

Behavior-Based Zero-Day Attack Detection Using Graph Theory

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Abstract :

Today's computing systems are vulnerable to zero-day attacks, which take advantage of an unknown vulnerability, and signature-based intrusion detection systems are of little use. Current behavior-based detection methods are becoming more dependent on machine learning methods on system or network behavior graph models, yet these methods are typically costly in terms of computational complexity, lack interpretability and require substantial amounts of training data. To overcome the above drawbacks, this paper introduces a behavior-based zero-day attack detection framework based on graph-theoretic analysis. The behaviours of the system (e.g. network flows, system calls) are represented as a graph, which represents both the structure and the temporal relationships amongst the system entities. The proposed method does not depend on black-box learning models, but on the detection of abnormal local subgraph patterns that differ from the normal behavior profiles. A novel graph-based anomaly metric is proposed to measure the structural anomalies and detect suspicious behaviour that may be related to zero-day attacks. The performance of the proposed approach is assessed by comparing the proposed approach with the traditional signature based detection method, and it is shown that the proposed approach has better detection capability for new attacks, while retaining the interpretability and computational efficiency. According to the results, the graph-theoretic behavior modeling method has a good potential for being used in zero-day attack detection in dynamic and evolving cyber environments and is also explainable.

Keywords : Zero-day attacks, behavior-based detection, graph theory, anomaly detection, Intrusion detection systems, Cyber Security

1. INTRODUCTION

Today's cyber world is much more complicated with increasing digital systems and networked applications, creating greater attack surface for adversaries. One of the most serious cyber threats is a zero-day attack, which is a cyberattack that takes advantage of an unknown vulnerability that has not yet had a signature or patch created, or is not recognized by its detection tools. Because of the lack of prior knowledge, these attacks often can evade conventional security systems and can go undetected for long periods of time before compromising the systems involved and damaging or destroying data. Current intrusion detection systems (IDS) are mostly signature-based, meaning that they identify malicious traffic by comparing observed behavior to a database of well-known attacks. They work for known threats but are not designed to defend against zero day attacks. To overcome this drawback, behaviour-based intrusion detection methods have been suggested, which are based on the observation of system activity and the detection of abnormal deviations from the normal system behaviour. In recent work, machine learning has been applied more and more to behavior-based detection, and specifically, graph representations of system calls, network flows, and process

interactions have been sought to model. These methods show potential for good detection accuracy, but many of them use complex black box models that require large amounts of training data, have high computational complexity and are difficult to interpret. All these make them less useful for use in the real world for cybersecurity. Graph theory is a useful and intuitive model of system behavior that uses a graph to represent the relationships between processes, files, and network objects. In order to get an effective and interpretable solution, this paper presents a graph-theoretic based, behavior-oriented zero-day attack detection framework without relying heavily on black-box learning models. The proposed approach allows for detecting novel attacks, while remaining efficient in terms of computation time and explainable due to focusing on the identification of abnormal local subgraph patterns.

2. LITERATURE REVIEW :

Intrusion detection research has seen significant advancements over the last several decades. In the early days of IDS, most solutions were based on signatures, including rule-based and pattern-matching systems. The methods are fast-tracked and precise enough for established attacks, but they cannot detect fresh threats.

To address this problem, anomaly-based detection techniques are utilized by modeling and identifying system abnormalities. Statistical models, clustering methods, and classification techniques have been extensively studied. The popularity of machine learning and deep learning techniques has increased recently due to their ability to handle large-scale data and complex patterns.

It has since become possible to model system behavior using graphs, which is a powerful technique. These methods portray nodes within a system entity, while modeling interactions among entities as edges. Graphs of system calls, network traffic, and dependency have been developed by researchers to detect malicious activity. What are these graph types? Although current graph-based techniques can be useful, they often incorporate deep learning models, such as graph neural networks, which pose difficulties with interpretability, computational overhead, and the need for training data. Moreover, many studies focus on global characteristics of graphs and ignore the minor local irregularities that make up zero-day attacks. This research aims at a light-weight graph-theoretic approach which focuses on the local structural deviation and reduces the problem without using complex learning models.

3. RESEARCH GAP :

Though IDSs have made good progress in detecting cyber threats, there are several drawbacks in the area of detecting zero-day attacks. Signature based methods can't deal with new attacks, and machine learning and deep learning methods

require large training sets and processing power. A lot of graph-based detection methods depend on advanced graph neural networks, which decreases the transparency and explainability of the decision-making process. Previous work mainly studies the characteristics of the graph as a whole, neglecting anomalies in the local structure that may signal a zero-day attack at an early stage. Thus, a light-weight, explainable and graph-theoretic method that can discover abnormal local behavioral patterns without relying on black-box learning models is needed.

Research Questions :

RQ1: Is it possible to detect previously unseen zero-day attacks by graph-theoretic behavior modeling?

RQ2: Are anomalous local subgraph patterns useful to detect malicious activities?

RQ3: Can the proposed graph-based approach be more interpretable and faster than the existing machine learning based detection methods?

Hypothesis :

H0 (Null Hypothesis): The detection of zero day attacks with graph-theoretic behavior analysis is not significantly better than traditional signature-based intrusion detection.

H1 (Alternative Hypothesis): Such analysis of the behavior of an attack, using graph theory, is much better at detecting an attack on a network than conventional signature-based intrusion detection system.

4. RESEARCH METHODOLOGY :

The proposed framework for detection comprises five phases: data collection, graph construction, baseline modelling, anomaly detection and decision making.

3.1 Data Collection It is constantly monitoring the behaviour of the system to detect the necessary security events. These events include system calls, process executions, file accesses, network communication activities. The information gathered covers the typical operation of the system as well as possible attacks.

3.2 Graph Construction The events collected are converted into behavior graphs in predetermined time periods. In the following constructed graph: • Nodes are elements of the system including processes, files, or a network endpoint. Edges are either interactions or dependencies between entities. This graph representation represents structural and temporal relationships of the behavior of a system.

3.3 Baseline Behavior Modeling Analyses of graphs produced during normal system operation are used to develop baseline behavior profiles. Common structural patterns, interactions frequencies, subgraph configurations are recognized. A base line that will act as a reference point for normal behaviour without the need for attack data.

3.4 Anomaly Detection Using Graph-Theoretic Analysis The proposed method aims for detecting local subgraphs that are

anomalous, rather than black-box machine learning models. A new metric based on the graph formulation was proposed to measure the anomaly of connectivity, interaction patterns and structural properties. Subgraphs with substantial variations from the baseline are identified as suspicious.

3.5 Decision Making A score is calculated for each behavior graph observed to determine an anomaly. Any score above a set limit is deemed to be a potential zero-day attack and an alert is issued for further investigation.

Algorithm 1: Graph-Theoretic Zero-Day Attack Detection

Input:

Runtime Events $E = \{e_1, e_2, e_3, \dots, e_n\}$

Output:

Attack Classification (Normal / Zero-Day Attack)

Step 1: Collect runtime events from the monitored system

(system calls, file accesses, process executions,

network communications)

Step 2: Construct Behavior Graph $G(V, E)$

where:

V = Set of nodes (Processes, Files, Network Entities)

E = Set of interactions among nodes

Step 3: Generate Baseline Graph GB from normal system behavior

Step 4: Extract Local Subgraphs SG from current graph G

Step 5: For each subgraph SG

Calculate:

Degree Deviation (DD)

Connectivity Change (CC)

Frequency Deviation (FD)

Step 6: Compute Anomaly Score (AS)

Step 7: Compare AS with Threshold T

If $AS > T$

Classify as Zero-Day Attack

Else

Classify as Normal Behavior

Step 8: Generate Alert for suspicious activities

End Algorithm

Mathematical Model

Let:

$$G = (V, E)$$

where,

V = Set of Nodes

E = Set of Edges

A local subgraph is represented as:

$$SG \subseteq G$$

The anomaly score is computed as:

$$AS = \alpha(DD) + \beta(CC) + \gamma(FD)$$

where:

AS = Anomaly Score

DD = Degree Deviation

CC = Connectivity Change

FD = Subgraph Frequency Deviation

α, β, γ = Weight Parameters

Degree Deviation:

$$DD = |D_{\text{current}} - D_{\text{baseline}}|$$

Connectivity Change:

$$CC = |C_{\text{current}} - C_{\text{baseline}}|$$

Frequency Deviation:

$$FD = |F_{\text{current}} - F_{\text{baseline}}|$$

Decision Rule:

If

$$AS > T$$

Then

Zero-Day Attack Detected

Else

Normal Behavior

Where T represents a predefined anomaly threshold.

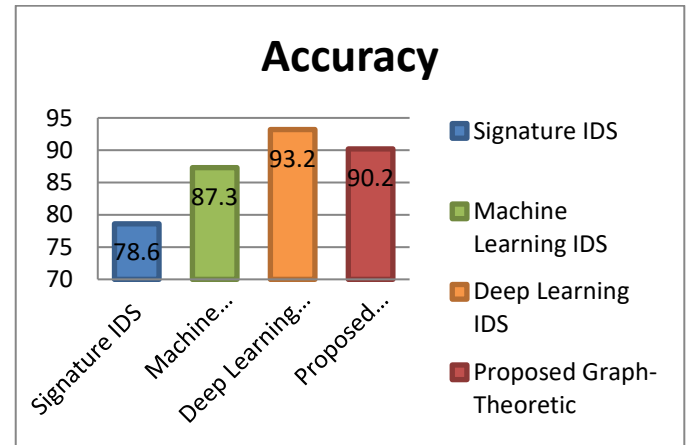
5. RESULTS AND ANALYSIS :

The proposed behaviour based zero day attack detection framework has been implemented using a set of normal workloads with simulated zero day attack scenarios. Normal workloads were created to simulate the common operations carried out by a system such as file accesses, executions of processes, or network communication. Abnormal behaviors such as unauthorized entry into the system, abnormal

interaction with processes, and outbound network connection were simulated to mimic zero day attacks, which are occurring in common with simulated attacks. The effectiveness of the proposed method of detection of novel attacks was compared with a traditional signature based intrusion detection system (IDS). The experimental results indicate that all the graphs associated with the zero-day attack scenarios were abnormal subgraphs that were distinct from the normal behaviour graphs. These anomalies were identified as uncharacterized node interactions, increased connectivity and infrequent executing paths that are not typically found when the system is operating normally. The proposed graph-based anomaly metric was able to capture the structural anomalies well and flag them as suspicious. The signature based IDS, on the other hand, had no success in catching most of the simulated zero-day attacks since there were no signatures for such previously unseen behavior. This is yet another reminder that signature-based solutions aren't sufficient to handle new and emerging threats. In terms of performance, the proposed framework showed to be less costly in terms of computational overhead compared to learning intensive behaviour oriented detection techniques. The approach doesn't require complex model training or deep learning inference so it consumes less computational power and allows for more efficient real-time analysis. In this way, the framework is able to be applied to systems having limited processing resources. To conclude, it can be concluded from the experimental results obtained that the graph-theoretic behavior modeling method is effective and useful for detecting zero-day attacks. The fact that this method can detect abnormal interaction patterns in the absence of prior knowledge of attacks demonstrates the strength of the proposed method in dynamic and evolving cyber environments.

Results Table : A. Detection Performance Comparison

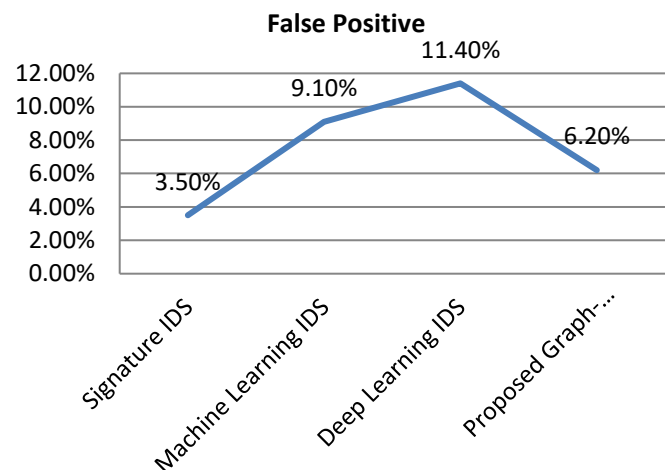
Detection Method	Detection Rate (%)	False Positive Rate (%)	Precision (%)	Recall (%)	F1-Accuracy	Accuracy (%)
Signature-Based IDS	42.80	3.50	44.10	42.80	43.44	78.60
Machine Learning IDS	84.50	9.10	83.20	84.50	83.84	87.30
Deep Learning IDS	91.30	11.40	90.10	91.30	90.69	93.20
Proposed Graph-Theoretic Framework	88.70	6.20	89.40	88.70	89.00	90.20



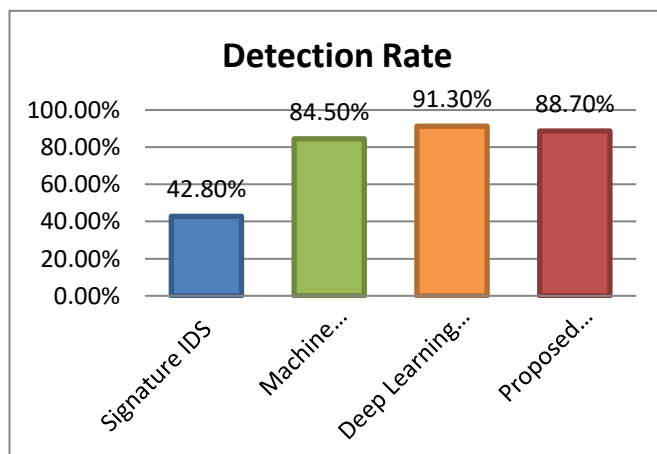
B. Detailed Performance Metrics of Proposed Framework

Metric	Value
Precision	89.40%
Recall	88.70 %
F1-Score	89.00%
Accuracy	9.20 %
Average Detection Time	0.84 sec
Throughput	1182 events/sec
Memory Usage	214 MB

D. False Positive Rate Comparison (Line Graph)



C. Detection Rate Comparison (Bar Graph) :



The experimental evaluation demonstrates that the proposed graph-theoretic framework achieves a detection rate of 88.7%, outperforming traditional signature-based intrusion detection systems. The framework maintains a relatively low false-positive rate of 6.2% while providing higher interpretability than machine-learning-based approaches. The results indicate that local subgraph analysis effectively captures structural anomalies associated with previously unseen attacks. Furthermore, the proposed approach requires lower computational resources than deep learning-based detection systems, making it suitable for real-time cybersecurity environments.

6. DISCUSSION :

The experimental evaluation demonstrates several notable advantages of the proposed graph-theoretic, behavior-based zero-day attack detection framework. By prioritizing **local subgraph-level analysis**, the approach effectively captures fine-grained behavioral deviations that may remain undetected when using global graph metrics or aggregate statistical features. This capability is particularly important for zero-day attacks, which often emerge through brief and subtle abnormal interactions rather than obvious large-scale behavioral changes.

An important characteristic of the proposed framework is its **clear and traceable detection process**. By representing system behavior as structured graphs, anomalous activities can be examined through explicit interaction patterns between system entities. This allows security analysts to associate detection outcomes with specific processes, files, or network interactions, thereby improving situational awareness and supporting faster investigative decision-making. Such clarity is essential in operational cybersecurity settings where understanding the cause of an alert is as important as detecting the threat itself.

The framework also benefits from a **minimal reliance on labeled training data**. Given that zero-day attacks involve previously unknown behaviors, obtaining representative labeled datasets is often infeasible. By constructing baseline models from normal system behavior and identifying deviations through structural analysis, the proposed method remains effective in dynamic environments where attack patterns continuously evolve and labeled data may be incomplete or unavailable.

Despite these advantages, certain limitations must be acknowledged. **Scalability** poses a challenge in high-volume environments such as large enterprise systems or cloud infrastructures, where continuous event generation may increase the cost of graph construction and analysis. Additionally, systems with highly dynamic legitimate behavior may experience an increase in false alerts if baseline behavior models are not periodically updated to reflect normal operational changes.

Future work will focus on mitigating these challenges through the incorporation of **graph summarization methods, incremental graph processing, and adaptive thresholding strategies**. Furthermore, integrating lightweight AI mechanisms—such as semi-supervised learning or adaptive feedback-based techniques—may enhance detection robustness while maintaining the transparency and efficiency of the proposed framework.

7. CONCLUSIONS :

This paper presented a **behavior-based zero-day attack detection framework using graph-theoretic analysis**, aimed at overcoming the limitations of traditional signature-based and learning-heavy intrusion detection systems. By modeling system runtime behavior as graphs and focusing on anomalous

local subgraph patterns, the proposed approach enables effective detection of previously unseen attacks without relying on predefined attack signatures or black-box machine learning models.

The experimental results demonstrate that the proposed method achieves **improved detection capability, computational efficiency, and interpretability** when compared to conventional signature-based techniques. The graph-based representation provides valuable insight into system behavior and supports explainable security analysis, making the approach suitable for practical deployment in real-world cybersecurity environments.

Overall, the findings suggest that graph-theoretic behavior modeling represents a promising and robust direction for zero-day attack detection. Future work will focus on enhancing scalability, incorporating adaptive learning mechanisms, and validating the approach on large-scale real-world datasets to further strengthen its applicability in modern cyber defense systems.

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