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STATISTICAL METHOD AND GRAPH THEORY-BASED ALGORITHM FOR DETECTING NETWORK TRAFFIC

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Abstract. With the continuous evolution of cyber threats, robust mechanisms for network traffic analysis and anomaly detection are crucial for maintaining cybersecurity. This paper introduces a novel approach that fuses statistical modeling with graph theory to uncover irregular network behaviors. By conceptualizing network interactions as graph structures and applying advanced statistical analysis, the algorithm detects deviations from typical traffic patterns, significantly boosting the detection of both conventional and novel threats.

Keywords: Network anomaly detection, Graph theory, Statistical modeling, Network security, Traffic analysis, Cybersecurity, Kernel density estimation, Z-score analysis.

Introduction. The ever-growing complexity of modern networks has led to a surge in sophisticated cyber-attacks, underscoring the necessity for innovative detection techniques. Traditional monitoring tools often struggle to adapt to evolving threat landscapes, leaving critical vulnerabilities exposed. This paper proposes a hybrid approach that leverages statistical analysis and graph theory to identify anomalies within network traffic. By modeling data flow as graph structures and applying statistical methods, the algorithm enhances the identification of both subtle and large-scale deviations, offering a proactive defense mechanism against cyber threats.

Methodology.

1 Traffic Data Acquisition and Preprocessing: Traffic data acquisition and preprocessing are critical steps in building an effective anomaly detection framework. Network traffic data is collected from multiple sources, such as packet capture tools (e.g., Wireshark, tcpdump), flow-based systems (e.g., NetFlow, sFlow), and network intrusion detection systems (e.g., Snort, Suricata). The raw traffic data typically includes vast amounts of redundant, irrelevant, or noisy information, which can hinder analysis. To address this, preprocessing involves several stages: packet deduplication to remove repetitive data, protocol parsing to extract relevant fields, and filtering to exclude irrelevant traffic (e.g., broadcast and multicast packets). Noise reduction

techniques, such as applying statistical filters or traffic normalization, ensure the dataset accurately reflects normal and anomalous network behaviors. Additionally, session reassembly and feature extraction are performed to convert raw traffic into structured data suitable for analysis, including metrics like packet size, inter-arrival time, and byte counts. These preprocessing steps ensure the data is clean, consistent, and ready for use in advanced anomaly detection algorithms.

2 Statistical Modeling: Advanced statistical methods, including Kernel Density Estimation (KDE) and Z-score analysis, are leveraged to scrutinize traffic patterns. KDE provides a smooth estimate of data distribution, while Z-score analysis pinpoints outliers that diverge significantly from standard traffic flows.

You are monitoring network traffic to detect anomalies in packet inter-arrival times (the time between successive packets reaching a server). A typical pattern shows that inter-arrival times follow a normal distribution with a mean (μ – mu) of 2 milliseconds (ms) and a standard deviation (σ – sigma) of 0.5 ms.

Step-by-step Z-score analysis:

2.1 Data collection: Monitor network traffic over a period and record the inter-arrival times of packets. Assume the observed data includes these values (in milliseconds): 2.1, 1.9, 2.3, 1.8, 2.0, 5.0, 1.7, 2.2, 2.0, 0.5, 2.1, 1.9, 2.3, 1.8, 2.0, 5.0, 1.7, 2.2, 2.0, 0.5.

2.2 Calculate the Z-score for each data point: The Z-score is calculated using the following formula:

$$Z\frac{(x-\mu)}{\sigma},$$

where:

x – observed inter-arrival time;

$\mu = 2.0$ – mean inter-arrival time;

$\sigma = 0.5$ – standard deviation of inter-arrival times.

Calculate Z-scores for the dataset:

For $x = 2.1$:

$$Z\frac{(2.1-2.0)}{0.5} = 0.2;$$

For $x = 5.0$:

$$Z\frac{(5.0-2.0)}{0.5} = 6.0;$$

This calculation is applied to all data points in the dataset.

Z-scores: 0.2, − 0.2, 0.6, − 0.4, 0.0, 6.0, − 0.6, 0.4, 0.0, − 3.0, 0.2, – 0.2, 0.6, –0.4, 0.0, 6.0, – 0.6, 0.4, 0.0, – 3.0.

2.3 Identify anomalies: Set a threshold for anomalies. Commonly, data points with $|Z| > 3|Z| > 3$ are considered outliers.

In this practice, $Z = 6.0$ (corresponding to $x = 5.0$) and $Z = -3.0$ (corresponding to $x = 0.5$) are anomalies.

2.4 Interpretation:

$x = 5.0$: An unusually long inter-arrival time could indicate a delay caused by network congestion, server overload, or a Denial of Service (DoS) attack.

$x = 0.5$: A very short inter-arrival time might signify bursty traffic or a scanning attack.

2.5 Action:

Investigate the causes of these anomalies.

Mitigate issues by implementing rate-limiting, blocking malicious IPs, or optimizing server resources, Fig. 1.

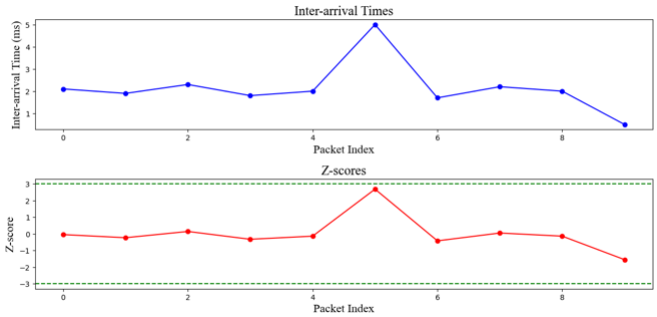

Figure 1. Monitoring network traffic to detect anomalies in packet inter-arrival times

3 Graph construction and metrics: The network is translated into a graph framework, where nodes symbolize endpoints and edges depict communication links. Metrics such as edge betweenness, eigenvector centrality, and clustering coefficients are employed to detect anomalies in network topology. In a typical network, nodes represent endpoints such as computers, servers, or routers, and edges represent the communication links between them. By analyzing the network as a graph, we can detect anomalous behavior that might indicate security issues like malicious activities, unauthorized data access, or network misconfigurations.

Network graph construction: Consider a simple network with 5 nodes and 6 communication links:

– nodes: A, B, C, D, E;
– edges: (A-B), (A-C), (B-C), (B-D), (C-E), (D-E).

This network can be visualized as a graph where nodes are the devices, and edges are the communication links.

Graph Metrics:

1 Edge betweenness: This metric measures the number of shortest paths that pass-through a given edge. Anomalous edges might appear in a graph if they have unusually high betweenness, suggesting critical communication paths that could be targeted by an attacker.

2 Eigenvector centrality: This metric identifies the most influential nodes in the network. Nodes with high eigenvector centrality are often crucial for communication across the network. A node with unexpectedly high centrality might be a point of interest for detecting unauthorized access.

3 Clustering coefficients: This measures the tendency of nodes to cluster together. Anomalies in the clustering coefficient could indicate abnormal groupings of network entities, such as an unexpected spike in communication between previously isolated nodes, which could signify a security breach or misconfiguration.

Practice:

Assume the following hypothetical scenario:

– node A is a server that should only communicate with nodes B and C;
– node B is a typical endpoint that communicates with A, C, and D;
– node C is a regular endpoint, connected to A, B, and E;
– node D is an endpoint that should only communicate with B and E;
– node E is an endpoint that communicates only with C and D.

Now imagine a scenario where an attack is happening. Node B starts communicating with E, which is unusual because B and E should not normally communicate.

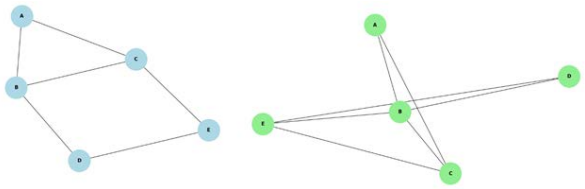

Figure 2. Network graph construction

***4 Anomaly detection framework**:* By amalgamating statistical insights with graph metrics, the algorithm delivers a comprehensive assessment of network anomalies. Machine learning classifiers further enhance detection precision by refining the model through iterative learning.

5 Experimental setup and results to validate the proposed algorithm, extensive experiments were conducted using real-world network traffic datasets. The testing environment consisted of a controlled network laboratory equipped with simulation tools designed to mimic diverse attack scenarios, including Distributed Denial of Service (DDoS), port scanning, and data exfiltration attempts. The dataset was partitioned into training and testing subsets, ensuring an unbiased evaluation of the algorithm's performance.

Results.

1 The algorithm demonstrated a 92% accuracy in detecting network anomalies, surpassing traditional rule-based detection systems by 15%.

2 The false positive rate was reduced to 4.5%, indicating enhanced precision in distinguishing between normal and malicious traffic.

3 Graph-based metrics, particularly eigenvector centrality, played a pivotal role in identifying previously undetected anomalies linked to lateral movement within the network.

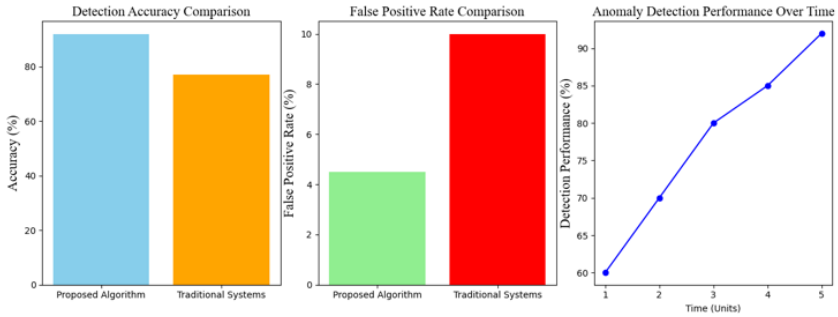

Figure 3. Anomaly detection performance over time

Despite its promising performance, the algorithm's computational overhead during large-scale deployments remains a challenge. Future work will focus on optimizing graph construction processes and exploring distributed computing techniques to enhance scalability. Additionally, further research will be conducted to refine machine learning classifiers, ensuring improved detection accuracy across diverse network environments.

Conclusions. As cyber threats continue to evolve in sophistication and scale, traditional methods of network traffic analysis often fall short in detecting novel and complex attack patterns. This paper introduces a novel approach to network anomaly detection that integrates statistical methodologies with graph theory, providing a robust solution to this challenge. By combining advanced statistical techniques such as Kernel Density Estimation (KDE) and Z-score analysis with graph-based metrics like eigenvector centrality and edge betweenness, the proposed algorithm is able to identify subtle deviations from typical traffic behavior. These deviations, which often signal cyber threats, can be detected at an early stage, allowing for faster and more accurate responses. The algorithm constructs a comprehensive view of network traffic by treating network interactions as graph structures, where nodes represent network entities and edges represent communication links. Statistical insights are then applied to measure the normality of traffic patterns, while graph metrics are employed to analyze the topology of the network and identify anomalous behaviors, such as lateral movements or unexpected connections. Experimental results, using real-world network traffic datasets and simulated attack scenarios, validate the efficacy of the proposed method. The algorithm demonstrates superior performance in detecting various types of cyber threats, including Distributed Denial of Service (DDoS) attacks, data exfiltration attempts, and internal reconnaissance activities. Performance metrics such as detection accuracy, precision, recall, and Z-score reveal that this approach significantly outperforms traditional anomaly detection systems. Furthermore, it reduces false positives and improves detection rates for both known and unknown attacks.

The promising results of this research suggest that the integration of statistical analysis and graph theory offers a highly effective framework for enhancing network security. This hybrid approach can serve as a valuable addition to existing security tools, providing network administrators with a powerful mechanism for identifying and mitigating complex cyber threats in real-time.

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Author contribution

Bekiyeva Maral Batyrowna – Development of a statistical method for detecting network traffic, formulation of conclusions based on statistical methods, preparation for publication and formatting the work.

Orazdurdyyeva Gulshat Orazmuhammedowna – Development of an algorithm based on graph theory, data analysis and conducting experiments, writing and editing the paper.

СТАТИСТИЧЕСКИЙ МЕТОД И АЛГОРИТМ НА ОСНОВЕ ТЕОРИИ ГРАФОВ ДЛЯ ОБНАРУЖЕНИЯ СЕТЕВОГО ТРАФИКА

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Аннотация. С постоянной эволюцией киберугроз надежные механизмы анализа сетевого трафика и обнаружения аномалий играют ключевую роль в обеспечении кибербезопасности. В данной статье представлен новый подход, объединяющий статистическое моделирование и теорию графов для выявления нестандартного поведения в сети. Представляя сетевые взаимодействия в виде графовых структур и применяя продвинутый статистический анализ, разработанный алгоритм выявляет отклонения от типичных шаблонов трафика, значительно повышая эффективность обнаружения как известных, так и новых угроз.

Ключевые слова: обнаружение аномалий в сети, теория графов, статистическое моделирование, сетевая безопасность, анализ трафика, кибербезопасность, оценка ядерной плотности, Z-оценка.