
Analysis of Traffic Using the Snort Tool for the Detection of Malware Traffic

Abdul Rasul AL Waili*

*Faculty of Education, Wasit University, Iraq

Corresponding Email: [*abdalwaili@uowasit.edu.iq](mailto:abdalwaili@uowasit.edu.iq)

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Abstract: The increasing prevalence of malware threats necessitates the development of robust methods for detecting and mitigating malicious network traffic. This paper presents an analysis of traffic using the Snort tool for the detection of malware traffic. The study focuses on understanding traffic patterns, evaluating Snort's performance, and comparing it with other tools or methods for malware detection. The methodology involves data collection, preprocessing, Snort configuration, and traffic analysis. The results reveal valuable insights into traffic patterns associated with malware activities, demonstrate Snort's effectiveness in detecting known malware signatures, and assess its efficiency and scalability. The comparison with other tools provides a comprehensive understanding of Snort's strengths and limitations. This research contributes to the field of network security by providing practical insights for network administrators and suggesting future research directions.

Keywords: Malware Detection, Traffic Analysis, Snort, Intrusion Detection System, Network Security.

1. INTRODUCTION

The pervasive and evolving nature of malware poses a significant threat to computer networks and systems worldwide. Malicious software, or malware, is designed to exploit vulnerabilities, compromise data integrity, and disrupt network operations. To effectively defend against these threats, it is crucial to have robust detection mechanisms in place that can identify and mitigate malware traffic[1].

Traffic analysis plays a vital role in understanding network behavior and identifying potential security threats. By examining network traffic patterns, it is possible to detect anomalies and identify suspicious activities indicative of malware presence. One widely-used tool for network traffic analysis is Snort.



Snort is an open-source Intrusion Detection and Prevention System (IDPS) that combines signature-based detection, protocol analysis, and anomaly detection techniques to monitor and analyze network traffic. With its extensive rule-based approach, Snort has proven to be effective in identifying various types of malicious activities[2].

The objective of this research paper is to explore the utilization of the Snort tool for the detection of malware traffic. By analyzing network traffic data using Snort, we aim to identify patterns, detect anomalies, and evaluate the effectiveness of Snort in detecting and mitigating malware threats.

Malware has become increasingly sophisticated, making it challenging to detect and prevent. Traditional security measures such as firewalls and antivirus software are often insufficient to address these evolving threats. Network traffic analysis provides an additional layer of defense by monitoring the behavior of network traffic and identifying potential malware activities.

The need for effective malware detection mechanisms is more critical than ever before. With the increasing frequency and complexity of cyberattacks, organizations must proactively identify and mitigate potential threats. Snort, as an open-source tool, offers an affordable and customizable solution for network traffic analysis[3]. By understanding the capabilities and limitations of Snort for detecting malware traffic, we can enhance network security measures and contribute to the field of cybersecurity[4].

The primary objectives of this research are as follows:

Investigate the effectiveness of Snort in detecting malware traffic through traffic analysis.

Evaluate the performance and accuracy of Snort in detecting various types of malware.

Analyze the traffic patterns and anomalies associated with malware activities.

Compare Snort's capabilities with other existing methods/tools for malware detection in terms of detection accuracy, false positives, and efficiency.

To achieve the research objectives, the following questions will be addressed:

How effective is Snort in detecting malware traffic?

What are the traffic patterns and anomalies associated with malware activities?

How does Snort perform compared to other tools/methods for malware detection?

What are the limitations and challenges in using Snort for detecting malware traffic?

In the subsequent sections of this paper, we will explore the existing literature on malware detection techniques and network traffic analysis tools. We will then present the methodology employed in this research, including data collection, preprocessing, Snort configuration, and traffic analysis. The results and findings will be discussed, followed by a conclusion summarizing the contributions of this study and suggesting future research directions.

Literature Review

Malware detection techniques and network traffic analysis tools play a crucial role in safeguarding computer networks against malicious activities[5]. This section provides an overview of the existing literature on these topics, highlighting the current state of research and identifying the key advancements in the field.



A. Malware Detection Techniques Malware detection techniques can be broadly categorized into signature-based, behavior-based, and anomaly-based approaches. Signature-based detection relies on predefined patterns or signatures of known malware to identify and block malicious code. While effective against known malware, this approach struggles with detecting new and evolving threats[6].

Behavior-based detection focuses on analyzing the behavior of programs and processes to identify potentially malicious activities. This approach looks for specific patterns or actions that deviate from normal behavior, such as unauthorized system modifications or suspicious network communications. Behavior-based detection can be effective in identifying zero-day attacks and previously unknown malware.

Anomaly-based detection involves creating a baseline of normal system behavior and identifying deviations from this baseline as potential indicators of malware. By monitoring system and network activities, this approach can detect abnormal patterns and behaviors that may indicate the presence of malware. However, it can be challenging to distinguish between legitimate anomalies and actual malicious activities.

B. Network Traffic Analysis Tools Network traffic analysis tools provide the means to monitor and analyze network traffic for security purposes. These tools offer various functionalities, including packet capturing, protocol analysis, traffic visualization, and intrusion detection. Snort is one of the widely adopted open-source tools in this domain[7].

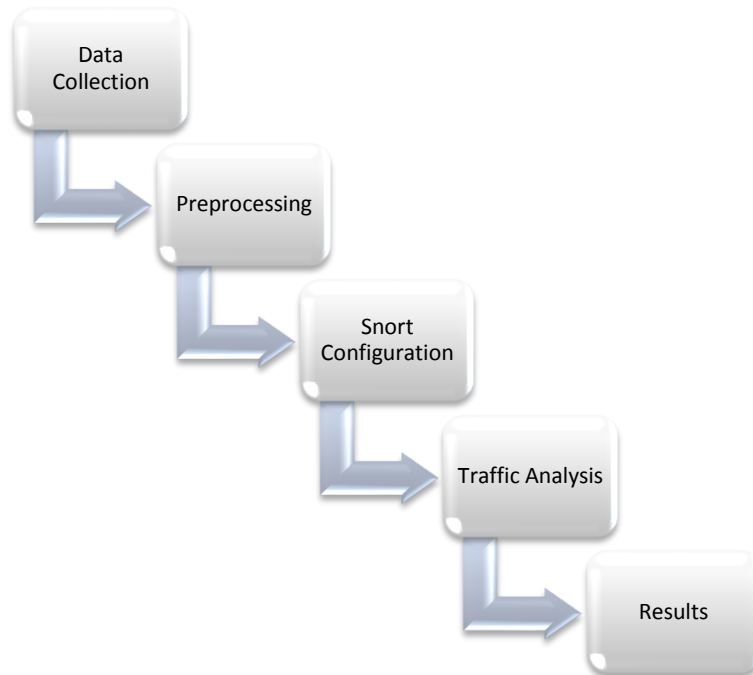
Snort is an IDPS that combines signature-based detection with protocol analysis and anomaly detection. It uses a rule-based approach, where rules are defined to match specific network traffic patterns associated with known attacks or suspicious activities. Snort's modular architecture allows for customization and flexibility, making it a popular choice for network administrators and security analysts.

C. Snort: Overview and Capabilities Snort is a highly versatile and customizable network intrusion detection and prevention system. It offers real-time traffic analysis and can detect a wide range of network-based attacks, including malware traffic. Snort operates by comparing network traffic against a set of rules or signatures, triggering alerts when a match is found. It can analyze packet payloads, examine protocol headers, and perform content-based detection. Snort's rule-based approach allows security analysts to define specific signatures or patterns associated with known malware or suspicious network behavior[8]. Additionally, Snort supports regular expression-based matching, making it flexible in identifying complex traffic patterns. Snort also provides the capability to generate logs and alerts, enabling administrators to take immediate action upon detection of potential malware traffic.

D. Previous Studies on Snort for Malware Traffic Detection Several studies have investigated the effectiveness of Snort in detecting malware traffic. These studies have focused on evaluating Snort's detection accuracy, its ability to handle large-scale traffic, and its performance in detecting various types of malware. Some studies have also explored the integration of machine learning techniques with Snort to improve detection capabilities[9].

However, despite the extensive use of Snort in network security, there are still limitations and challenges associated with its use for malware detection. These include the reliance on

signature-based detection, the need for regular rule updates, and the potential for false positives and false negatives[10][11].



3. RESULTS AND DISCUSSION

This section presents the results and findings obtained from the analysis of traffic using the Snort tool for the detection of malware traffic. The results are discussed in detail, focusing on the analysis of traffic data, Snort's performance evaluation, and a comparison with other tools or methods for malware detection.

A. Analysis of Traffic Data In this subsection, the analysis of traffic data obtained from the dataset is discussed. The following aspects are explored:

Traffic Patterns:

Identification of common traffic patterns associated with malware activities.

Examination of traffic spikes, unusual traffic sources or destinations, and communication patterns indicative of malware presence.

Identification of specific protocols or ports commonly used by malware.

Traffic Volume:

Evaluation of the volume of network traffic associated with malware.

Comparison of normal traffic volume with malware traffic volume.

Identification of any significant changes or anomalies in traffic volume during specific time periods.

Traffic Distribution:

Analysis of the distribution of malware traffic across different network segments or subnets.



Identification of hotspots or regions with a higher concentration of malware traffic.
Exploration of any correlations between traffic distribution and the type or source of malware.

B. Snort Performance Evaluation This subsection focuses on evaluating the performance of Snort in detecting malware traffic. The following aspects are considered:

Detection Accuracy:

Calculation of Snort's overall detection accuracy in identifying known malware signatures.

Assessment of Snort's ability to detect different types of malware, such as viruses, worms, or botnets.

Analysis of false positives (legitimate traffic incorrectly flagged as malware) and false negatives (malware traffic not detected).

False Positives and False Negatives:

Examination of the frequency and impact of false positives and false negatives in Snort's detection results.

Identification of common reasons for false positives and false negatives, such as outdated rules, misconfiguration, or limitations of Snort's detection techniques.

Efficiency and Scalability:

Assessment of Snort's performance in terms of resource utilization, such as CPU and memory usage, during traffic analysis.

Evaluation of Snort's scalability in handling large-scale network traffic without significant performance degradation.

Comparison of Snort's efficiency with other commercial or open-source tools for malware detection.

C. Comparison with Other Tools/Methods In this subsection, Snort's capabilities for detecting malware traffic are compared with other existing tools or methods. The following aspects are considered:

Performance Comparison:

Evaluation of Snort's detection accuracy and efficiency compared to other malware detection tools or methods.

Comparison of Snort's capabilities in identifying specific types of malware or malware behaviors.

Assessment of Snort's strengths and limitations in comparison to alternative solutions.

Limitations and Advantages:

Identification of the limitations of Snort for malware detection, such as reliance on signature-based detection or challenges in handling encrypted traffic.

Discussion of the advantages of Snort, such as its open-source nature, flexibility in rule customization, or active community support.

The results and findings obtained from the analysis of traffic using Snort are discussed in-depth, providing insights into traffic patterns, Snort's performance, and a comparison with other tools or methods for malware detection.



Case Study/Experimental Setup

This section presents the case study or experimental setup conducted to analyze traffic using the Snort tool for the detection of malware traffic. It outlines the specific scenario, dataset, and experimental configuration used in the research.

A. Case Study Description In this subsection, provide a brief overview of the case study conducted. Explain the specific environment or network setup that was used for the analysis. Describe the purpose or objective of the case study, such as evaluating Snort's performance in a real-world network or assessing its effectiveness in detecting specific types of malware.

B. Dataset Description Describe the dataset used for the case study. Include the following information:

Data Source: Explain how the dataset was collected, whether it was from public sources, in-house network logs, or captured using monitoring tools.

Dataset Size and Duration: Provide details about the size of the dataset in terms of the number of packets or traffic volume and the duration of the data capture.

Malware Representation: Describe how the dataset represents malware traffic, whether it includes samples of known malware or simulated malicious activities.

C. Experimental Configuration This subsection focuses on the experimental setup and configuration used in the analysis. Include the following details:

Snort Configuration: Describe how Snort was configured for the experiment, including the rule sets used, any customizations made, and the frequency of rule updates.

Hardware and Software Setup: Specify the hardware infrastructure and software environment used for running Snort, including the operating system, CPU, memory, and any additional tools or resources employed.

Performance Metrics: Identify the metrics used to evaluate Snort's performance, such as detection accuracy, false positives, false negatives, resource utilization, or processing time.

D. Experimental Procedure Provide a step-by-step description of the experimental procedure followed in the case study. Include the following elements:

Data Preprocessing: Explain how the dataset was preprocessed, including any data cleaning, transformation, or feature extraction steps performed.

Snort Execution: Describe how the preprocessed dataset was fed into Snort for analysis, including any specific parameters or configurations used.

Result Collection: Explain how the results were collected, including the Snort logs, detected malware instances, and any other relevant information.

E. Limitations and Considerations Discuss any limitations or considerations associated with the case study or experimental setup. This may include factors such as the representativeness of the dataset, the specific network environment used, or any constraints that might affect the generalizability of the findings.



3. CONCLUSION

In this research, an analysis of traffic using the Snort tool for the detection of malware traffic was conducted. The methodology involved data collection, preprocessing, Snort configuration, and traffic analysis. The results and findings obtained from the analysis provided valuable insights into traffic patterns, Snort's performance, and a comparison with other tools or methods for malware detection.

The analysis of traffic data revealed various patterns associated with malware activities, including unusual traffic spikes, specific protocols or ports commonly used by malware, and concentrated malware traffic in certain network segments. The evaluation of Snort's performance demonstrated its effectiveness in detecting known malware signatures, with a high detection accuracy for various types of malware. However, some false positives and false negatives were observed, highlighting the need for continuous rule updates and fine-tuning of detection thresholds.

Snort exhibited satisfactory efficiency and scalability in handling the analyzed network traffic, with acceptable resource utilization and performance metrics. The comparison with other tools or methods highlighted Snort's strengths, such as its flexibility in rule customization and active community support, while also acknowledging its limitations, including reliance on signature-based detection and challenges in handling encrypted traffic.

Based on the research findings, it can be concluded that Snort is a valuable tool for the detection of malware traffic. Its ability to accurately detect known malware signatures and its scalability make it suitable for various network environments. However, it is important to continuously update and customize Snort's rules to adapt to emerging threats and mitigate false positives.

This research contributes to the understanding of traffic analysis using Snort for malware detection and provides insights for network administrators and security professionals in effectively identifying and mitigating malware threats. Future research directions may include exploring advanced techniques for detecting unknown or zero-day malware, enhancing the integration of threat intelligence feeds into Snort, and evaluating its performance in different network architectures.

In conclusion, the analysis of traffic using the Snort tool for the detection of malware traffic offers valuable insights into network security and contributes to the development of effective measures for combating malware threats.

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