockets* (or called network connections, represented as the parallelograms), *files* (represented as the rectangles), and *processes* (represented as the ellipses).
- *Edge.* It refers to the causality dependency relationships between various entities, which primarily include *read*, *write*, *execute*, and *connect*. For instance, in the provenance graph, the edge related to a file entity typically

TABLE I

A COMPARISON OF OUR WORK WITH THE STATE-OF-THE-ARTS IN PROVENANCE GRAPH-BASED APT DEFENSE (PG: PROVENANCE GRAPH)

Ref	Method	Advantages	Limitations	Priori knowledge	Network-level PG audit	APT evasion attack	Adversarial attack
StreamSpot[12]	Sketch-based Prov	Dynamically Maintainable	Work for Small-scale Graph	✗	✗	✗	✗
UNICORN[6]	Sketch-based Prov	Slow-acting Attack Defense	High-false Alarm Rate	✗	✗	✓	✗
ProvDetector[7]	Stealthy Malware Detection	Hidden Attack Detection	Only Support Offline Detection	✓	✗	✗	✗
SLEUTH[9]	Dependency Graph Abstraction	Attack Scenario Reconstruction	Prone to 0day Threats	✓	✗	✗	✗
NODOZE[10]	Frequency Dependency Prov	Entities Diffusion Analysis	Covert Attack Ineffectiveness	✗	✗	✗	✗
Poirot[11]	CTI Graph Alignment	CTI Reconstruction Graph	Need Excessive Prior Knowledge	✓	✗	✗	✗
HOLMES[12]	High-level Scenario Graph	Advanced Semantic Mapping	Requisite for Extensive Expertise	✓	✗	✗	✗
ATLAS [1]	End-to-end Attack Story	End-to-end Traceability	Covert Attack Ineffectiveness	✓	✗	✗	✗
DEPIMPACT[14]	Dependency Graph Weight	Causality Graph Reconstruction	Prone to Poisoning Attack	✗	✗	✗	✗
PROVNINJA[15]	Process Gadget Chains	Adversarial Attack Achievement	Lack of Defensive Measure	✗	✗	✗	✓
<b>Ours</b>	CPA+LDA, Trust model, HMM	Network-level Audit, APT Evasion-resist, Adversarial Robust	Only Prototype, Lack of Large-scale Actual Deployment	Partly	✓	✓	✓

represents a read or write operation. In the case of a process entity, the edge usually indicates an execute operation; while for a socket entity, its edge typically represents a connect operation.

### B. State-of-the-Arts

The pioneering work of SLEUTH [8] introduced the provenance graph approach for real-time APT attack scenario reconstruction, by leveraging causal relationship tracking and provenance graph modeling. Besides, the attack process is reconstructed in [8] through the construction and annotation of a lower-level event dependency graph. Subsequently, NODOZE [9] further devised novel algorithms for threat detection and heterogeneous graph construction, while Poirot [10] designed subgraph querying and matching algorithms, thereby addressing the alignment challenge between APT attack primitives and provenance graphs. HOLMES [11] innovatively merged the high-level scenario graph (HSG) with the ATT&CK attack framework, thus resolving semantic alignment issues and effectively mitigating noise problems stemming from irrelevant sequences. However, the efficiency shortcomings of the aforementioned approaches hindered the practical deployment of APT provenance graph auditing services.

The state-of-the-art literature on APT defense enhancements mainly focuses on three perspectives: reducing latency, countering highly covert APT behaviors, and causal relationship analysis. In terms of latency reduction, StreamSpot [12] and UNICORN [5] introduced a novel real-time runtime analysis framework for local hosts, which achieves attack detection without prior attack knowledge and demonstrates high accuracy with low false positive rates. Pertaining to defense against fileless attacks, ProvDetector [6] introduced provenance graphs into concealed malicious attack detection and presented novel path algorithms to identify potential portions within provenance graphs, in order to establish recognition profiles for anomalous processes in each program. Through context of

causal relationship analysis and natural language processing (NLP) techniques, ATLAS [1] proposed a sequence-based model based on audit logs, facilitating the end-to-end attack story generation. Additionally, DEPIMPACT [13] extended ATLAS by introducing attack dependency subgraph weights, exploiting the similarity and closeness of attack sequences to achieve provenance graph compression and efficient auditing.

Nevertheless, the above advanced approaches primarily target host-level APT detection, failing to account for network-level (i.e., the entire network consisting of multiple hosts) provenance auditing, thus lacking collaborative defense strategies among hosts. Furthermore, current APT defense strategies are susceptible to intelligent attacks such as APT evasion and adversarial subgraphs, resulting in a significant decline in the effectiveness of provenance graph detection. Table I shows the comparisons of our work with existing state-of-the-arts.

### C. Challenges of Provenance Graph-Based APT Audit

- *Low-Cost Lateral Attack Chain Reconstruction at the Network Level.* APT attacks are typically characterized by the high degree of stealth and prolonged persistence. A significant challenge is efficiently filtering relevant data from millions of provenance logs and establishing meaningful correlations to rapidly reconstruct APT attack chains. Current provenance graph audit schemes are confined to single-host operating systems, whereas real APT attacks exhibit a highly organized nature, often involving distributed and multi-point infiltrations. Relying solely on the auditing of a single host is inadequate to comprehensively reconstruct the complete attack event. Hence, it is imperative to devise a network-level collaborative provenance audit approach involving multiple hosts, while effectively compressing and aggregating the extensive and multi-source provenance graphs. This is beneficial to the cost-effective reconstruction of APT lateral attack chains within complex and dynamic scenarios.

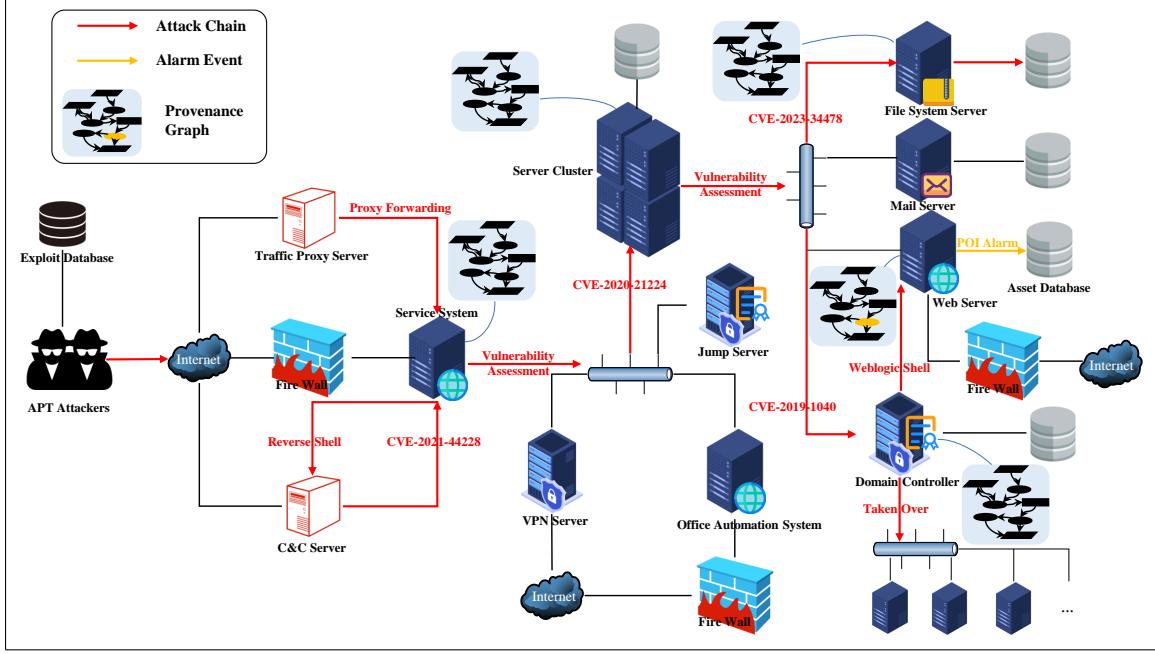


Fig. 2. An Illustration of Network-Layer Distributed Provenance Graph Audit for Lateral Attack Chain Reconstruction.

- *Dynamic Detection of APT Evasion Behaviors with Temporal Correlations.* A team of APT attackers frequently employ various evasion strategies, such as interspersing numerous unrelated IPC sequences within attack primitives, to evade audit approaches based on provenance graphs. Consequently, the availability of APT detection services diminishes. However, existing provenance graph auditing approaches rarely account for APT evasion attacks, resulting in a demand for large-scale and granular APT evasion behavior identification. Due to the massive and multi-source provenance graphs across diverse platforms, temporal correlations of entity interactions within provenance graphs, and intelligent poisoning behaviors for targeted manipulation, it is challenging to design rapid stealthy evasion behavior detection mechanisms in such dynamic and uncertain environments.
- *High-Robust and Self-Adaptive Adversarial Subgraphs Defense.* Existing APT defense strategies based on provenance graphs commonly rely on subgraph matching mechanisms, rendering them susceptible to adversarial attacks. Attackers can construct adversarial provenance subgraphs that evade matching detection without compromising the attack primitives, thereby eroding the reliability of APT detection services. Nevertheless, adversarial attacks are scarcely considered in current works. As a result, there is a rising need for countering adversarial attacks. Given the concealed nature of adversarial subgraphs, the diversity of adversarial attack patterns, and the real-time and dynamically transmissible requirements of defense strategies, the design of robust and self-adaptive defense mechanisms against adversarial subgraphs is challenging.

### III. SOLUTIONS TO PROVENANCE GRAPH-BASED APT AUDIT

Aimed to address the challenges of lateral movement reconstruction, evasion behavior detection, and adversarial subgraph defense in current provenance graph based APT defense, this section delves into the perspective of cost-effective and robust provenance graph based APT defense approaches, including network-level distributed provenance graph audit model (Sect. III-A), trust-oriented dynamic APT evasion behavior detection strategy (Sect. III-B), and HMM-based adversarial subgraph detection strategy (Sect. III-C).

#### A. Network-Layer Distributed Provenance Graph Audit

In this subsection, we devise a distributed provenance graph audit model to efficiently reconstruct lateral attack chains from two perspectives: network-level global auditing and graph data compression. As shown in Fig. 2, it encompasses (i) a graph data compression module based on causality preserved aggregation (CPA) to address the issue of graph dependency explosion, (ii) a graph weight aggregation module based on linear discriminant analysis (LDA) to construct weighted provenance graphs, and (iii) a distributed APT lateral attack chain construction module using weighted provenance graphs.

1) *CPA-Based Graph Data Compression:* The CPA algorithm is utilized to effectively streamline the dependencies within the provenance graph involving extensive volume of data entities (e.g., IPC and file). Specifically, for two interconnected entity flows ( $\rightarrow U \rightarrow V \rightarrow$ ) with a dependency relationship, the following conditions are considered. (i) *Forward ingress aggregation condition:* When the occurrence times of all ingress event edges into entity  $U$  precede the event edge  $U \rightarrow V$ , the timestamp of the last ingress edge is designated as the global ingress time. (ii) *Backward egress aggregation condition:* When the occurrence times of all egress event edges

from entity  $V$  follow the event edge  $U \rightarrow V$ , the timestamp of the initial egress edge is designated as the global egress time. (iii) *Backward egress aggregation condition*: For entity flows that meet both forward and backward aggregation conditions, the two entities are equivalently aggregated as the same one.

2) *LDA-Based Weighted Graph Aggregation*: The LDA model is leveraged to trace PoI alert events by constructing weighted sub-provenance graphs. Internally, three primary features, i.e., file size correlation, temporal relevance, and in-out degree ratio, are employed for extracting the entities in the provenance graph. Subsequently, the edges of the provenance graph are clustered through the multi-round K-means++ algorithm. Next, the LDA model is employed to compute the projection vectors that maximize the Fisher criterion for alarm-related edges versus non-alarm-related edges within the differentiated two groups of edges.

3) *Lateral Attack Chain Construction via Weighted Provenance Graphs*: Given the bidirectional interactivity in APT attack chains (i.e., the triggering of a PoI alert at the entry point evolves into a positive propagation toward linked sockets), the *file* (for payload delivery) and *socket* (for network connections) are two primary elements. Firstly, the positive weights of PoI events are initialized. Then, based on the magnitude of out-degrees, the weights are evenly distributed and progressively reduced with successive convergence. For the subsequent layer of new incoming events, the weight factors are computed based on aforementioned three features. The weight factors serve as discriminative markers for lateral movement, aiding in the restoration of the corresponding APT lateral infiltration chain.

### B. Trust-Oriented Dynamic APT Evasion Behavior Detection

In this subsection, we devise a dynamic APT evasion behavior detection, which encompass (i) temporal correlation for attack-related substructure optimization in provenance graph, and (ii) dynamic trust assessment for suppressing behavioral sequences from untrusted entities.

1) *Optimized Attack-Related Substructures of Provenance Graph*: Adversaries can launch APT evasion attacks by extending the completion time of their attack infiltration primitives and introducing irrelevant operations to saturate the payload entity flow with benign entities. Thereby, they can evade traditional pattern-matching based provenance graph detection [5], [12]. To address this issue, a *forgetting factor* for PoI alert events is introduced, which is associated with the penalty coefficient, the current time slot, and historical interactions. The penalty coefficient for an attacker represents the number of detected attack subgraphs within a specific time window (the length of which depends on the value of the forgetting factor). For an attacker, if his penalty coefficient surpasses a predefined threshold, the causal dependencies of his distributed attack primitives can be temporarily correlated via the stack. This allows the construction of provenance entity links related to the original attack behaviors, resulting in an optimized attack-related substructure within the original provenance graph. Furthermore, it helps reduce the impact of intentionally introduced benign entities by adversaries during trust evaluation.

2) *Dynamic APT Evasion Behavior Analysis based on Trust Evaluation*: As shown in Fig. 3, a defender (i.e., assessment

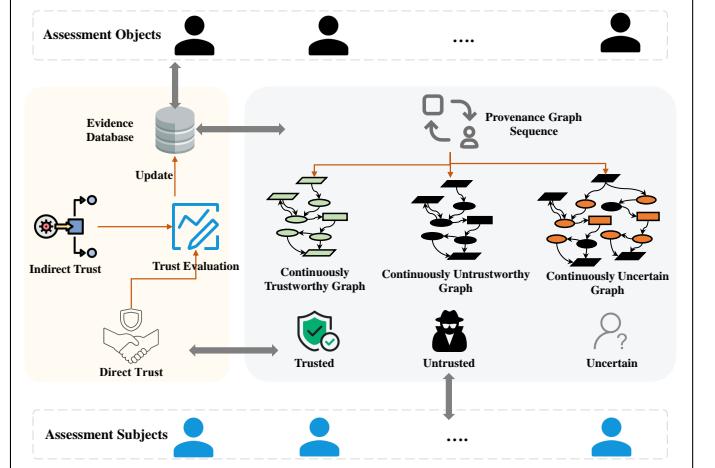


Fig. 3. An Illustration of Trust-Oriented Dynamic APT Evasion Behavior Detection.

subject) can obtain a sequence of optimized provenance graphs about an attacker (i.e., assessment object) from the evidence repository. This sequence records the attacker's historical trustworthiness in chronological order, while each provenance graph in the sequence records the attacker's historical interactions with the victim host within a fixed time window. Through sequence extraction methods, the sequence can be divided into three parts: subsequences of continuously trustworthy operations, continuously untrustworthy operations, and continuously uncertain operations. Then, we design a trust mechanism to distinguish an APT evasion attacker from an innocent user due to misoperations by evaluating the trustworthiness from both *direct* and *indirect* trust aspects. The direct trust is evaluated based on the Dempster-Shafer theory, considering the time span of continuously trustworthy/untrustworthy/uncertain operations and time decay effects. It rewards users for continuously providing trustworthy interactions while penalizing users for malicious or uncertain behaviors. The indirect trust obtained from third-party recommendations can help enhance the accuracy of trust evaluation, especially when direct interactions are infrequent [15]. Afterward, the latest trust evaluation results are stored in the evidence database.

### C. HMM-Based Adversarial Sub-provenance Graph Defense

This subsection devises (i) a fast adversarial subgraph modeling method to explore adversaries' evasion principles during infiltration attacks, and (ii) a HMM-based self-evolving adversarial subgraph detection algorithm.

1) *Fast Adversarial Subgraphs Modeling*. It comprises three steps. *Step 1: Test model construction based on subgraph matching*. We train a general test AI model for discriminating adversarial subgraphs, by optimizing the loss function, which is defined as one minus the average number of successful attack subgraph matches for all subgraphs. *Step 2: Proof-of-concept (PoC) framework design for adversarial subgraphs*. Initially, we utilize the subgraph deconstruction method [10] to disassemble the subgraphs into individual substructures. These substructures are then summarized into an  $N$ -dimensional vector using an encoding function. Subsequently, we employ

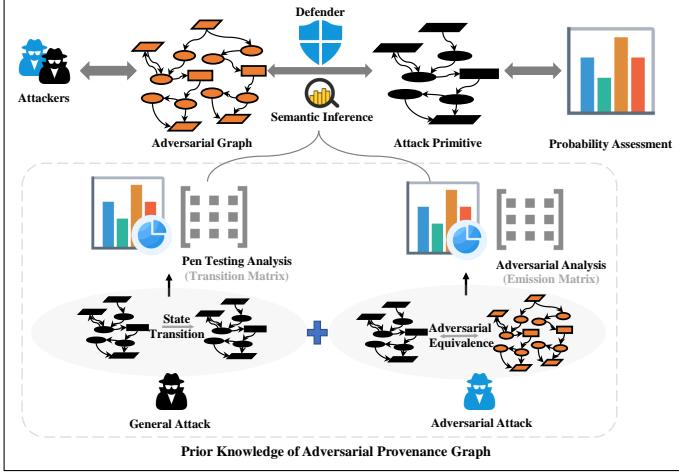


Fig. 4. An Illustration of HMM-Based Adversarial Subgraphs Defense.

a cosine distance-based discriminant function to determine if the subgraph is adversarial. This is achieved by comparing the cosine distance to a preset threshold. *Step 3: Adversarial subgraphs construction.* This step aims to create adversarial subgraphs without disrupting the original attack primitives. Initially, we select benign substructures to replace parts of the original graph's structure, with the objective of minimizing the cosine distance. Then, we update the cosine distance by applying the distance discriminant function to the modified subgraph. The above processes are repeated until the test model incorrectly classifies the subgraph as normal, resulting in the generation of an adversarial subgraph.

#### 2) Robust Adversarial Subgraphs Detection Based on HMM.

As depicted in the lower left of Fig. 4, we first construct a general attack subgraph using the ATT&CK model<sup>2</sup> and the DARPA transparent computing dataset<sup>3</sup>. Next, we count the attack directions (i.e., the potential entities to be linked next in the graph) within the APT to create a transfer matrix. Then, as shown in the lower right of Fig. 4, based on the adversarial equivalent graph obtained from our proposed fast modeling method, we count the adversarial transformation entities (i.e., the benign entities equivalent to the malicious entities) to derive the emission matrix. Finally, utilizing the obtained transfer matrix and emission matrix, we use the HMM Viterbi algorithm on the captured stream of provenance graphs to determine the most probable sequence of attack entities (i.e., those with the highest hit rate). When the hit rate surpasses a predefined threshold, the entity is identified as an adversarial subgraph.

## IV. IMPLEMENTATION AND EVALUATION

### A. Experimental Setup

We implement an APT penetration test prototype with 15 servers to simulate a real enterprise network. Six types of vulnerabilities are considered: *buffer overflow*, *domain controller hijacking*, *living-off-the-land (LoL)*, *data leakage*, *maintaining access*, and *middleware exploitation*. These vulnerabilities are

distributed across 15 servers, and each server is equipped with a lightweight provenance graph interface. The network-layer APT lateral movements, APT evasion attacks, and adversarial subgraph attacks are considered in our prototype.

### B. Experimental Results

Fig. 5(a) illustrates the number of compromised nodes as the number of pivot servers (used for lateral movements) increases. As depicted in Fig. 5(a), different APT attack modes yield varying outcomes. For instance, in mode 1, the adversary executes a hijacking attack during the 4th round of lateral movement, successfully taking control of both the domain controller and domain users. In contrast, the adversary in mode 6 only succeeds in taking control of one server throughout the lateral movement attempts. Fig. 5(b) shows the evolution of the trust value of the assessment object as the number of interactions increases under the APT evasion attack. It can be observed that the proposed approach exhibits significant improvement compared to the traditional probabilistic trust model [15]. Fig. 5(c) shows the detection performance with and without adversarial subgraphs under various attack scenarios. It can be seen that adversarial subgraphs significantly deteriorates the defensive effectiveness of conventional StreamSpot [12] and Unicon [5] schemes. Furthermore, the proposed scheme effectively defends against adversarial attacks and outperforms the mimicry-StreamSpot and mimicry-Unicon approaches, while maintaining a smaller performance gap compared to conventional StreamSpot and Unicon schemes without adversarial attacks.

## V. FUTURE DIRECTIONS

This section explores the future directions that necessitate further research investigation in APT detection based on provenance graphs.

### A. Fusing Provenance Graphs and Knowledge Graphs for APT Detection

Combining provenance graphs and knowledge graphs in APT detection is imperative to address semantic gaps and enhance threat provenance. Provenance graphs capture fine-grained system interactions, while knowledge graphs provide semantic context. The synergy offers comprehensive insights for accurate attack detection and attribution to achieve holistic and efficient APT detection. Effective fusion of heterogeneous data and knowledge representation remains the major challenge.

### B. Tamper-Resistant Provenance Graph Storage

The integrity of the kernel-level provenance graph can be compromised by unauthorized modifications, posing risks to the reliability of audit trails. Cryptographic methods, such as digital signatures and secure hashing, offer a potential remedy against tampering threats. Immutable ledger technologies, such as blockchain, further bolster resistance to tampering by dispersing storage and enforcing consensus-based verification. Nevertheless, obstacles persist, encompassing efficient

<sup>2</sup><https://attack.mitre.org/>

<sup>3</sup><https://github.com/darpa-i2o/Transparent-Computing>

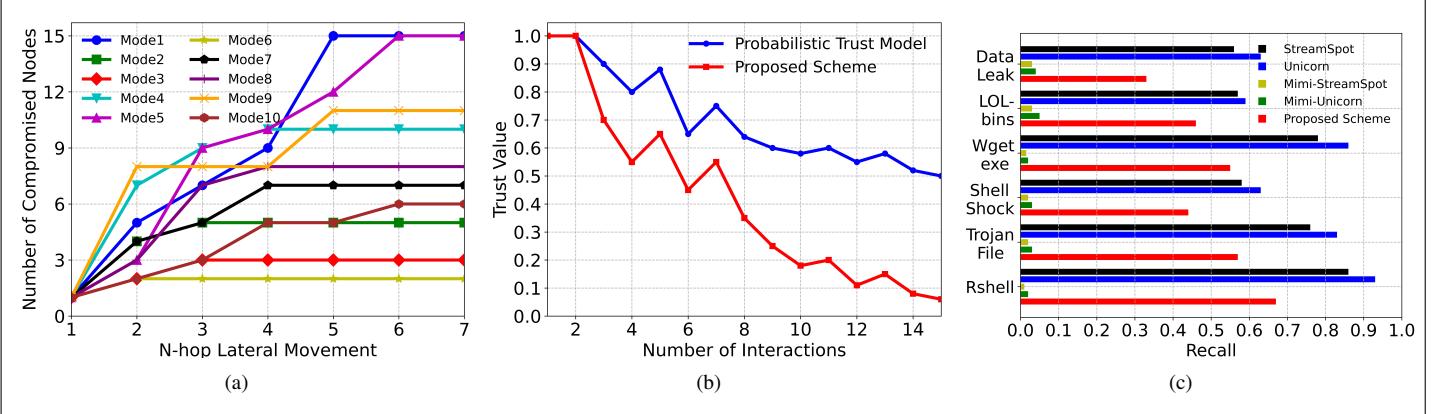


Fig. 5. a) Number of compromised nodes vs.  $N$ -hop lateral movement under 10 modes of attack paths. b) Trust value vs. number of interactions, compared with probabilistic trust model [15]. c) Successful detection rate with/without adversarial attacks, compared with StreamSpot [12], Unicorn [5], mimicry-StreamSpot, and mimicry-Unicorn. Note: As StreamSpot and Unicorn are designed for the settings without adversarial attacks, to be fair and objective, we implement them under adversarial settings and call their modified versions as *mimicry-StreamSpot* and *mimicry-Unicorn*, respectively.

querying of encrypted data and managing access control in distributed environments. Developing tamper-resistant mechanisms is vital to upholding the trustworthiness of provenance-based APT audits.

### C. Collaborative and Privacy-Preserving Threat Intelligence Sharing

APT threats often target multiple entities across sectors. Future research should focus on establishing collaborative frameworks for sharing threat intelligence derived from provenance graph-based auditing. However, organizations may be hesitant to share sensitive data due to confidentiality and privacy issues, raising needs for privacy-preserving threat intelligence aggregation and sharing without exposing sensitive information. Other issues remain to be investigated include standardizing data formats and incentivizing collaboration.

### D. Integration with Cloud and Edge Environments

Leveraging the integration of cloud and edge computing enhances APT detection services by enabling dynamic data correlation and analysis. Edge devices collect and preprocess local data for minimized latency. Cloud servers offer scalability and computational power for in-depth analysis and storage. This synergy optimizes APT detection, allowing real-time alerts at the edge and comprehensive analysis in the cloud. Research challenges include data synchronization, privacy preservation, and adaptation to resource constraints.

## VI. CONCLUSION

APT attacks have far-reaching consequences across various sectors including governments, critical infrastructures and corporations, necessitating effective defense strategies. While existing provenance graph-based research sheds light on APT defense, the effectiveness of APT detection remains hindered by intricate lateral attack patterns, dynamic evasion strategies and adaptive adversarial subgraphs. This study advocates for a novel approach for enhanced efficiency and robustness in existing provenance graph-based APT audit schemes, by devising a network-level distributed provenance graph audit

model, a dynamic evasion behavior detection strategy, and a robust adversarial subgraph detection strategy. Via prototype implementation and experimental evaluations, the potential of the proposed system is validated to significantly enhance APT defense capabilities. This work is anticipated to shed more light on ongoing exploration of comprehensive solutions against evolving APT threats in today's digital landscape.

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