OMNISEC: LLM-Driven Provenance-based Intrusion Detection via Retrieval-Augmented Behavior Prompting

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ABSTRACT

Recently, Provenance-based Intrusion Detection Systems (PIDSes) have been widely used for endpoint threat analysis. These studies can be broadly categorized into rule-based detection systems and learning-based detection systems. Among these, due to the evolution of attack techniques, rules cannot dynamically model all the characteristics of attackers. As a result, such systems often face false negatives. Learning-based detection systems are further divided into supervised learning and anomaly detection. The scarcity of attack samples hinders the usability and effectiveness of supervised learning-based detection systems in practical applications. Anomaly-based detection systems face a massive false positive problem because they cannot distinguish between changes in normal behavior and real attack behavior. The alert results of detection systems are closely related to the manual labor costs of subsequent security analysts. To reduce manual analysis time, we propose OMNISEC, which applies large language models (LLMs) to anomaly-based intrusion detection systems via retrieval-augmented behavior prompting.

First, OMNISEC uses lossless reduction technology to remove redundant information flows from the provenance graph. Second, OMNISEC builds two external knowledge databases: a benign behavior knowledge base based on normal behavior activities within the host and a threat intelligence knowledge base based on external threat intelligence. OMNISEC can identify abnormal nodes and corresponding abnormal events by constructing suspicious nodes and rare paths. By combining two external knowledge bases, OMNISEC uses Retrieval Augmented Generation (RAG) to enable the LLM to determine whether abnormal behavior is a real attack. Finally, OMNISEC can reconstruct the attack graph and restore the complete attack behavior chain of the attacker's intrusion. Experimental results show that OMNISEC outperforms state-of-the-art methods on public benchmark datasets.

1. Introduction

In the highly interconnected digital age, Advanced Persistent Threats (APTs) have become the primary means of disrupting the security of critical infrastructure and sensitive data [1]. These cyber-attack methods are characterized by high concealment, long-term persistence, clear targeting, and high modularity [2]. Attackers often carefully plan their attacks. They combine various methods and techniques to exploit vulnerabilities. Once inside, attackers persist undetected, stealing data, manipulating systems, or sabotaging operations, leading to severe financial and security consequences. For example, in the 2020 SolarWinds supply chain incident [3], attackers implanted malicious code in software updates, leading to the compromise of several US government departments and large enterprises. The attack lasted for months without being detected, causing serious national-level information leakage.

Facing the increasingly severe APT threats, Provenance-based Intrusion Detection Systems (PIDSes) have attracted widespread attention due to their advantages in detecting and tracing complex attacks [4, 5, 6, 7]. Compared with traditional Intrusion Detection Systems (IDSes), PIDSes construct provenance graphs to represent the causal relationships between events, recording low-level behaviors such as system calls and process communications, thereby achieving precise modeling of the attack chain and improving detection accuracy and event traceability.

However, existing PIDSes still face several challenges in practical applications. Although rule-based heuristic methods [8, 9, 10, 11] demonstrate high efficiency in detecting known malicious behaviors, they rely heavily on predefined rules and attack patterns, such as specific sequences of system calls, making it difficult for them to cope with the constantly emerging new types of attacks. Meanwhile, attackers may modify their attack strategies to evade static rules, leading to a high rate of false negatives in the system. On the other hand, supervised learning-based methods [12, 13] categorize system behaviors into benign and malicious classes and rely on a large amount of high-quality labeled data to train models. When there is sufficient data, they can achieve good detection results. However, the coverage of the training samples often limits their generalization ability [14], and they perform poorly when facing unknown attacks. In addition, supervised learning methods require a large amount of labeled data, which is costly to obtain and difficult to adapt to the complex and changing real-world operating scenarios.

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Anomaly detection methods identify potential abnormal behaviors by learning the normal behavior patterns of a system. These methods typically employ unsupervised learning to detect unknown attacks without requiring large amounts of labeled data. Currently, a significant amount of work has been done to build intrusion detection systems based on anomaly detection [15, 16, 17, 18, 19, 20, 21]. However, anomaly detection essentially uses "deviation from normal" as the sole criterion and is trained solely on benign behavior data [22]. This makes it difficult for the model to accurately distinguish between normal variations and actual attack behaviors, leading to a high rate of false positives when encountering new datasets. Moreover, this results in a large number of alerts in practical deployment, which still require manual filtering and confirmation, significantly increasing the cost of security. In an enterprise environment, anomaly detection models are usually trained on benign operation logs from hosts to learn their stable behavior patterns. When the user of the host changes, the behavior pattern may change as well. For example, a new employee may take over and perform operations that differ significantly from previous ones. These operations might still be legitimate. However, the model has only learned the existing behavior patterns. As a result, it may misjudge these new operations as anomalies, which further increases the false positive rate.

Detection methods that rely solely on a single knowledge source (such as normal behavior patterns) can identify abnormal behavior to some extent. However, since they do not combine other types of knowledge (such as known attack patterns or threat intelligence), they often fail to accurately distinguish between malicious and non-malicious anomalies when facing complex scenarios or changes in strategies [23] (**Challenge 1**). Some anomaly detection systems ([16, 18, 19]) only report anomaly results at the subgraph level, which also causes security analysts to spend a lot of time and effort confirming abnormal processes during actual deployment. In addition, Goyal et al. [24] point out that this type of detection system is at risk of receiving mimicry attacks, causing attack escape (**Challenge 2**). Although the node-level detection [15, 17] achieved by the latest studies can resist mimicry attacks to a certain extent, analysts still need to spend time restoring the attack chain to filter out false positives when the false positive rate is high (**Challenge 3**).

In recent years, large language models (LLMs) have been widely used in the field of cybersecurity, bringing a new research paradigm to the field. They have been widely applied to tasks such as threat intelligence analysis, log parsing, command line understanding, and automated response [25, 26, 27, 28]. Therefore, to address the above challenges, we propose OMNISEC, an intrusion detection framework that integrates the reasoning capabilities of LLMs with the ability to model security knowledge, to achieve more accurate threat perception. First, OMNISEC uses lossless compression technology to remove redundant edge information from the provenance graph while retaining semantic information. Second, OMNISEC constructs a benign behavior knowledge base from benign logs and a threat intelligence knowledge base by extracting attack knowledge from cyber threat intelligence (CTI). Third, OMNISEC filters out abnormal nodes and their events by constructing abnormal nodes and rare paths. OMNISEC can combine the two external knowledge bases using Retrieval Augmented Generation (RAG) to enable the LLM to assess abnormal nodes, achieving node-level detection while confirming malicious nodes (**for Challenges 1, 2**). Finally, OMNISEC, based on traceability mechanisms and attack graph reconstruction techniques, accurately locates the key paths and related nodes of the attack, helping analysts understand the attack process and assist in subsequent responses (**for Challenge 3**).

The contributions of this paper are summarized as follows:

- We propose a knowledge-driven provenance-based intrusion detection method.
- We have implemented the practice of applying LLMs to intrusion detection, emphasizing the key role of knowledge fusion in threat detection. To this end, we introduce the Retrieval-Augmented Behavior Prompting method to enhance the reasoning and judgment capabilities of LLMs.
- We propose OMNISEC[1], a provenance-based intrusion detection system that incorporates LLM. OMNISEC is capable of node-level anomaly detection and automated reconstruction of attack graphs. Experimental results show that OMNISEC can achieve performance superior to existing methods on public benchmark datasets.

2. Background and Motivation

2.1. Provenance Graph

A provenance graph is a graphical structure used to record the causal relationships between events in a system [29]. It can meticulously trace the chronological order of events and their invocation relations. It is widely used in forensic analysis, attack path tracking, and other tasks. A provenance graph typically relies on kernel-level system call logs. By monitoring the behavior generated by the system during runtime, it can reconstruct the interaction history between entities in the system (such as processes, files, sockets, etc.). In a provenance graph, nodes represent system objects, and edges represent causal dependencies triggered by system calls. Taking Linux as an example, kernel modules such as Auditd [30] and CamFlow [31] can be used to capture system call information in real time. This includes system calls like fork/clone (process creation), open/read/write (file operations), execve (program execution), connect/send/recv (network communication), and chmod/chown/setuid (permission operations). Based on these raw logs, a provenance graph can construct a complete path of system behavior, effectively detecting abnormal system behavior.As shown in Figure 1, it is a typical example of a source graph, illustrating

[1] https://github.com/Shike-Cheng/PIDS-with-LLM

the causal interaction relationships between processes, files, and sockets in the system.

2.2. Large Language Model

Large Language Models (LLMs) are natural language processing technologies based on deep learning models [32], typically employing a transformer architecture and trained on large-scale specialized corpora. By learning the statistical patterns and semantic relationships in language, LLMs demonstrate strong contextual reasoning and inference capabilities, which enable them to handle complex tasks such as question answering, text summarization, and dialogue generation.

In the field of cybersecurity, these capabilities make LLMs an emerging tool for understanding attack intentions, parsing security events, and aiding decision-making. For example, AutoAttacker [33] is an LLM-guided automated network attack system that can automatically generate attack strategies and commands based on target descriptions, achieving end-to-end automation of the attack process. RACONTEUR [34] developed an LLM-driven shell command interpreter that can parse and semantically interpret shell commands (especially malicious ones) in combination with contextual knowledge. UniLog [35] is an automatic logging framework based on LLMs and a context learning paradigm, which can automatically insert high-quality log statements according to program context, thereby enhancing system observability and problem tracking efficiency. LogParser-LLM [36] combines semantic understanding with statistical details to parse logs online without the need for hyperparameter tuning and labeled training data, demonstrating good cross-system adaptability. LLM-CloudSec [37] uses a retrieval-augmented generation mechanism and the Common Weakness Enumeration as an external knowledge base to achieve unsupervised fine-grained vulnerability analysis. Therefore, given the capabilities of LLMs in semantic reasoning and knowledge integration, we further explore their potential applications in provenance-based intrusion detection systems.

2.3. Motivating Example

We present a typical attack example (Figure 1). The attacker exploits a remote code execution vulnerability in the Firefox browser to gain initial control over the victim's workstation and writes two malicious payloads to the local directories `/home/admin/clean` and `/home/admin/profile`. Subsequently, leveraging a local privilege escalation vulnerability, the attacker further obtains the system's root privileges. After acquiring elevated permissions, the attacker uses the malicious file to establish communication with the remote command and control (C&C) server at `146.153.68.151`, downloading and executing additional malicious components. The attacker also opens and writes to the device file `/dev/glx_alsa_679`, utilizing this device as a covert channel for communication or data exfiltration to bypass conventional security detection.

Limitations of Existing Techniques: Rule-based systems [8, 10] can achieve fine-grained node-level detection, but their effectiveness relies on the completeness and update frequency of the rule repository. Since rule sets often fail to cover behavioral characteristics in the system dynamically, this results in significant detection blind spots in practice and consequently low node-level accuracy. The graph-level accuracy currently used for threat hunting largely depends on the effectiveness of the graph alignment algorithm, and few works [9, 38] have fully open-sourced it. Learning-based anomaly detection models have been widely used by researchers to achieve graph-level or node-level detection without requiring any expert experience. However, graph-level detection [18, 19] not only fails to help analysts locate threats but is also vulnerable to mimicry attacks. Moreover, anomaly detection models [16, 39, 15, 40] are susceptible to concept drift, which makes it difficult for the model to distinguish between changes in benign behavior and actual malicious behavior.

It is worth noting that current anomaly-based detection systems tend to misidentify the activities represented by the green nodes in Figure 1 as threat alerts. For example, the system detects data being written to `/dev/glx_alsa_679` by `fluxbox`, as well as communication between `/bin/dash` and the remote C&C server. In addition, the system observes that some processes, which share the same parent process as `profile`, access similar paths. Although these processes do not participate in the attack, they exhibit access patterns in the graph similar to the malicious process flow and are thus flagged by the system as potential threat nodes. This indicates that when the detection system is trained solely on benign samples, it lacks the ability to distinguish attack behaviors. Faced with overlapping behaviors among processes in complex environments, it tends to misidentify some normal activities as attack behaviors, leading to false positives.

During the application process, it is necessary to continuously retrain the model to adapt to anomalies in real business scenarios. Current technologies still face many challenges in accurately identifying complex threat behaviors, and knowledge fusion remains a trend in the latest research. To this end, OMNISEC leverages the knowledge integration and reasoning capabilities of LLMs to fuse multi-source data such as system audit logs and threat intelligence, and to provide a unified representation of threat behaviors. For nodes that are prone to being misjudged as threats, such as the writing behavior of fluxbox in Figure 1, the system compares and analyzes them in combination with the attack context and similar behaviors in the malicious knowledge base, further identifying that these behaviors are semantically closer to normal system activities, thereby avoiding false positives. OMNISEC not only reduces the dependence on rules and manual intervention but also effectively alleviates issues such as false positives and concept drift in existing methods while accurately identifying threat behaviors.

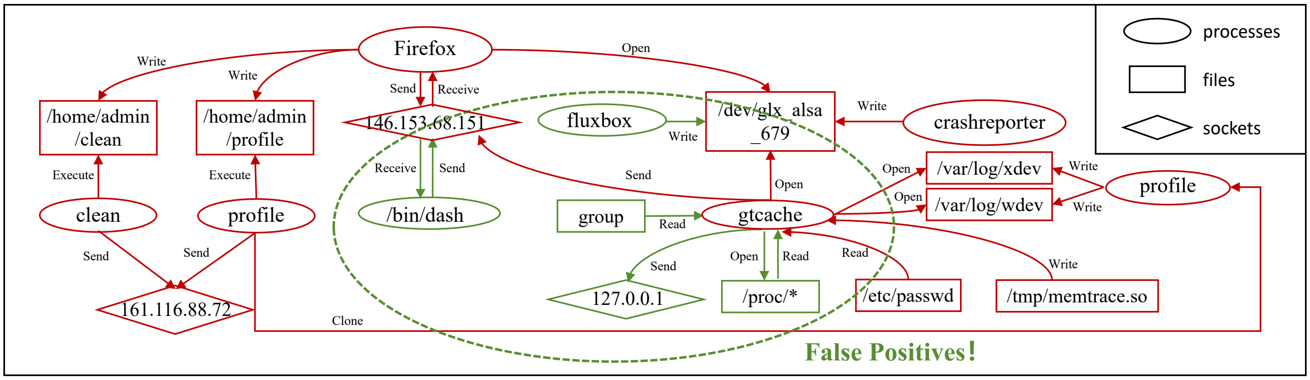


Figure 1: The DARPA E3-THEIA provenance summary graph, which provides a detailed description of the key activities in the attack example. Different shapes are used in the graph to represent different system entities: ellipses represent processes, rectangles represent files, and diamonds represent sockets. Additionally, different types of operations are labeled on the edges, including read, write, open, send, receive, clone, and execute. We have introduced different colors to represent different key information: red nodes and edges indicate confirmed attack behaviors, while green indicates identified suspicious activities, which are prone to false positives.

3. Threat Model

We assume that the attacker has stealthiness and can use a variety of means to evade traditional detection mechanisms, including exploiting zero-day vulnerabilities and encrypting obfuscated communications. These attack methods make malicious behaviors indistinguishable from normal behaviors on the surface, making it difficult to differentiate between the two. At the same time, attackers often proceed with the attack process in multiple stages and implement it slowly over a long period of time, presenting the typical characteristic of “low-and-slow”. This means that attack behaviors are distributed over different time periods, and the overall attack chain is easily fragmented and hidden among a large number of normal behaviors, increasing the difficulty of identifying abnormal behaviors and restoring attack intentions.

In the design of OMNISEC, we focus on combining system audit logs with external threat intelligence clues to form a multi-level, multi-dimensional security knowledge base. The system introduces the reasoning ability of large language models to identify malicious activities that are different from benign behaviors. To ensure the accuracy and reliability of the provenance graph construction, we also particularly emphasize the integrity and security of audit logs to prevent them from being tampered with and provide reliable support for subsequent analysis.

4. System Design

OMNISEC is a provenance-based intrusion detection system that combines a retrieval-enhanced behavior prompting mechanism to enhance the reasoning capabilities of large language models, enabling node-level anomaly detection and supporting the automatic reconstruction of attack graphs and identification of key paths. The architecture of OMNISEC is shown in Figure 2, which consists of the following four core modules:

Lossless Streaming Data Reduction (§4.2). Capture logs using system auditing tools, extract system entities and interaction events by parsing the logs, and merge equivalent events using data compression techniques to reduce the data processing burden while preserving the original semantics.

Knowledge Databases Construction (§4.3). Construct an external knowledge base by combining Word2vec and Doc2vec technologies. On one hand, model path information and statistically analyze event frequencies to extract common behavioral patterns in the system. On the other hand, vectorize threat intelligence texts using natural language modeling methods to capture potential attack features. Ultimately, form a unified, structured embedded index to support subsequent behavioral matching and reasoning.

Anomaly Detection with LLM (§4.4). Filter out suspicious nodes and rare paths using a benign path name embedding model and a rarity scoring algorithm. Further combine large language models with retrieval-augmented generation technology to semantically complete and threat-assess these candidate paths.

Attack Graph Reconstruction (§4.5). Combine system causal structures with anomaly scoring results to filter out real attack nodes and reconstruct the complete attack graph.

4.1. Design Goals

The design goals of OMNISEC are as follows: **G1: Lossless Streaming Data Reduction.** The system should be able to process streaming data and implement real-time data reduction. **G2: Knowledge Databases Construction.** Constructing knowledge databases that provide knowledge guidance for LLM. **G3: Anomaly Detection with LLM.** The system should be able to detect anomaly with LLM by using retrieval augmented generation (RAG) [41] with the help of knowledge databases. **G4: Attack Graph Reconstruction.** The system should be able to reconstruct attack graphs based on anomaly detection.

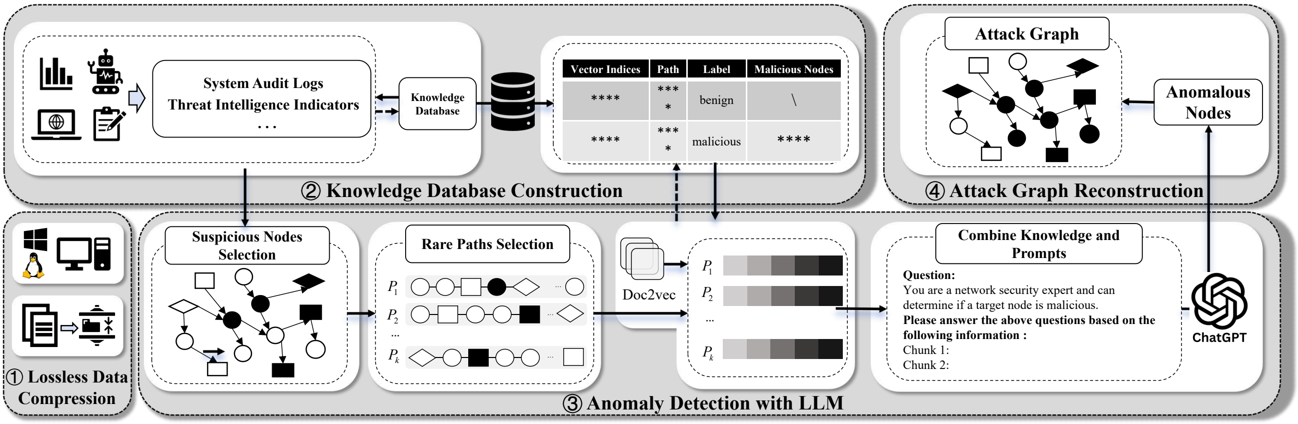

System Audit Logs
Threat Intelligence Indicators
...
Knowledge Database
Vector Indices
Path
Label
Malicious Nodes
****
***
*
benign
\
****
***
*
malicious
****
② Knowledge Database Construction
Attack Graph
Anomalous Nodes
④ Attack Graph Reconstruction
① Lossless Data Compression
Suspicious Nodes Selection
Rare Paths Selection
Doc2vec
Combine Knowledge and Prompts
Question:
You are a network security expert and can determine if a target node is malicious.
Please answer the above questions based on the following information :
Chunk 1:
Chunk 2:
ChatGPT
③ Anomaly Detection with LLM

Figure 2: Overview of OMNISEC' architecture.

Table 1
System entity, attributes, and dependencies.

Subject	Object	Edge Type	Entity Attributes
Process	File	Write, Execute	Process pathname, Uuid
	Process	Fork	
	Socket	Send	
File	Process	Read, Mmap	File pathname, Uuid
Socket	Process	Receive	Source IP, Destination IP, Uuid

4.2. Lossless Streaming Data Reduction

Similar to other PIDSes, OMNISEC collects audit data from system audit tools (such as event tracing for Windows [42], and audit for Linux platform [43]) that capture logs and construct provenance graphs that can represent topological and ordered events between entities. We focus on 3 types of entities (processes, files, and sockets) and 7 types of interaction events between entities. Among them, we convert events into edges with time and direction according to the flow of data and control flows and hold the key attribute information of the entity, as shown in Table 1.

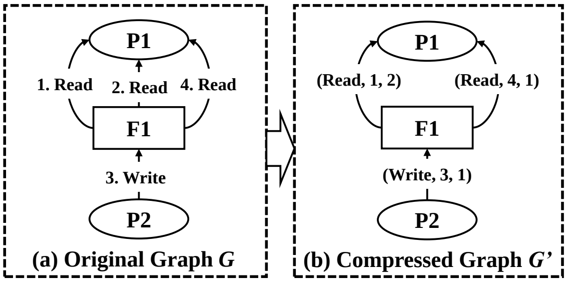


Figure 3: Global semantic based compression algorithms

The log parsing module sends system entities and events strictly according to the timestamp to our data reduction module as designed in Table 1. The idea of data reduction that maintains global semantics from existing work [44] is borrowed in this module: only the first event that has its effect on the target vertex is preserved, provided that the semantics of the source vertex are not changed.

It is important to emphasize that our work focuses on the change of semantic information by the temporal sequence of data flow, i.e., OMNISEC focus on the event types *Write*, *Read*, *Mmap*, *Send*, *Receive*. In addition, for equivalent events, OMNISEC remove them as redundant events but record their event frequency as an edge attribute to be saved in the retained edges. OMNISEC defines the compressed edge as (e_t, t, c), where c records the frequency of the event. As shown in Figure 3, the reduction strategy from the original graph G to the compressed graph G' is as follows: 1) $F1$ does not undergo a semantic change between $t = 1$ and $t = 2$, so the two *Read* events belong to the equivalent semantics, and the edge with $t = 1$ is retained and the frequency is recorded. 2) However, after $t = 2$, $F1$ is written with relevant data by $P2$, and the semantics change. Therefore, the semantics of $P1$ *Read* $F1$ at $t = 4$ is not equivalent to the first two *Read* events and is retained.

4.3. Knowledge Databases Construction

In order to realize the best practices of anomaly detection based on knowledge fusion, our work leverages the ability of LLM to integrate knowledge. However, although LLM has demonstrated its unique advantages and broad application prospects in several fields, it is prone to produce some inaccurate information when dealing with domain-specific or highly specialized queries. Therefore, many researchers have proposed various types of methods to alleviate this problem. Among them, RAG is a technique proposed by Lewis et al. [41] to effectively address this limitation. It integrates knowledge retrieved from an external knowledge base into the generation process, thus enhancing the model's ability to provide accurate and relevant responses. In this subsection we present the construction process of two external knowledge bases as follows.

4.3.1. Benign Behavior Knowledge Base

In the absence of attacks, hosts within an organization generate millions of log data every day. When an attack occurs, the attacker will generate malicious operations inside the host that are different from benign application behaviors due to their special purpose. Therefore, for different application environments and business processes of enterprises, OMNISEC can build a customized real-time updated benign behavior knowledge base, which can effectively reduce the misjudgment of normal behavior, thus reducing false alarms and improving the accuracy of security protection. We mainly focus on two pieces of information: 1) the path name of the underlying entity, i.e., we believe that the path information can be used as an important feature to help us characterize the behavior of the application. Therefore, OMNISEC considers the path name as a sequence of text and the parts in the path (e.g., folder, file name) as words, and uses Word2vec to get the embedding vector of each node and save an embedding model. 2) The frequency of interactions of different events between the entities, which can help us to analyze the execution flow and behavioral patterns of the application through the interactions between different entities, i.e., by keeping track of the files and resources that the application accesses, they can understand the sequence of its normal operations. The total frequency of pair of nodes $(src_{name}, dest_{name})$ is defined as $TotalFreq(s_n, d_n, e_t) = \sum_t count_{(s_n, d_n, e_t, t)}$, where $count_{(s_n, d_n, e_t, t)}$ is the frequency of e_t at t. In addition, the total out-degree and in-degree of each node v are defined respectively as:

$$\begin{aligned} OUT(v) &= \sum_{d,e} TotalFreq(v_n, d, e) \\ IN(v) &= \sum_{s,e} TotalFreq(s, v_n, e) \end{aligned} \tag{1}$$

OMNISEC stores the above data information into a relational database so that it can be quickly queried as a benign behavior knowledge base in subsequent attack detection.

4.3.2. Threat Intelligence Knowledge Base.

Threat events recorded in CTI reports include malicious IOCs and event interactions between them. The wealth of information (tools, resources, and attack behaviors) from these attackers can provide a knowledge complement to LLM. Currently, several studies [45, 46, 47] have parsed CTI reports. They work on constructing attack graphs similar to the structure of provenance graphs from natural language. Among them, OMNISEC draws on CRUcialG [47] and Extractor [46] to process CTI reports. OMNISEC uses natural language models to construct attack scene graphs (ASGs) by extracting the attack entities and the relations between the entities from CTI reports. Therefore, OMNISEC treats the longest path $path = \{v_1, e_1, v_2, e_2, ..., e_{n-1}, v_n\}$ composed of nodes and edges in ASGs as a sentence and embeds the path using the Doc2vec. In summary, OMNISEC converts malicious attack events into malicious paths and projects them into a numeric vector space to be stored in a database constituting a threat intelligence knowledge base.

4.4. Anomaly Detection with LLM

In the previous modules, we have constructed external knowledge bases for benign (§4.3.1) and malicious (§4.3.2) knowledge, respectively, in this subsection we will describe the LLM based anomaly detection process of OMNISEC using RAG.

4.4.1. Selection of Suspicious Nodes

The provenance graph grows in the number of entities over time, and to narrow down the scope of anomalies, OMNISEC screens the suspicious nodes in the provenance graph. Usually, processes often load or access the same set of libraries and configuration files at startup, or generate some temporary files and pipes during execution. These objects become noise information for suspicious node filtering. Therefore, OMNISEC uses the benign path name embedding model to embed the path names of the nodes in the monitoring process and calculate the cosine similarity with the nodes in the benign behavior database to filter out the suspicious nodes (suspicious nodes filtered out are often those that have not appeared in the knowledge base).

4.4.2. Selection of Rare Paths

The contextual information of the control and data flows interacting between nodes determines whether the node is involved in malicious behavior or not. However, the number of paths is exponentially related to the number of nodes, and directly extracting all the paths of anomalous nodes from the provenance graph may lead to the dependency explosion problem. To solve this problem, a path selection algorithm based on rarity scoring is proposed. For event $e_i = (v_s, v_d, e_t)$, the frequency score of e_i is defined as:

$$S(e_i) = D_{out}(v_s) F(e_i) D_{in}(v_d) \tag{2}$$

In Equation 2, $F(e_i)$ is defined as:

$$F(e_i) = \frac{TotalFreq(s_n, d_n, e_t)}{\sum_{d,e} TotalFreq(s_n, d, e)} \tag{3}$$

s_n and d_n represent the path names of the subject and object nodes, respectively. $F(e_i)$ is refers to the percentage of e_i in all events of s_n in the host. $D_{out}(v_s)$ and $D_{in}(v_d)$ are defined respectively as:

$$D_{out}(v_s) = \frac{OUT(s_n)}{\sum_i OUT(v_i)}, D_{in}(v_d) = \frac{IN(d_n)}{\sum_i IN(v_i)} \tag{4}$$

In order to reduce the complexity of path search and to ensure real-time detection, each anomalous node searches for k_1-hop neighbors forward and backward, respectively, according to the time sequence. Thus, for any anomalous node v with path $p_v = \{e_1, e_2, ..., e_{k_1}, ..., e_{2k_1}\}$, the rarity score is defined as:

$$R(p_v) = -\log_2 \prod_{i=1}^{2k_1} S(e_i) \tag{5}$$

By defining the rarity score, OMNISEC selects the top k_2 paths with the highest anomaly scores among the paths of the suspect nodes in the order of events. We also pay extra attention to these non-suspicious nodes involved in these rare paths. Similarly, OMNISEC will look for high-frequency (lowest anomaly scores) events where these nodes are involved and form benign paths in the benign behavior database. The benign paths will also be encoded using the Doc2vec model, and then together with the threat intelligence knowledge base to form a vector-indexed corpus for the RAG.

4.4.3. RAG with LLM

The LLM represented by ChatGPT proposed by OpenAI [48] is gradually used by various small domains to fine-tune it for downstream tasks. However, with the introduction of GPT-4, the cost of fine-tuning the large model gradually rises. Therefore, we draw on the typical RAG application workflow proposed by Gao et al. [49] to optimize the node-level anomaly detection to enhance the judgment capability of the LLM via the RAG as shown in Figure 2. First of all, the suspect node and its rare path will be entered into the LLM as a user query. The RAG will use the same encoding as in the indexing phase, i.e., it will transcode the paths of the query using Doc2vec. Next, it will proceed to compute the similarity scores between the query vectors and the vectorized blocks in the indexed corpus. OMNISEC prioritizes and retrieves the top K blocks that are most similar to the query. Finally, OMNISEC synthesizes the query with the retrieved relevant benign and malicious knowledge into a coherent cue to be fed into the LLM for anomalous node determination (prompt template and its structure can be found in Figure 2).

4.5. Attack Graph Reconstruction

Attack reconstruction has proved useful in reducing the time for analysts to perform forensic analysis as well as in understanding the complete attack story. OMNISEC performs anomaly judgment on suspicious nodes with LLM. However, anomalies are not equal to real attacks. OMNISEC uses causal analysis methods (we draw on some label-based PIDSes [8, 50] for representation of attack stages) to filter out the real attack nodes and reconstruct the complete attack graph. The key insight of OMNISEC in this process is that the attacker's complete attack activity relies on the contextualization. Therefore, the real attack nodes must have key events associated with each other (i.e., the real malicious nodes are connected to each other relying on the attack-related nodes, and we treat these attack-related nodes as an important part of the attack reconstruction as well). As shown in lines 1 to 25 in Algorithm 1, OMNISEC processes the LLM detection results, finds anomalous clusters related between nodes based on rare paths and reduces the attack graph based on causal relations between suspicious flows.

Algorithm 1: Attack Graph Reconstruction

```
   Input: Anomalous Nodes List $V_a$;
   Key_word = ['/etc/passwd', 'hostname', ...];
   Rare Event List (REL);
   Rare Event Score (RES);
   Output: Attack Graph $G$;
1  for $v_i \in V_a$ do
2      for $v_j \in V_a$ do
3          if $REL_{V_i} \cap Key\_word \neq \emptyset$ and
            $REL_{V_j} \cap Key\_word \neq \emptyset$ then
4              $v_i, v_j \rightarrow cluster$;
5          end
6          if $v_j \in REL_{V_i}$ then
7              $v_i, v_j \rightarrow cluster$;
8          end
9      end
10 end
11 Merge related node $Clusters$;
12 for $c \in Clusters$ do
13     if $len(c) == 1$ then
14         continue;
15     else
16         for $v \in c$ do
17             for $p \in REL_v$ do
18                 $P_{score} += RES_p$;
19             end
20         end
21     end
22     $c_{score} = P_{score}/\mathrm{len}(c)$;
23 end
24 $AttackNodes = \max(c_{score})$;
25 $AttackGraphReconstruction(AttackNodes, REL)$;
```

5. Evaluation

In this section, we first present the evaluation preparation, including the introduction of the dataset, the acquisition of ground truth, and the setting of the evaluation metrics. Our evaluation will be organized around answering the following questions:

- **RQ1:** Can OMNISEC accurately detect attacks and how does it compare to the state-of-the-art?
- **RQ2:** What is the size of the attack graph for OMNISEC reconstruction?
- **RQ3:** What is OMNISEC's end-to-end overhead?
- **RQ4:** How do hyperparameters affect OMNISEC's performance and overhead?

5.1. Evaluation Preparation

We deploy our implementation of OMNISEC on a computer with Intel (R) Core (TM) i9-10900K CPU @ 3.70GHz and 64GB memory. The LLM in the OMNISEC calls the "gpt-3.5-turbo" API from OpenAI ChatGPT [48].

DARPA Dataset. We obtain our experimental datasets from DARPA Transparent Computing [51]. From October 2016 to May 2019, the DARPA TC program has organized five larger scale red and blue adversarial engagement exercises. Different technical teams operate around different operating systems to execute real APT attacks by simulating corporate networks. For the experimental evaluation of

Table 2

Detail of attack scenarios in DARPA datastes.

Datasets	Description	Timestamp Fragment (yyyy-mm-dd HH:MM:SS)	# of Attack Nodes
E3-CADETS-1	Nginx Backdoor with Drakon In-Memory	2018-04-06 00:00:00 - 2018-04-07 00:00:00	75
E3-CADETS-2		2018-04-11 16:36:27 - 2018-04-12 22:24:07	80
E3-THEIA-1	Firefox backdoor with drakon APT in memory	2018-04-10 00:00:00 - 2018-04-11 00:00:00	57
E3-THEIA-2	Browser extension with drakon APT on disk	2018-04-12 10:35:21 - 2018-04-12 14:57:12	65
E5-CADETS	Firefox Drakon APT (Failed)	2019-05-17 00:00:00 - 2019-05-17 11:00:00	11
E5-THEIA	Firefox Drakon APT BinFmt-Elevate Inject	2019-05-15 00:00:00 - 2019-05-16 00:00:00	33

Table 3

Experimental evaluation results of OMNISEC at the node-level.

Datasets	TP	TN	FP	FN	Precision	Recall	Accuracy	F1-score
E3-CADETS-1	74	55956	0	1	1.000	0.987	1.000	0.993
E3-CADETS-2	71	55950	2	9	0.973	0.888	1.000	0.928
E3-THEIA-1	56	112223	0	1	1.000	0.982	1.000	0.991
E3-THEIA-2	60	53982	0	5	1.000	0.923	1.000	0.960
E5-CADETS	8	528,201	0	3	1.000	0.727	1.000	0.842
E5-THEIA	31	157392	13	2	0.705	0.939	1.000	0.805

OMNISEC, we choose the part attack data from CADETS and THEIA in Engagement #3 [52] and #5 [53]. To ensure the fairness of the comparison experiments, we test on the same datasets as state-of-the-art. For example, ThreaTrace [15] and Flash [40] only expose part of the trained weights model in DARPA Engagement #3.

Ground Truth. DARPA Engagement #3 and #5 provide ground truth reports for researchers to label attack nodes. Currently, some studies have manually labeled ground truth to evaluate PIDS performance. For example, Kairos provides supplementary material [39] and Jason et al. [54] publish standardizing ground truth labels. In the evaluation of OMNISEC, we refer to these studies and open-source our ground truth (we publish the uuid of the manually labeled attack nodes)[2]. In contrast to these studies, we label all attack nodes from campaigns implemented by each team (i.e., CADETS and THEIA) at different times (i.e., these teams implemented various attacks at different times, and some open-source PIDSes [15, 40] also chose different evaluation time periods on the same dataset). Table 2 details the 6 attack scenarios we selected from DARPA and reports the number of attack nodes we labeled.

Evaluation Metrics. Since anomalous subgraphs or time windows still require further analysis if the analyst wants to locate the real attack event, we believe that node-level evaluation granularity better reflects the detection performance of PIDSes. We measure *true positives* (TPs), *false positives* (FPs), *true negatives* (TNs) and *false negatives* (FNs). TP refers to nodes that are recognized by OMNISEC as true attacks, FP refers to nodes that OMNISEC recognizes as attack but are not, TN refers to nodes that OMNISEC correctly recognizes as non-attacks, and FN refers to nodes that OMNISEC recognizes as non-attacks but are real attacks.

Table 4

Comparison with the Kairos in terms of window-level detection accuracy.

Datasets	Systems	Precision	Recall	F1-score	# of Alert Node	% Alert Node
E3-CADETS-1	OMNISEC	1.00	1.00	1.00	74	0.1321
	Kairos	0.80	1.00	0.89	221	0.3944
E3-THEIA-1	OMNISEC	1.00	1.00	1.00	56	0.0499
	Kairos	0.80	1.00	0.89	5,525	4.9207
E5-CADETS	OMNISEC	1.00	1.00	1.00	8	0.0015
	Kairos	1.00	1.00	1.00	660	0.1249
E5-THEIA	OMNISEC	0.50	1.00	0.67	44	0.0279
	Kairos	0.67	1.00	0.80	382	0.2426

5.2. Detection Performance

To respond **RQ1**, we simulate OMNISEC to monitor the underlying anomalous behavior of the host in real time and evaluate OMNISEC performance on each dataset. In addition, we selected the SOTA PIDSes Kairos [55], ThreaTrace [15], and Flash [40] for comparison with OMNISEC. The reasons for choosing these studies are as follows: 1) These studies have released their high-quality and complete open-source code for us to reproduce locally. 2) They achieve a fine-grained level of anomalous detection. 3) As Kairos said, other work is closed source or missing key component code.

Table 3 shows the precision, recall, accuracy, and F1-score results for all datasets. We compute these metrics based on node level. From Table 3, we can see that OMNISEC is able to accurately detect most of the attacks and produce fewer false positives. In E5-THEIA, OMNISEC has more obvious FPs. Through our analysis, these FPs are nodes affected by the malicious process “sshd”. That is, when the malicious process “sshd” is labeled as a malicious node by LLM, the node involved in its subsequent rare events is also reconstructed as part of the attack. However, even though the inclusion of FPs affects the accuracy, it does not prevent security analysts from analyzing the reconstructed attack graph.

Comparison Study. Comparing systems fairly with SOTA is difficult due to differences in evaluation protocols. Therefore, we respect the protocols of each system’s evaluation and compare the performance of the systems as fairly as possible. Table 4 and Table 5 show the performance of the OMNISEC against Kairos, ThreaTrace and Flash on the Darpa dataset.

Kairos. OMNISEC uses time windows to compute the evaluation metrics (the generated attack graphs are divided according to time windows), as in Kairos (the authors consider the time window containing the manually labeled ground truth to be anomalous). During the attack reconstruction process, Kairos uses anomalous triples whose reconstruction error exceeds the threshold for performing community discovery. Since Kairos still needs expert knowledge to find the real attack after generating the candidate summary graph, we report the number of anomalous alert nodes in the table. As can be seen from Table 4, excluding E5-THEIA, OMNISEC exhibits comparable or even better performance than Kairos. The reason why OMNISEC exhibits higher FPs in E5-THEIA is as we analyze earlier. Nevertheless, the number of alert nodes reported by OMNISEC is much

[2] https://github.com/Shike-Cheng/PIDS-with-LLM/tree/main/Ground_Truth

Table 5
Comparison with the ThreaTrace and Flash in terms of node-level detection accuracy.

Datasets	Systems	Precision	Recall	F1-score	# of Alert Node	% Alert Node	# of Attack Nodes in Ground Truth
E3-CADETS-2	OMNISEC	0.97	0.89	0.93	73	0.0204	80
	ThreaTrace	0.90	0.99	0.95	20,104	5.6286	12,858
	Flash	0.95	0.99	0.97	13,854	3.8788	
E3-THEIA-2	OMNISEC	1.00	0.92	0.96	60	0.0210	65
	ThreaTrace	0.87	0.99	0.93	28,134	9.8518	25,363
	Flash	0.93	0.99	0.96	27,591	9.6616	

smaller than that of Kairos, and sysadmins can directly analyze the attack graphs reconstructed by OMNISEC without having to spend time sifting through candidate summary graphs. Kairos emphasizes that it does not require any prior knowledge, but we believe that relying solely on learning benign behavior patterns leads to a large number of FPs in the results. Although Kairos uses community discovery algorithms to simplify the detection results into candidate summary graphs, removing FPs requires not only manual analysis of these summary graphs by analysts but also retraining of the model with FPs.

ThreaTrace and Flash. ThreaTrace [15] and Flash [40] can achieve node-level detection. And Flash uses the ground truth published by ThreaTrace and its reported number of malicious nodes is comparable to that of ThreaTrace. As stated by Kairos, authors of ThreaTrace manually mark nodes in the ground truth and their 2-hop ancestors/descendants as anomalous, even if neighboring nodes are not involved in the attack. In the ground truth published by ThreaTrace, there are 12,858 malicious nodes in CADETS and 25,363 malicious nodes in THEIA (more than 100 times the number of nodes we labeled). In particular, 22,250 malicious nodes we find reported by ThreaTrace in E3-THEIA-2 are isolated nodes that OMNISEC is unable to locate without event interactions. In addition, Wang et al. [56] also point out that ThreaTrace and Flash do not specify a data labeling policy or context, and that the number of malicious labels tagged is excessive (e.g., more than 12,000 nodes are tagged as malicious during the 30 hours of CADETS), which is impractical for a real-world SOC. Therefore, to ensure fairness, we do not evaluate these three systems on any evaluation protocol. Instead, we care more about how much the detection results can help analysts reduce manual labour costs. As shown in Table 5, the number of alert nodes in OMNISEC can be far less than ThreaTrace and Flash while ensuring low FNs. In our opinion, the time it takes for sysadmins to find FNs by tracing back the known attack graph is much less than the time it takes to sift out FPs from more than 15K alert nodes on average.

5.3. Reconstruction Performance

The reconstruction of the attack graph not only provides PIDS with the explanation of the attack but also helps security analysts quickly grasp the whole picture of the attack. OMNISEC is able to find all malicious nodes that constitute an attack, and generates the attack graph based on the judgment result of LLM combined with the traceability analysis automatically. In particular, we take all event interactions between malicious nodes as the edges of the attack graph. This is because even if the system generates false alarm nodes, the analyst can rule them out by observing interaction events between the false alarm nodes and real attack nodes. To respond **RQ2**, as shown in Table 6, compared to the original provenance graph, we generate the attack graph to be small (where the edge parsimony reaches 67K times).

Table 6
Size of attack graphs on all DARPA dataset.

Dataset	# of Attack Nodes	# of Attack Edges	# of Total Nodes	# of Total Edges
E3-CADETS-1	74	246	56,031	311,587
E3-CADETS-2	73	295	56,032	323,192
E3-THEIA-1	56	108	112,280	662,882
E3-THEIA-2	60	117	54,047	269,047
E5-CADETS	8	10	528,212	3,897,079
E5-THEIA	44	504	157,438	2,528,278

Table 7
Size of application behavior database on all DARPA datasets. The fourth column shows the size of the database as a percentage of the original dataset.

Dataset	Days (yyyy-mm-dd)	Size of Knowledge Database	
		Database	Database / Original
E3-CADETS	2018/04/02-2018/04/04	24.58MB	0.37%
E3-THEIA	2018/04/03-2018/04/05	33.92MB	0.12%
E5-CADETS	2019/05/08-2019/05/11	250.75MB	0.09%
E5-THEIA	2019/05/08-2019/05/09	20.76MB	0.13%

5.4. End-to-end Overhead

In this section, we focus on the overhead of OMNISEC to response **RQ3**. The overhead of OMNISEC is mainly caused by the following aspects: 1) the storage overhead of the application behavior database and the threat intelligence database; 2) the time overhead of OMNISEC to construct rare paths for the suspicious nodes during attack detection; and 3) the capital overhead of OMNISEC to call gpt-3.5-turbo's API for suspicious nodes judgement.

Storage Overhead. As described in Section 4.3, only the node characteristics from the benign logs and the interaction characteristics between the nodes are stored in the application behavior Database, including the embedding vectors of the node path names, the frequency of interactions between the nodes, and the out-degree and in-degree of the nodes. Table 7 shows the benign days segments selected by OMNISEC on each dataset, the size of the application behavior database, and the size of the database in terms of the original dataset, respectively. As shown in Table 7, the application behavior knowledge base occupies only a tiny portion of the original dataset. This helps the system to significantly reduce the storage overhead. In addition, the threat intelligence database stores the malicious paths as well as path embedding vectors for constructing the attack scene graphs from CTI reports. Currently, we have collected 5,231 CTI reports and constructed 10,532 malicious paths from them, and the database size is 45.27M.

Runtime Overhead. OMNISEC processes the streaming system log, feeds the suspicious nodes and their rare paths to the LLM for judgment. Meanwhile, the main time overhead affecting OMNISEC for real-time detection is imposed by the selection of rare paths. We show in Table 8 the

Table 8
Rare paths are constructed in all datasets at all times. The second column indicates the number of suspicious nodes. The third, fourth and sixth columns denote the minimum and maximum time to find a rare path for a suspicious node, respectively. The fifth column represents the total time to find a rare path for all the suspicious nodes.

Dataset	# of Suspicious Nodes	Min (ms)	Max (s)	SUM (s)	AVG (s)
E3-CADETS-1	438	0.00004	14.33000	310.01427	0.70770
E3-CADETS-2	98	0.00001	11.41969	54.63248	0.55747
E3-THEIA-1	548	0.00001	146.75913	365.64470	0.66723
E3-THEIA-2	131	0.00002	7.72443	34.91193	0.26650
E5-CADETS	9	0.00003	0.00019	0.00208	0.00023
E5-THEIA	913	0.19145	48.59543	59.88906	0.06560

Table 9
The number of rare paths and the total amount spent by OMNISEC on all DARPA datasets.

Dataset	# of Rare Paths	US$ Spent (gpt-3.5-turbo)
E3-CADETS-1	3,775	0.150
E3-CADETS-2	481	0.030
E3-THEIA-1	618	0.100
E3-THEIA-2	831	0.120
E5-CADETS	5	0.001
E5-THEIA	55	0.002

minimum time for OMNISEC to construct a rare path for a suspicious node on each dataset, the maximum time, the total time to construct all rare paths, and the average time to construct a rare path for each suspicious node. From the results in Table 8, we can find that the time for rare path construction is not very much correlated with the number of rare nodes. Upon analysis, we believe that it depends on the complexity of the events in which the suspicious nodes are involved. For example, in E5-THEIA, the types of suspicious nodes are mostly sockets and these nodes are involved in fewer events in the logs. Throughout the experiments, the maximum average time for the system to process a suspicious node is 0.71s, and the maximum time to process all anomalous nodes is 365.6s (less than the maximum time required by Kairos to process a time window, 376.2s). Therefore, we consider this time to be an acceptable time to achieve real-time detection.

Monetary Expenses. To the best of our knowledge, OMNISEC is the first intrusion detection system to apply LLM at the provenance graph level. OMNISEC calls the API of OpenAI's gpt-3.5-turbo for suspicious node research. According to OpenAI's official pricing standards, the input pricing of gpt-3.5-turbo is $0.5 / M, and the output pricing is $1.5 / M (1 M = 1 million token). Upon analysis, the monetary overhead of OMNISEC's inputs is mainly brought about by the number of rare paths of the suspicious nodes (although benign and malicious paths matched from the knowledge database also affect the number of tokens, this is also mainly affected by the number of rare paths). We restrict the output of the LLM to "benign" or "malicious" in the input prompt. We count the number of rare paths in each dataset and their corresponding monetary overheads in Table 9. As shown in Table 9, the money overhead is proportional to the number of rare paths. In addition, we believe that users can reduce the number of tokens by continuously optimizing the prompt, which leads to less overhead.

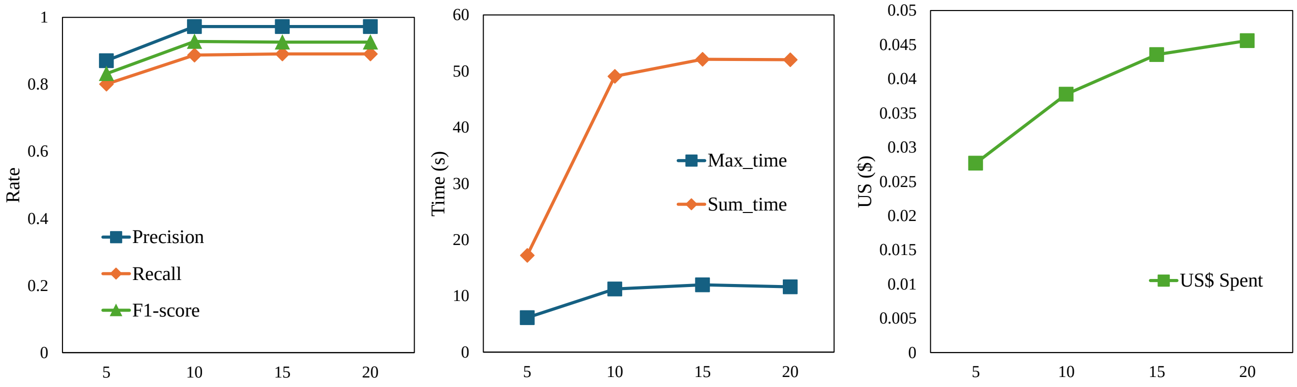
5.5. Hyperparameter Impact on Performance and Overhead

The number of neighbor hops of a suspicious node is the key to the performance of OMNISEC. To response **RQ4**, Figure 4-(a) shows the effect of the number of neighbor nodes k_1 on the detection performance of the system on E3-CADETS-2. From the experimental results, it is clear that the detection performance improves significantly as we increase the number of neighboring nodes. However, after k_1 reaches 10, the performance improvement is no longer significant. This is due to the fact that most of the nodes in the dataset have fewer than 15 neighbor nodes. when k_1 is increased above 15 there is hardly any better performance. Both Figure 4-(b) and Figure 4-(c) illustrate the effect of parameter k_1 on the system overhead. As the number of neighbor nodes grows, the rare path finding time increases. This is because the growth of neighbor nodes increases the time complexity of the path algorithm search. Secondly, the number of neighbor nodes equally affects the length of rare path construction, which in turn increases the token spend. Finally, we find $k_1 = 10$ to be ideal among all datasets. Similarly, we get the optimal $k_2 = 10$ and $K = 5$.

6. Discussion

In this work, we approach from the perspective of knowledge modeling. We explore the feasibility and methodological approaches of integrating large language models into host-based intrusion detection systems. We analyzed the challenges faced by existing PIDSes in practical applications, including the dependence of rule-based methods on predefined rules, the demand for high-quality labeled data by supervised learning methods, and the difficulty of anomaly detection methods in distinguishing between normal variations and real attack behaviors. We propose an insight: leveraging LLM to facilitate multi-source security knowledge modeling and reinforce the "last line of defense" in threat detection. We also validate this through the application of LLM in threat detection. Our practice also provides a possibility for applications of LLM in PIDSes. However, there are still some future challenges for research in this direction.

LLM Hallucination. When a LLM is presented with a question that is not supported by sufficient facts, it may produce false or misleading outputs when answering it (i.e., the "LLM hallucination" [57]). In threat detection, hallucinations are often caused by the fact that we do not give LLM sufficient external threat knowledge (or sufficiently fine-tuned training datasets). In real threat scenarios, unfounded answers from LLM may result in a large number of false alarms. Therefore, to address such challenges, we need to enrich the knowledge database (for local models, we need to introduce diverse datasets during model training) and



(a) Detection performance (b) Runtime Overhead (c) Monetary Expenses

Figure 4: The performance (detection performance, runtime overhead, and monetary expenses) of OMNISEC on E3-CADETS-2 with varying k_1.

provide as much relevant knowledge as possible to enhance the judgment of LLM.

LLM Poisoning. Attack escape is a strategy used by an attacker to avoid the surveillance of the detection system. Thus, an attacker may try to bypass the detection system by confusing LLM with adversarial samples. In our scenario, there are two possible ways for an attacker to poison. The first type of poisoning is when an attacker poisons a continuously updated benign behavior knowledge base by performing some low and slow action (suspicious but not triggering an alert). Thus, we need update the knowledge base in a trusted environment to avoid poisoning. Another form of poisoning is a new threat called "retrieval poisoning" [58] , targeting LLM-powered applications, which exploits the design features of LLM application frameworks to perform imperceptible attacks during RAG. These authors suggest two possible defenses and point out developing more effective defense mechanisms remains a critical need.

LLM Overhead. The computational and storage requirements of LLM are very high. When we use online LLM for real-time detection, we need to consider not only the network latency problem, but also the resource overhead caused by the number of tokens fed into the LLM. When we use offline LLM, we need to consider the training cost of local base LLM and the problem of insufficient resources or high latency during real-time detection. To address such issues, we can use distillation models (small models) to help us reduce the computational requirements. For example, in our practice, the selection of suspicious nodes and rare paths in the scoring system can be replaced by small models. In addition, small models can also be used to help us generate the best knowledge prompts.

Data Privacy and Compliance. Threat detection typically involves large amounts of sensitive data, such as user activity logs, system configurations, etc. When using LLM, data transfer and storage risks may be involved, which are especially evident in cloud-based models. Therefore, to ensure that models and data are stored and processed in compliance with relevant privacy regulations, we should try to deploy models locally or anonymize data to prevent sensitive information leakage.

7. Related Work

In this section, we summarize and analyze the existing PIDSes into two categories (heuristic-based and learning-based). Additionally, to our knowledge, OMNISEC is the first to apply LLM to PIDS, and research on LLM in other security fields has also provided us with inspiration for future improvements.

Heuristic-based Instrusion Detection. Holmes [8] matches rules based on the information flow between low-level entities in the system according to the TTP patterns in the ATT&CK framework and constructs high-level scenario graphs (HSGs) to identify attack behaviors. RapSheet [11] also designs ATT&CK behavior matching rules to construct tactical provenance graphs (TPGs) for identifying causally related threat behavior sequences. POIROT [9] constructs query graphs based on the correlation of CTI and models threat detection as a graph matching problem between query graphs and provenance graphs. APTSHIELD [50] designs process and file labels and their propagation rules to achieve real-time attack response and alerting. Sleuth [10] employs label-based attack detection and reconstruction techniques. Unlike these systems, OMNISEC does not require fixed rule templates and can detect unknown threats by utilizing the information in the provenance graph.

Learning-based Instrusion Detection. These methods can generally be divided into supervised learning and unsupervised learning. Supervised learning methods identify the characteristics of attack behaviors by training on large amounts of labeled data. ATLAS [12] trains sequence-based learning models to establish key patterns of attack and non-attack behaviors, identifies nodes with attack symptoms, and thus discovers more attack nodes. TREC [59] uses neural networks for few-shot learning to identify APT tactics/techniques.Unsupervised learning methods identify abnormal events that deviate from the distribution by modeling normal system behavior. Kairos [17] constructs an intrusion detection framework for full-system provenance data from four dimensions: scope, attack-agnostic, timeliness, and attack reconstruction, and is capable of detecting and reconstructing complex attacks without any prior knowledge. Flash [40] effectively encodes the semantic and structural attributes of nodes by integrating a graph neural network-based context encoder and Word2Vec embeddings, generating high-quality node embeddings. ThreaTrace [15] detects host-based node-level threats through a multi-model framework based on GraphSAGE. However, as shown in Section 5.2, these methods have certain limitations in terms of detection granularity and label management, which can still lead to false positives.

Applications of LLM in the field of security. RAAD-LLM [60] proposes an adaptive anomaly detection framework that integrates RAG with large language models, capable of dynamically adapting to changes in normal states without fine-tuning and enhancing anomaly detection performance in time series by incorporating multimodal semantic information. ShieldGPT [61] presents an LLM-based DDoS mitigation framework that can generate interpretable attack detection and response strategies. CmdCaliper [62] introduces a command-line semantic embedding model that detects malicious commands by combining pairs of similar commands generated by LLMs. Patil et al. [63] use LLMs to detect zero-day vulnerabilities in cloud networks. APT-LLM [64] captures anomalous behavioral patterns by combining LLMs with autoencoders for semantic embedding modeling. LocalIntel [65] leverages large language models in conjunction with global threat intelligence and local knowledge bases to generate customized threat intelligence and mitigation strategies for organizations. Unlike the aforementioned works, OMNISEC integrates large language models with external knowledge bases. Through a retrieval-enhanced prompting mechanism, it not only enables anomaly detection in the provenance graph but also supports the automated reconstruction and tracking of attack paths.

8. Conclusion

Addressing the issues of poor generalization ability, high false alarm rates, and high costs of manual analysis in existing PIDSes under complex scenarios, this paper proposes OMNISEC, an intrusion detection system that integrates LLMs and external security knowledge bases. OMNISEC achieves precise identification of system abnormal behaviors and automatic reconstruction of attack paths by combining lossless compression, knowledge base construction, and retrieval-enhanced prompting mechanisms. By introducing the reasoning capabilities of LLMs and joint modeling with external knowledge, OMNISEC significantly improves detection performance while ensuring interpretability. Experimental results show that OMNISEC achieves performance superior to state-of-the-art methods on public benchmark datasets.

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References

[1] Kai Xing, Aiping Li, Rong Jiang, and Yan Jia. A review of apt attack detection methods and defense strategies. In *2020 IEEE Fifth International Conference on Data Science in Cyberspace (DSC)*, pages 67–70. IEEE, 2020.

[2] Meicong Li, Wei Huang, Yongbin Wang, Wenqing Fan, and Jianfang Li. The study of apt attack stage model. In *2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS)*, pages 1–5. IEEE, 2016.

[3] Bill Whitaker. Solarwinds: How russian spies hacked the justice, state, treasury, energy and commerce departments. *CBS News, February*, 14, 2021.

[4] Jun Zengy, Xiang Wang, Jiahao Liu, Yinfang Chen, Zhenkai Liang, Tat-Seng Chua, and Zheng Leong Chua. Shadewatcher: Recommendation-guided cyber threat analysis using system audit records. In *2022 IEEE symposium on security and privacy (SP)*, pages 489–506. IEEE, 2022.

[5] Wajih Ul Hassan et al. Nodoze: Combatting threat alert fatigue with automated provenance triage. In *NDSS*, 2019.

[6] Wajih Ul Hassan et al. This is why we can't cache nice things: Lightning-fast threat hunting using suspicion-based hierarchical storage. In *ACSAC*, pages 165–178, 2020.

[7] Shiqing Ma et al. Protracer: Towards practical provenance tracing by alternating between logging and tainting. In *NDSS*. Internet Soc, 2016.

[8] Sadegh M Milajerdi et al. Holmes: real-time apt detection through correlation of suspicious information flows. In *S&P*, pages 1137–1152. IEEE, 2019.

[9] Sadegh M Milajerdi et al. Poirot: Aligning attack behavior with kernel audit records for cyber threat hunting. In *CSS*, pages 1795–1812, 2019.

[10] Md Nahid Hossain et al. {SLEUTH}: Real-time attack scenario reconstruction from {COTS} audit data. In *USENIX*, pages 487–504, 2017.

[11] Wajih Ul Hassan et al. Tactical provenance analysis for endpoint detection and response systems. In *S&P*, pages 1172–1189. IEEE, 2020.

[12] Abdulellah Alsaheel et al. {ATLAS}: A sequence-based learning approach for attack investigation. In *USENIX*, pages 3005–3022, 2021.

[13] He Zhang, Xingrui Yu, Peng Ren, Chunbo Luo, and Geyong Min. Deep adversarial learning in intrusion detection: A data augmentation enhanced framework. *arXiv preprint arXiv:1901.07949*, 2019.

[14] Zhendong Wang, Zeyu Li, Junling Wang, and Dahai Li. Network intrusion detection model based on improved byol self-supervised learning. *Security and Communication Networks*, 2021(1):9486949, 2021.

[15] Su Wang et al. Threatrace: Detecting and tracing host-based threats in node level through provenance graph learning. *TIFS*, 17:3972–3987, 2022.

[16] Fan Yang et al. {PROGRAPHER}: An anomaly detection system based on provenance graph embedding. In *USENIX*, pages 4355–4372, 2023.

[17] Zijun Cheng, Qiujian Lv, Jinyuan Liang, Yan Wang, Degang Sun, Thomas Pasquier, and Xueyuan Han. Kairos: Practical intrusion detection and investigation using whole-system provenance. In *2024 IEEE Symposium on Security and Privacy (SP)*, pages 3533–3551. IEEE, 2024.

[18] Xueyuan Han et al. Unicorn: Runtime provenance-based detector for advanced persistent threats. *arXiv preprint arXiv:2001.01525*, 2020.

[19] Emaad Manzoor et al. Fast memory-efficient anomaly detection in streaming heterogeneous graphs. In *SIGKDD*, pages 1035–1044, 2016.

[20] Yulai Xie et al. Pagoda: A hybrid approach to enable efficient real-time provenance based intrusion detection in big data environments. *TDSC*, 17(6):1283–1296, 2018.

[21] Qi Wang et al. You are what you do: Hunting stealthy malware via data provenance analysis. In *NDSS*, 2020.

[22] Weiyu Zhang, Qingbo Yang, and Yushui Geng. A survey of anomaly detection methods in networks. In *2009 International Symposium on Computer Network and Multimedia Technology*, pages 1–3. IEEE, 2009.

[23] Noam Ben-Asher and Cleotilde Gonzalez. Effects of cyber security knowledge on attack detection. *Computers in Human Behavior*, 48:51–61, 2015.

[24] Akul Goyal et al. Sometimes, you aren't what you do: Mimicry attacks against provenance graph host intrusion detection systems. In *NDSS*, 2023.

[25] Jie Zhang, Haoyu Bu, Hui Wen, Yongji Liu, Haiqiang Fei, Rongrong Xi, Lun Li, Yun Yang, Hongsong Zhu, and Dan Meng. When llms meet cybersecurity: A systematic literature review. *Cybersecurity*, 8(1):1–41, 2025.

[26] Thomas Quinn and Olivia Thompson. Applying large language model (llm) for developing cybersecurity policies to counteract spear phishing attacks on senior corporate managers. 2024.

[27] Farzad Nourmohammadzadeh Motlagh, Mehrdad Hajizadeh, Mehryar Majd, Pejman Najafi, Feng Cheng, and Christoph Meinel. Large language models in cybersecurity: State-of-the-art. *arXiv preprint arXiv:2402.00891*, 2024.

[28] Ismayil Hasanov, Seppo Virtanen, Antti Hakkala, and Jouni Isoaho. Application of large language models in cybersecurity: A systematic literature review. *IEEE Access*, 2024.

[29] Zhenyuan Li et al. Threat detection and investigation with system-level provenance graphs: a survey. *Computers & Security*, 106:102282, 2021.

[30] Thomas E Daniels and Eugene H Spafford. A network audit system for host-based intrusion detection (nashid) in linux. In *Proceedings 16th Annual Computer Security Applications Conference (ACSAC'00)*, pages 178–187. IEEE, 2000.

[31] Thomas Pasquier et al. Practical whole-system provenance capture. In *SOCC*, pages 405–418, 2017.

[32] Humza Naveed, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian. A comprehensive overview of large language models. *arXiv preprint arXiv:2307.06435*, 2023.

[33] Jiacen Xu et al. Autoattacker: A large language model guided system to implement automatic cyber-attacks. *arXiv preprint arXiv:2403.01038*, 2024.

[34] Jiangyi Deng, Xinfeng Li, Yanjiao Chen, Yijie Bai, Haiqin Weng, Yan Liu, Tao Wei, and Wenyuan Xu. Raconteur: A knowledgeable, insightful, and portable llm-powered shell command explainer. *arXiv preprint arXiv:2409.02074*, 2024.

[35] Junjielong Xu, Ziang Cui, Yuan Zhao, Xu Zhang, Shilin He, Pinjia He, Liqun Li, Yu Kang, Qingwei Lin, Yingnong Dang, et al. Unilog: Automatic logging via llm and in-context learning. In *Proceedings of the 46th ieee/acm international conference on software engineering*, pages 1–12, 2024.

[36] Aoxiao Zhong, Dengyao Mo, Guiyang Liu, Jinbu Liu, Qingda Lu, Qi Zhou, Jiesheng Wu, Quanzheng Li, and Qingsong Wen. Logparser-llm: Advancing efficient log parsing with large language models. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 4559–4570, 2024.

[37] Daipeng Cao and W Jun. Llm-cloudsec: Large language model empowered automatic and deep vulnerability analysis for intelligent clouds. In *IEEE INFOCOM 2024-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pages 1–6. IEEE, 2024.

[38] Enes Altinisik et al. Provg-searcher: A graph representation learning approach for efficient provenance graph search. In *SIGSAC*, pages 2247–2261, 2023.

[39] Zijun Cheng. Kairos: Practical intrusion detection and investigation using whole system provenance (supplementary material, 2023. https://github.com/ProvenanceAnalytics/kairos/blob/main/supplementary-material.pdf.

[40] Mati Ur Rehman et al. Flash: A comprehensive approach to intrusion detection via provenance graph representation learning. In *S&P*, pages 139–139. IEEE, 2024.

[41] Patrick Lewis et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *NeurIPS*, 33:9459–9474, 2020.

[42] Windows event tracing.

[43] The linux audit daemon.

[44] Tiantian Zhu et al. General, efficient, and real-time data compaction strategy for apt forensic analysis. *TIFS*, 16:3312–3325, 2021.

[45] Zhenyuan Li et al. Attackg: Constructing technique knowledge graph from cyber threat intelligence reports. In *ESORICS*, pages 589–609, 2022.

[46] Kiavash Satvat et al. Extractor: Extracting attack behavior from threat reports. In *EuroS&P*, pages 598–615. IEEE, 2021.

[47] Wenrui Cheng et al. Crucialg: Reconstruct integrated attack scenario graphs by cyber threat intelligence reports, 2024.

[48] OpenAI. Openai: Introducing chatgpt., 2023. https://openai.com/blog/chatgpt.

[49] Yunfan Gao et al. Retrieval-augmented generation for large language models: A survey. *arXiv preprint arXiv:2312.10997*, 2023.

[50] Tiantian Zhu, Jinkai Yu, et al. Aptshield: A stable, efficient and real-time apt detection system for linux hosts. *TDSC*, 2023.

[51] Darpa transparent computing engagement, 2020.

[52] Darpa transparent computing engagement #3, 2018.

[53] Darpa transparent computing engagement #5, 2020.

[54] Jason Liu et al. Reapr: Recovery every attack process. https://bitbucket.org/sts-lab/reapr-ground-truth, 2023.

[55] Zijun Cheng et al. Kairos: Practical intrusion detection and investigation using whole-system provenance. In *S & P*, pages 3533–3551, 2024.

[56] Lingzhi Wang, Xiangmin Shen, Weijian Li, Zhenyuan Li, R Sekar, Han Liu, and Yan Chen. Incorporating gradients to rules: Towards lightweight, adaptive provenance-based intrusion detection. *arXiv preprint arXiv:2404.14720*, 2024.

[57] Joshua Maynez et al. On faithfulness and factuality in abstractive summarization. In *ACL*, pages 1906–1919, 2020.

[58] Quan Zhang et al. Human-imperceptible retrieval poisoning attacks in llm-powered applications. In *FSE*, pages 502–506, 2024.

[59] Mingqi Lv et al. Trec: Apt tactic/technique recognition via few-shot provenance subgraph learning. In *CCS*, pages 139–152, 2024.

[60] Alicia Russell-Gilbert. *RAAD-LLM: Adaptive Anomaly Detection Using LLMs and RAG Integration*. PhD thesis, Mississippi State University, 2025.

[61] Tongze Wang, Xiaohui Xie, Lei Zhang, Chuyi Wang, Liang Zhang, and Yong Cui. Shieldgpt: An llm-based framework for ddos mitigation. In *Proceedings of the 8th Asia-Pacific Workshop on Networking*, pages 108–114, 2024.

[62] Sian-Yao Huang, Cheng-Lin Yang, Che-Yu Lin, and Chun-Ying Huang. Cmdcaliper: A semantic-aware command-line embedding model and dataset for security research. *arXiv preprint arXiv:2411.01176*, 2024.

[63] Kapil Patil and Bhavin Desai. Leveraging llm for zero-day exploit detection in cloud networks. *Asian American Research Letters Journal*, 1(4), 2024.

[64] Sidahmed Benabderrahmane, Petko Valtchev, James Cheney, and Talal Rahwan. Apt-llm: Embedding-based anomaly detection of cyber advanced persistent threats using large language models. *arXiv preprint arXiv:2502.09385*, 2025.

[65] Shaswata Mitra, Subash Neupane, Trisha Chakraborty, Sudip Mittal, Aritran Piplai, Manas Gaur, and Shahram Rahimi. Localintel: Generating organizational threat intelligence from global and local cyber knowledge. In *International Symposium on Foundations and Practice of Security*, pages 63–78. Springer, 2025.