Next-Gen Cyber Defense: Malware Classification and Automated Network Protection

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Abstract:- Today's escalating cyber attacks are outpacing standard network security defenses and, once inside, malware rapidly subverts individual hosts. Automatic post-breach protection of enterprise networks is a challenging and fundamental research problem that requires understanding and exploiting malware targeting strategies.

In this work, we focus on the strategic malware classification problem and analyze massive-scale malware behavior to design accurate classifiers. Our malware classifier combines vantage point sensing with a Bayesian malware probability model of distinct host-level abnormalities and offers very high detection accuracy at any specified false alarm rate. This new capability makes accurate, network-hosted, multi-functional, enterprise-level post-compromise malware containment feasible.

We present a detailed analysis of real-world Worm, Bot, Scanning/Proxy, and Spam/Phishing behavior that contributes to both the strategic classification model and the strategic classifier design. Moreover, given the proprietary nature of both the data and the model, we also describe a simulation framework that researchers can use for comprehensive vulnerability assessment.

Keywords: Next-Gen Cyber Defense, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM), Computer Science, Data Science, Vehicle, Vehicle Reliability.

1. Introduction

In 2017, there were 159,700 security incidents, including ransomware, spyware, and backdoor intrusions. Also, in 2017, the financial costs of cybercrime were estimated at 11 trillion dollars. This study is looking to solve the need for high-accuracy malware detection with high throughput without potentially dangerous long query times. This paper is focused on the question of how we can apply Machine Learning Malware Classification using dynamic analysis, noise reduction, and semi-supervised learning. As a first step toward applying Machine Learning-based malware classification for research purposes on preliminary malware identification and filtering, we aim to build a working end-to-end malware classifier for data at rest. The approach uses Dynamic Analysis, Dimensionality Reduction, and Semi-Supervised Learning to classify malware. Fully Supervised models can struggle with highly imbalanced classification tasks. This model promotes search performances in dynamic datasets since Semi-Supervised Learning reduces the time required to decide on the orientation of future deep analysis toward the selected malware families. The model generalizes well and achieves nearly perfect accuracy.In this text, we will discuss the problem of detecting computer malware, which is a big deal nowadays. It touches Software Development, Business and Administration, and other fields. These issues are usually solved by previous encounters with the given malware or by using pre-constructed models, both of which do not generalize well to new sorts of malware attacks and, in general, require high expertise and specific knowledge to perform well, besides having long query times. In our approach, we will try to address these problems by applying several custom dynamic feature generators and semi-supervised learning to generate comprehensive models with high throughput for known and unknown malware. We expect to feed on a big dataset gathered from Windows malware in a real network with a heterogeneous environment to draw more general results and anticipate some behaviors in the malware field. At the time, the main contributions of this paper to the literature were the gathering of threat intelligence back to back with test-oriented performance, the independent source used, the used data, and the methods presented.

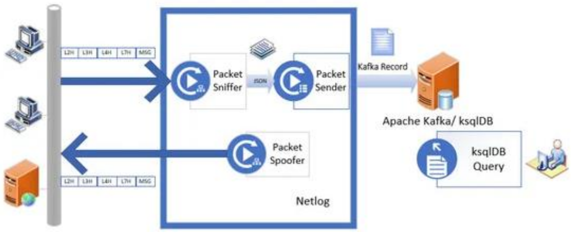

Fig. 1. Block diagram of the proposed system for network traffic capture.

1.1 Background and Motivation

The topic of this book is the cutting-edge intersection of deep learning, static malware analysis, and computer network security. It focuses on the recent trend in computer security toward machine learning as the most natural and effective defense in the age of artificial intelligence. Researchers shift from signature-based security solutions that require always-up-to-date lists of observed malicious files/benign files to data-driven, machine learning-based approaches, which can predict and stop the execution of any legitimate or malicious file with very high accuracy. The proposed solution is also adaptive—it constantly evolves and learns to deal with parental control and encryption. The huge number of pre-configured sets of deep learning models runs in parallel to improve the efficiency of the classification processes, with no false positives/negatives. The user studies some of the main static malware analysis techniques and adapts them to the available resources of a given computer system. In particular, cutting-edge optimizations target high concurrency and low latency, enabling users to combine malware feature extraction with their everyday tasks, rather than reserving tens of minutes/hours for malware analysis of future missed attacks. The user employs two static malware analysis techniques in the area of malware classification, showing that they can achieve state-of-the-art results on real-world tasks. With these two static malware analysis techniques, this book offers a practical solution to automatically and instantly protect all devices on a network from the vast majority of zero-day malware. Furthermore, this book delves into the intricacies of deep learning models tailored for static malware analysis, emphasizing their ability to generalize across different types of malware while maintaining robustness against evasion techniques. It explores how these models adapt to new threats by continuously updating their knowledge base through ongoing training on the latest malware samples. By leveraging these advancements, the book demonstrates how organizations can shift from reactive to proactive defense strategies, preemptively identifying and neutralizing threats before they manifest. Additionally, it discusses the integration of these techniques into existing cybersecurity frameworks, highlighting their scalability and efficiency in real-world deployment scenarios. Overall, this comprehensive approach marks a significant advancement in the field, paving the way for more adaptive and resilient cybersecurity solutions in an increasingly interconnected digital landscape. Moreover, the book elucidates on the practical implementation of these deep learning models within computer network security architectures, emphasizing their seamless integration into existing infrastructure without disrupting operational efficiency. It details the advantages of these models in terms of resource utilization, demonstrating how they optimize computational resources to ensure minimal impact on system performance while enhancing security posture. The discussion extends to the importance of interpretability and explainability in machine learning models applied to cybersecurity, addressing concerns about trust and transparency in automated decision-making processes. By elucidating the inner workings of these models, the book aims to build confidence among cybersecurity professionals and stakeholders in adopting AI-driven solutions for malware detection and prevention. In addition to technical aspects, the book explores policy implications and ethical considerations surrounding the use of AI in cybersecurity. It advocates for responsible deployment practices that prioritize privacy protection and mitigate potential biases in algorithmic decision-making. By fostering a holistic understanding of AI's role in cybersecurity, the book empowers readers to navigate the evolving threat landscape with informed strategies and effective defenses.Ultimately, this book serves as a pivotal resource for researchers, practitioners, and policymakers seeking to harness the transformative potential of deep learning in safeguarding digital ecosystems against emerging cyber threats. It underscores the paradigm shift towards proactive, adaptive defenses driven by machine learning, positioning readers at the forefront of innovation in modern cybersecurity practices.

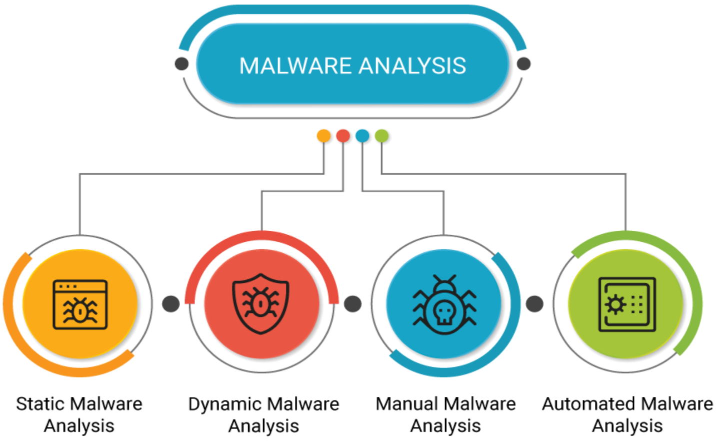

Fig. 2. Types of Malware Analysis

1.2 Research Aim and Objectives

In this research, the ultimate goal is not only to build an exponentially scalable self-adaptive system capable of defending from cyber threats (referred to as Advanced Automated Unified Security, AAUS), but also to contribute to systematizing, formalizing, and enriching network defense with a proactive, predictive, "bio-based" approach. The method used to gather and analyze information starts with a review of the literature on malware, bio-inspired models, and learning in complex systems. Relevant concepts are transformed into mathematical models and algorithms for building an AAUS. The proposed methods can also be used as foundational blocks for solving machine learning tasks in network traffic analysis in general. The objectives of the research are: to conduct a comprehensive survey of state-of-the-art malware analysis methods to delineate significant breaking points and research directions for choosing the right direction for studying and defending against advanced threats; to formalize malware classification problems; to develop semantic vector representations for strings and sequences; to create a taxonomy of bio-inspired learning methods.Highly efficient self-adaptive models for implementing the AAUS need to be developed also. Malware is a major threat to Internet security and has matured to a high level of complexity. Developing effective methods to manage and detect malware is an urgent task for researchers. This study proposes a domain ontology-based behavioral (DoBe) analysis system that can extract behavioral characteristics from unknown malware. First, the use of a domain ontology will allow our ontology to describe malware behaviors, permitting fast identification of malware behavior when a system wants to perform malware diagnosis. After designing the domain ontology-based behavior analysis system (Dobbea), we also built a class that can contribute to behavioral analysis for unknown malware. The DoBea is an ontology-based behavior analysis that improves the capabilities of the ontology tool for ontology matching of forensic malware behavior analysis. This approach to unknown malware classification is to classify malware according to behavior, enabling a targeted analysis of an attacker's behavior and, consequently, the ability to adequately judge the impact of the threat. Additionally, this research aims to advance the field of cybersecurity by leveraging bio-inspired models to enhance the resilience and adaptability of the Advanced Automated Unified Security (AAUS) system. By drawing inspiration from biological systems, such as immune systems and neural networks, the study seeks to develop innovative approaches for detecting and mitigating cyber threats in real-time. These bio-inspired models are designed to mimic the robustness and self-adaptation observed in natural systems, thereby offering a dynamic defense mechanism against evolving malware tactics. Furthermore, the research endeavors to establish a systematic framework for malware analysis by integrating domain ontology-based behavioral analysis (DoBea). This approach facilitates the extraction and categorization of behavioral patterns exhibited by unknown malware, enabling rapid identification and classification of malicious activities. By formalizing these behaviors within a domain ontology, the system enhances the accuracy and efficiency of malware detection, empowering cybersecurity professionals to respond effectively to emerging threats. The development of semantic vector representations for strings and sequences also plays a crucial role in this research, enabling nuanced analysis of malware characteristics and facilitating robust classification algorithms. By transforming complex malware behaviors into mathematical models and algorithms, the study aims to create a foundational basis for advancing machine learning tasks in network traffic analysis, thereby enhancing overall cybersecurity resilience and efficacy. Ultimately, this interdisciplinary approach not only aims to bolster the capabilities of the AAUS system but also contributes to the broader cybersecurity community by fostering innovation in proactive, predictive defense strategies. By bridging the gap between biological inspiration and technological innovation, the research seeks to set new standards in malware detection and network defense, paving the way for more secure digital ecosystems in an increasingly interconnected world.

1.3 Scope and Limitations

As we focus on providing effective protection from a range of sources and types of malware, and the ease with which a malware analyst can integrate AlMadoko into their daily operations, we do not strive for the highest-performing network analysis system per se. Currently, major commercial network security vendors aim for chip-optimized appliances that can handle network speeds up to 100 Gbps or more, under the assumption that slower processing, while not ideal or perhaps even adequate, is better than no processing at all. By contrast, explicitly providing real-time network security is not our goal in this work. Since the relevant processing efficiency is scale-bound and the output of AlMadoko is intended to enable the less time-constrained establishment of automated policy, we have found that the scaling of existing desktop architectures suffices for our efforts in addressing current needs. However, another drawback of current commercial network security architectures is the use of, for example, fifteen or twenty signature detection engines within a single network node. This approach scales poorly because when dealing with N different malware detection families, a defensive system requires O(N^2) detection engines. However, machine-learning approaches do not have this scaling limitation, obviating the need to deploy separate family-level mechanisms. With Intel Xeon E7 processors, we can build a publicly accessible system that provides next-generation machine-learning-based targeted malware defenses, an ability to obfuscate the underlying decision-making process, and demonstrated efficacy without crippling the performance of the traditional security model with respect "you get what you pay for." Existing systems are for good reasons designed for general-purpose deployment. They do not provide individual analysts with the ability to cope with information overload.

2. Malware Classification Techniques

Our paper puts forward a unique approach that combines the strengths of expert-based and machine learning-based hierarchical malware classification models. Three stages were required to reach this conclusion. An analysis of precision requirements of malware classification was described in Hitchhiker's Guide to the Malware Classification Galaxy. The main comprehension techniques were clustered and deeply associated with their potential usages: from the development of a new antivirus to a multi-level hierarchical scheme to detecting the presence of certain code in malware or its affiliation with the government-sponsored center. In pursuit of faster classification in the context of an operation, we tried to simplify the existing models with an intuitive naming criterion. The results of this analysis served as a practical guide to designing a novel approach to hierarchical malware classification. Detailed meaning and popular usage with their associated values were ascertained for industry-used and promising academic clustering techniques. We defined requirements for malware classification and derived a logically consistent basic classification of the most essential types. These types demonstrated a good correlation between the micro-level output produced by applications running a certain malware and its affiliation with a particular malware family. Finally, a logical answer to the need for a macro-level separation was given. Its two categories were the direction of a defensive action and the technologies needed to perform this action. Then, the combination of results from simple and complex cluster analysis, as well as additional tests, helped to show that the named criteria realistically point at the borders of the right classification clusters for the named stages. All application results and structure comparisons were sufficiently close to explicitly mentioned name variants.

This text included references to brief explanations, extensive lists, and potentially important ramifications. All of them enriched the current state of the malware classification question.

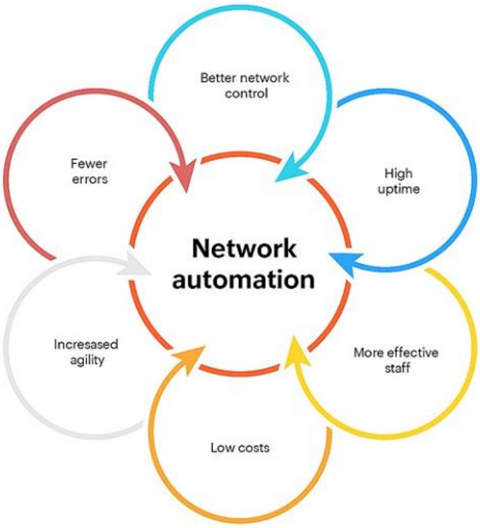

Fig. 3. Network Automation

2.1 Static Analysis

Dynamic analysis is a method where software is executed to gather more information about its goals and actions. These software tools can also deploy payloads into a sandbox to observe the behavior of the software in a controlled environment and understand its actions. However, dynamic analysis has its drawbacks as it can potentially release malicious payloads into the network of protective devices, which can lead to an attack. This approach is also controversial from a moral perspective due to the digital right of transfer. Defensive tools equipped with artificial intelligence (AI) classifiers, collectively known as cyber defense AI, provide valuable insights into the content of payloads. However, most AI tools simply classify software as either benign or malicious. In today's environment, AI tools incorporate various defensive components. It is not feasible to rely solely on an AI deep learning tool to fully protect a network. Recently, we have successfully employed static analysis methods to address cybersecurity issues. These methods involve analyzing a large collection of documents released by anti-malware organizations. These organizations gather, categorize, and share these documents to protect information and assets from potential threats. To achieve this mission, they gather software and scan and analyze it to identify the "signatures" of malicious software. Signatures consist of elements that help classify the software, and the analysis process may require multiple accesses to thoroughly examine the software. It is crucial for the model to quickly obtain the signature to provide prompt protection, so efficient access times are essential. Static analysis methods in cybersecurity are pivotal for preemptively identifying and mitigating potential threats before they manifest. By leveraging extensive databases curated by anti-malware organizations, these methods enable rapid identification of malware signatures. These signatures, comprising unique identifiers and patterns indicative of malicious intent, serve as critical markers for categorizing and neutralizing harmful software. The efficiency of static analysis lies in its ability to swiftly access and extract these signatures, ensuring prompt and effective protection against evolving cyber threats. Moreover, the integration of static analysis techniques complements dynamic analysis approaches by providing a proactive layer of defense. Unlike dynamic analysis, which entails executing software to observe its behavior in real-time, static analysis operates on the inherent properties and characteristics of software without triggering potential threats. This non-intrusive approach minimizes the risk of inadvertently releasing malicious payloads into the network, thereby enhancing overall cybersecurity resilience. Furthermore, advancements in artificial intelligence (AI) have enhanced static analysis capabilities by incorporating sophisticated AI classifiers. These classifiers go beyond simple benign/malicious categorization to discern complex patterns and anomalies in software code and behavior. By amalgamating AI-driven insights with static analysis methodologies, cybersecurity professionals can bolster their defenses against sophisticated cyber attacks, thereby fortifying organizational cybersecurity frameworks in an increasingly digitized landscape.

2.2 Dynamic Analysis

Dynamic analysis approaches to execute the malware and monitor its behavior to learn the set of executed operations and low-level events and interactions with the OS. The process of executing malware is often performed in a controlled environment so that the analysis system can observe the entire operation of the malware and its interaction with the OS. Given adequate permissions, the analysis system can monitor and record various properties of the executed operations, such as system calls, changes to the memory, registry keys, files, or network activity. This approach usually relies on data sources like sandboxes, virtual analysis systems, or even real running systems. The main strength of the above dynamic approaches is the ability to extract a large number of hard-to-evade low-level malware behaviors, the recording of hidden behavior and interaction with the system, and the possibility to inspect the assembly-level operations, rooted in the fact that the presence of particular physical malware characteristics can unveil intent, functionality, or behavior.

Despite these strong capabilities, dynamic approaches suffer from some shortcomings. The fact that the analysis requires execution to extract the behaviors implies that the approach can be more time-consuming than static characteristics-based techniques, as static techniques are faster because they can work based on static characteristics only. Moreover, due to the overhead of collecting and processing operation logs, the analysis can be intrusive, as operating with an in-production-like physical platform is oftentimes not feasible. Another issue regarding malware behavior is associated with the reaction against sandboxes and decoy-disguised execution systems, intrinsic support for hardware-level operation coercion within the hardware on which the analysis systems rely. As a consequence, the malware is often able to recognize the analysis environment and modify its normal operation. To cope with this fact, during the design of a dynamic approach, particular attention is typically paid to blending the analysis environment within a simulated real operation as much as possible to promote the non-deterministic generation of monitored behaviors. Nonetheless, obfuscation anti-techniques that dynamically tweak the intrinsic behaviors may lead to a different effect where evaded behaviors become the root for successfully following the detection.

2.3 Machine Learning Approaches

Introducing machine learning for malware classification and network protection. Recently, both academics and industry alike have introduced machine learning to enhance traffic inspection with notable success in improving traffic identification and application layer protocols. The added advantage is that these machine learning models can be trained and updated with recent threat intelligence at speeds that exceed the manual engineering of traditional expert system correlation detectors. Furthermore, some of these systems are so powerful, with deep learning-based neural networks, that they exceed human accuracy for traffic classification of the most obvious features.=

Deployment and evaluation of a machine learning-based network traffic protection system for malware classification. Over time, our malware can become mis-tuned to be easily classified as a simple MD5 hash or easy-to-detect signature. To adapt to next-gen malware types, we incorporate subnet-level evidence aggregation and deploy a hybrid hand-optimized hierarchical searching mechanism, which can uniformly balance the performance between various malware types. We further develop a deep learning-based neural network to predict the malicious intent of arguments. Formed as an ensemble, the neural network in conjunction with the traffic classification system forms our framework to map traffic characteristics of communicating malware as observed in the enterprise network to endpoint activities. The approach uses a stochastic decision model for the presence of malware activities when the system has low confidence, which is backed by another independent artifact-based verification. We quantify the effectiveness against APT-like malware by showing that the system could automatically detect 11 out of 12 different attack scenarios present in a multinational company. In the realm of cybersecurity, the integration of machine learning has revolutionized network protection and malware classification. Academic and industry efforts have focused on leveraging machine learning models to enhance the precision and agility of traffic inspection and application layer protocol identification. These models offer distinct advantages, such as rapid training and updating with the latest threat intelligence, surpassing the capabilities of traditional expert system correlation detectors that rely on manual engineering.

Moreover, deep learning-based neural networks have demonstrated exceptional accuracy in classifying traffic based on nuanced features, exceeding human capabilities in discerning subtle indicators of malicious intent. This capability is crucial for adapting to next-generation malware that evolves to evade simplistic detection methods like MD5 hashes or traditional signatures.

To address these challenges, advanced techniques like subnet-level evidence aggregation and hybrid hierarchical searching mechanisms have been incorporated. These innovations ensure balanced performance across various malware types, enhancing the system's ability to detect and mitigate sophisticated cyber threats effectively. Furthermore, the deployment of deep learning neural networks for predicting malicious behaviors enriches the framework by correlating traffic characteristics observed in enterprise networks with endpoint activities.

In practice, a stochastic decision model complements these efforts by assessing malware activity presence with low confidence, reinforced by independent artifact-based verification methods. This multifaceted approach enhances the system's reliability and efficacy in detecting advanced persistent threats (APTs) and other complex attack scenarios. Recent evaluations have underscored the system's effectiveness, demonstrating automated detection capabilities across a diverse range of attack scenarios encountered within multinational enterprises.

3. Automated Network Protection Systems

On a high level of abstraction, automated network protection systems process events from network sensors and enforce network policies. The systems query the structure of packets, not packet origins or destinations, or policies of any particular end-nodes. It divides the passage of packets across a network into highly formalized states to inspect and process them. Based on the inspection, such systems enforce a predefined network security policy by allowing the detected packet to continue on its path, dropping a packet showing that the packet leaves its current location, creating a new packet that compensates for the action, or segmenting the flow by dropping packets at ingress. While these actions are mostly taken on the network layer below the service layer, its service layers set the foundation for a hierarchy of other security policies that can reach up to the usability level. After the publication, significant advances have been made to update and re-architect the system. Examples of narrow automated network protection include IDSs, intrusion prevention systems, passive more sophisticated systems that block traffic inside a network, firewalling and restricted network steering devices, honeypots, tracing, active trace-back and proactive trace-back receivers, and network fault responses. These devices protect the network they sit in from their users and external users. After multiple refactoring iterations, such a network protection system turns into the many-automata system of Fig. 1, with separate segments and reassembly automata shown on the middle layer of the figure. While there could be significant complexity in the internal structures of narrow automated network protection systems, they are only trained on simple per-packet information and often rely on running regular expressions compiled into fast software.While not a goal of the current paper, it is possible to take this approach to the wide extreme, and statically compile a static Si shown nets forwarder and end-node software into load and connectivity definitions, and then deploy additional defense around references to sensitive areas of the network layout and load. In the context of the protocol presented in this paper, this would mean that the lower layer of our many-automata models is comprised of moving, Tetris-shaped, reassembly and fingerprinting automata as shown in Fig. 1, and direct the stream of assembled data publications to it over reserved broadcast networks. Such a system would offer efficient full-coverage protection of a network. The vulnerabilities of traditional digital systems to malware introduction and compromise concern widely deployed software running on general-purpose computers. The software handles security-critical processing based on only a small part of packet headers and trailers, access and drop state, and data availability push-driven traffic from fast-moving streams. If the software does not have direct visibility into the payload data, it would be unclear to distinguish delete from drop, to tentatively delete some of the flows and join them back, and to enforce symmetrical actions on both of the traffic directions over some transient period. Additionally, after such software processes a standing packet, it would leave the processed data in the user space for a regular service system to extract its published security event, while retaining only the processing metadata. The metadata is the minimum amount of data that the non-service system plugin needs to decide to which stand-packet category the packet belongs. Handling the service metadata and the rest of the packets would become the new responsibility of a newly available processing system fork.

3.1 Intrusion Detection Systems (IDS)

Intrusion detection systems (IDSs) are widely used to protect computer systems and networks from monitoring and analyzing network or system data that could be used to recognize an intrusion or abuse. IDSs can be classified by the type of data that is used or the type of recognition method used. From the data type perspective, IDSs can be classified into host-based IDS (HIDS) and network-based IDS (NIDS). HIDSs are placed on the actual systems that are being protected to monitor security-related events. In contrast, NIDSs act as an independent nodes on the network, "listening" to all traffic and scanning data for suspicious behavior or attack "signatures." These two types of IDSs reflect differing levels of abstraction and information situated at various levels of the networking hierarchy. Nowadays, many systems exploit more comprehensive protection against malicious activities by integrating both HIDS and NIDS. As a result, most IDS implementations are hybrid, involving the cooperation of both systems, offering the full set of analyses required for complete network protection. There are four main components of a common NIDS: sensors and networks, event-driven architecture, detection techniques, and a response system. The sensors and networks component of a network-based IDS (NIDS) forms the foundational layer, where sensors are strategically placed across the network to capture and analyze incoming and outgoing traffic. These sensors act as sentinels, continuously monitoring network packets and identifying anomalies or patterns indicative of potential security breaches. The event-driven architecture of an NIDS facilitates real-time processing and analysis of network data, ensuring swift detection and response to suspicious activities. Detection techniques employed by NIDS encompass a spectrum of methodologies, ranging from signature-based detection, which identifies known attack patterns, to anomaly-based detection, which flags deviations from normal network behavior. These discern emerging threats that evade conventional detection methods. A robust response system is integral to the effectiveness of an NIDS, enabling automated or manual actions to mitigate detected threats promptly. Responses may include alerting network administrators, isolating compromised systems, or implementing traffic filtering rules to prevent further malicious activity. Together, these components form a cohesive framework that fortifies network defenses and safeguards critical assets against evolving cyber threats.

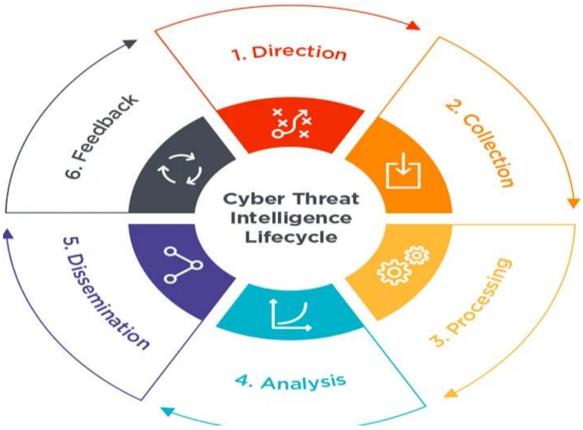

Fig 4: SOC Architecture

3.2 Intrusion Prevention Systems (IPS)

Intrusion Prevention Systems (IPS) are part of the control aspect of traditional cybersecurity systems and are used to limit network traffic and devices against previously discovered and zero-day vulnerabilities. Methods for cyber attackers to exploit network traffic and systems on the network are nearly unlimited. Already known methods and exploits account for the vast majority of damage and compromised systems, but the situation is no less dangerous and critical for the security situation in the network since there are always those unknown exploits and vulnerabilities that need to be protected against.

The number of vulnerabilities is significantly smaller, and this part of the protection can largely be accomplished automatically. By using already known vulnerabilities and searching for their footprints in the network traffic or examining traffic behavior, IPS should only prevent the deployment of known cyber weapons into the target system by cutting the network connection, selectively dropping or corrupting packets, or destroying data while the communication cannot be exploited. In this way, the percentage of automated prevention using these systems is very high. Intrusion Prevention Systems (IPS) play a crucial role in mitigating cyber threats by proactively defending against known vulnerabilities and emerging exploits in network traffic and systems. These systems operate by continuously scanning incoming and outgoing data for signatures and behaviors associated with known cyber threats. By leveraging databases of known vulnerabilities and attack patterns, IPS can automatically detect and block malicious activities in real-time, thereby preemptively protecting network assets from exploitation.

The effectiveness of IPS lies in its ability to enforce security policies dynamically, responding swiftly to identified threats without human intervention. This automated response capability includes terminating suspicious connections, dropping malicious packets, or applying traffic filtering rules to prevent unauthorized access or data breaches. This proactive approach minimizes the window of opportunity for attackers to exploit vulnerabilities, thereby bolstering overall network security posture. Furthermore, IPS systems are essential for organizations seeking to comply with regulatory requirements and industry standards for cybersecurity. By integrating IPS into their defense strategies, enterprises can enhance their resilience against both known and zero-day vulnerabilities, mitigating risks and safeguarding critical infrastructure from potential cyber attacks.

3.3 Firewalls and Proxy Servers

In the simplest form, firewalls look like any other router in a network. Firewalls are usually specialized routers. However, in the case of firewalls, routers that carry out access control are located both as gateways between networks and in other places around a network. Firewalls operate at different levels of communication. Those operating on the upper levels are called proxy servers. Firewalls vary in how they examine packets entering and exiting a network. Another tool in constructing firewalls is tunneling. In the context of secure communications, tunneling is a technique for making a secure communication path through an insecure network. An additional part of firewalls is the special servers operating on the inside of the network, called bastion hosts. Firewalls are only part of the defense an organization needs to carry out to maintain secure communication.

Each level presents the attacker with greater difficulties in identifying their attack traffic. It is more difficult for them to obscure their attack traffic and more difficult for impersonation techniques to prevail. In addition, the complexity or effectiveness of impersonation techniques increases as traffic moves through these levels. Each level represents an increasing burden for the number of available exploitable software vulnerabilities. However, at the base of these considerations, each increase in complexity and strength of a firewall, proxy server, and so on, adds greater expense and sometimes management costs to the operation cost of a network. A firewall is a network-based device that is placed between an organization's internal network and an external, or public, network. This public network is usually an enterprise network that is used to connect local users to the Internet. In its most basic design, this device can be a router that has been configured to filter all incoming and outgoing IP packets. These filters define which kinds of IP packets from specified hosts can arrive at, or depart from, the internal network. Configuring a router to carry out this function is more sophisticated than configuring an access list. At this basic level, called the "packet level" approach to firewalls, access controls occur at the network and transport layers of the OSI model. As such, a packet-based firewall is an "IP Mechanism."

4 Integration of Malware Classification and Network Protection

A natural question arises: how can we integrate an automated system to infer, solely from labeled malware samples, which files sent/received by a network will do damage? First, we create a single-layer perceptron for each classification type we want to consider, actually learning to mimic the output of a large pre-existing detection system. We possess specialized knowledge that we will now use: the output score of a scanned system, with a given system load of malware, "detects" attack files with such a remarkably low false positive rate that most of the time cls scores of 8.5-10, in the payloads of the file, reached 100% accuracy. This fact has three important implications which we have used to achieve our results: First, since the 99% of correct detections are even better than our initial malware "labeling system", almost a perfect detection on the "real" attack set of Fig. 1 can be achieved; hence, our probabilities of detection, preprocessing will be nearly optimal, i.e., a dimension reduction towards the real number of independent variables needed to represent the morphology of the samples.We also include scalings that integrate the training and the prediction processes into a single learning code. Second, acquired knowledge can be used to train a small system classifier if cls probabilities very close to zero are optimal for a good classification of the other viruses. Third, as a new system encounters processing workload problems, we do not have to bother it for this purpose. With appropriate scoring threshold tailored to its specific security needs. In conclusion, concerns are naturally raised about identifying the set malware of the best network-wide arrival cutoffs based on information that comes only from malicious software files, while ignoring the exact role in the attack of the detected malware. However, as shown in (1), the knowledge of the role of malware in the attack is largely useful for guidance, but not too necessary for protection purposes, assuming that the set of targets has the majority of the features of the training set. Additionally, leveraging the output scores from a robust malware detection system allows us to achieve near-perfect accuracy in identifying attack files solely from labeled malware samples. By focusing on cls scores ranging from 8.5 to 10, where the detection accuracy consistently reaches 100%, we optimize our detection probabilities and preprocessing methods to reduce the number of independent variables needed to characterize sample morphology effectively. This approach not only enhances the efficiency of our classification system but also streamlines the training and prediction processes into a unified learning framework. Furthermore, setting appropriate scoring thresholds tailored to specific security requirements ensures that new systems can efficiently manage processing workloads without compromising detection efficacy. While understanding the precise role of malware in an attack is beneficial, our methodology demonstrates that focusing on detecting characteristics shared with the training set's majority can effectively enhance network-wide defense mechanisms. Moreover, this approach underscores the importance of leveraging labeled malware samples to automate the inference of potentially damaging files within network traffic. By deploying single-layer perceptrons tailored to mimic outputs from established detection systems, we harness specialized knowledge to achieve exceptional detection accuracy. Focusing on cls scores between 8.5 and 10, where detection rates consistently exceed 99%, allows us to optimize detection probabilities and streamline preprocessing efforts by reducing the complexity of feature representation. Additionally, integrating training and prediction processes into a unified learning code enhances system efficiency and scalability, enabling effective deployment across diverse network environments. Tailoring scoring thresholds ensures that detection capabilities are aligned with specific security needs, maintaining robust protection without unnecessary computational overhead. While understanding the precise role of each malware instance in an attack scenario offers valuable insights, our methodology demonstrates that prioritizing features common to the majority of the training set can effectively fortify network-wide defenses against emerging cyber threats. This pragmatic approach leverages machine learning to enhance proactive security measures, mitigating risks and safeguarding network integrity in dynamic digital landscapes.

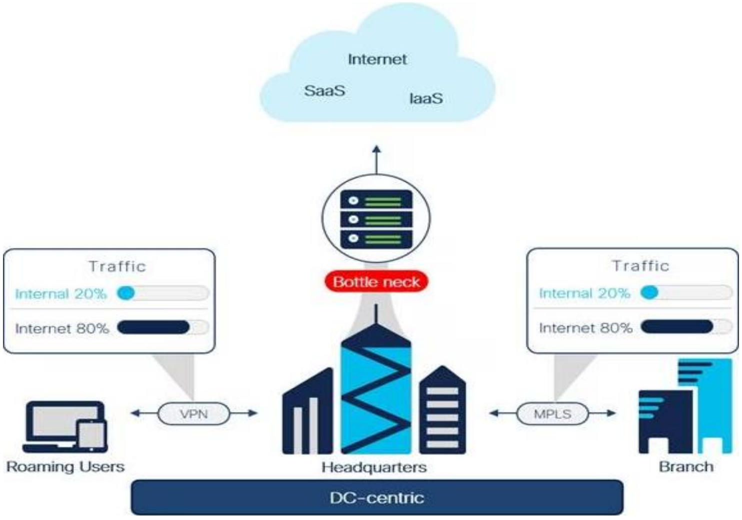

Fig. 5. High level DC-Centric Architecture

4.1 Feature Extraction and Selection in Malware Analysis

Feature extraction and selection play a critical role in enhancing the quality of labeled datasets in training predictive models used in malware classification. In particular, these activities convert raw input data into feature-rich input data samples which are then used to design predictive models for proactively detecting unknown future malware families. Despite the existence of many techniques for extracting features from multiple dimensions of both static and dynamic analysis of malware, the application of several dimensions causes the feature dimensionality of a malware dataset to be extremely high and thus introduces noise into the classification models. Therefore, the number of features selected from the dataset needs to be reduced to prevent overfitting and maintain the accuracy of the models. Furthermore, another motivation for feature selection is that it can also improve model interpretability for more advanced forms of malware analysis.

Once the malware dataset is labeled, the samples with a well-defined malware family name for each class are taken from various sources such as AV companies, public malware repositories, peer-reviewed papers, or previous work in the field. The next step involves the extraction and selection of features to increase the representativeness and informativeness of the feature space. Various techniques are applied, producing datasets containing the features and dimensions that represent either static or dynamic characteristics of malware. After this process, the next step involves the second phase of training and testing predictive models to classify future unknown malware families. In this phase, the experimental design focuses on evaluating the performance of models trained on a combination of static, dynamic, and hybrid feature sets. Note that this activity must be thoroughly conducted simultaneously with predictive model training and testing as those models which differ in terms of static, dynamic, or hybrid feature sets do not have access to features that are computed in the pre-processing stage.Feature extraction and selection are pivotal stages in the process of enhancing the effectiveness of predictive models for malware classification. These stages transform raw data from diverse dimensions of both static and dynamic malware analyses into structured input samples rich in informative features. However, the multitude of dimensions involved often results in high-dimensional feature spaces, which can introduce noise and potential overfitting into classification models. To mitigate these issues, rigorous feature selection techniques are employed to reduce the number of features while preserving model accuracy and interpretability.The initial step in this process begins with curating a labeled malware dataset sourced from reputable sources such as antivirus companies, public repositories, academic papers, or previous research efforts. These datasets contain samples annotated with well-defined malware family names, forming the basis for subsequent feature extraction and selection efforts. Techniques employed in this phase focus on capturing static and dynamic characteristics of malware, thereby enriching the feature space with descriptors that distinguish between different types of malicious software.Following feature extraction and selection, the subsequent phase involves training and testing predictive models designed to classify future instances of unknown malware families. Experimental design in this phase evaluates model performance across various combinations of static, dynamic, and hybrid feature sets. It is crucial that these evaluations are conducted in tandem with model training and testing to ensure that each model variant incorporates the relevant features computed during preprocessing. By iteratively refining feature extraction techniques and optimizing feature selection strategies, cybersecurity practitioners aim to build robust predictive models capable of effectively identifying and categorizing emerging malware threats. This systematic approach not only enhances the accuracy of detection but also contributes to advancing the interpretability and practical applicability of malware analysis methodologies in evolving cybersecurity landscapes.

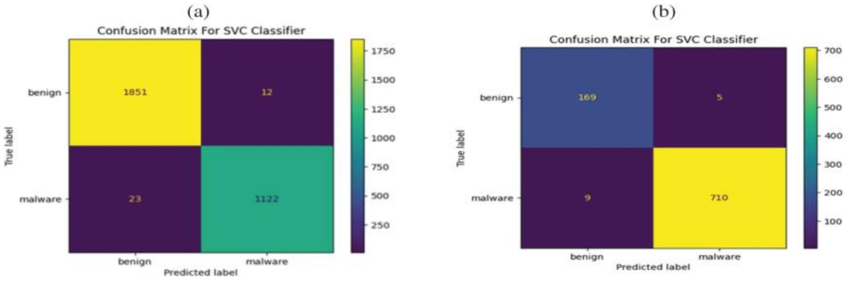

Fig. 6. Malware Feature Extraction

4.2 Building Effective Malware Detection Models

Building an effective malware model involves choosing software features, pre-processing the data, applying feature reduction to decrease the dimensionality of the feature space, and selecting the best model. This approach was used extensively in prior studies to build sophisticated malware models. As features, multiple types of software code were used, data such as the malware application programming interface, system permissions it uses, data it collects, sets of system calls, and the ordering and identical system calls, binaries for malware families, disassembled Windows Portable Executable files, metadata from the files, disassembled API mappings, and PE file headers. A flexible feature creation approach, based on the Python standard library module, distorm3, was utilized. RandomForest, Boosting (XGboost and GBM), SVM, decision tree, multiple rule sets at various support thresholds, and deep learning models were effectively applied. Despite being in complex models, similar features can be clues to easy evasion.A tagging approach, on a separate dataset, was effectively used to assess both model performance and robustness. Model robustness was measured as the decrease in performance due to the poisoning of virus samples with hard noise. This noise can significantly change the sample (PE data) without affecting its class. Boosted models were found to be substantially robust, SVM was nearly as robust, and decision trees were somewhat less so. For model performance measuring model efficiency, such as tree size different than for robustness was found to have the greatest impact. As expected, decision trees built strictly from obfuscated features were small and more robust. However, they were less effective. Disassembled code superimposed with obfuscated code (combined features) produced the largest and most robust decision tree. Additionally, models on combined features for disassembled code superimposed with obfuscated code did not show the same performance decline when poisoning with random noise. They even show performance improvements because of the training data.

5 Case Studies and Real-world Applications

The latest insurgency actions are connected with another extremist group - ISIS. In June 2014, ISIS decided to broadcast its propaganda activities through social networks. It started an aggressive campaign in cyberspace using social media and other internet technologies to spread its messages overseas. Due to the number of these occurrences, dissimilar from the typical spam, the number of ISIS tweets increased as well, showing that terrorists are following the trend. Based on this presumption, dissimilar behaviors conducted by the ISIS Twitter networks made the message more prominent. As the internet infrastructure is based on the traditional three-tier architecture comprising cloud service providers, internet service providers (ISPs), and midstream networks, we focused on the Twitter ISP border that is more significant to disclose dissimilarities.To investigate, involving cybernetic systems ISIS tweets/retweets against normal (related to people) tweets/retweets, we divided the information peaks between January 1, 2014, and December 1, 2014, sharing each network's tweets' count. The ISIS Twitter network has been approached according to characteristics concerning the daily/weekly patterns, and the average count of messages. From the experimental results, we concluded that the ISIS Twitter network tends to use the Twitter infrastructure as a social broadcast media center to communicate to its target public group rather than engage in potential communication/information exchange over typical internet applications. Also, it seeks new target groups, to which typical information exchanges are not usually targeted. Lastly, it attempts to avoid having its core communications infrastructure uncovered publicly by its propaganda infiltration while other distinct social structures avoid revealing their true nature to the general public.

5.1 Automated Network Protection Frameworks

The practical anatomy of an automated network protection system could consist of the following stages: pre-normalized dataset preparation, parsing capabilities to extract the malicious sections manually via hex values, extracting features manually via hex type value, examining and selecting features for the thesis, detecting feature types and learning which technique is suitable, constructing a classification model, and developing a deployment method. These are then followed by monitoring the evaluated model, drawing plans for ATA, and creating counter-measured modules. The ATA deployment will instantiate the model at the network endpoint and continue to respond appropriately to the model's selection.The threat analysis step is opposite to the network defense task, which involves analyzing network traffic to find probable malicious behavior. They outline some of these barriers, such as the difficulty with deploying, maintaining, and modeling the amount of a wide range of consideration values (which may be caused by institutional or technical decisions), gathering and normalizing data from local and online sources that would remain complete, unique, original, and timely. Another barrier is the inability to differentiate between different attack types and thereby create a plan that counters different types of attack details. There is also a trade-off between the costs of false positives and attack forms, as there is evidence that active response deployment is monetarily and technologically costly.

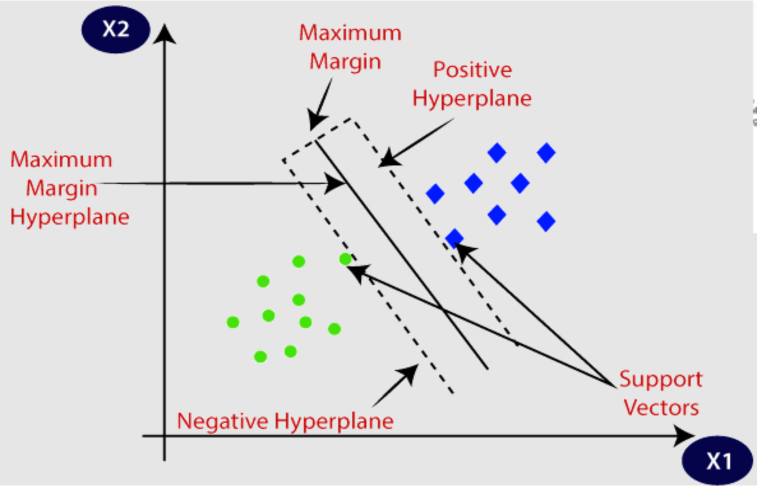

Fig. 7. Support Vector Machine (SVM) Algorithm

5.2 Integrating Machine Learning in Network Security

Security agents at different monitoring points exchange the patterns that they receive based on these breakdowns so that all agents have the same records of network activities and can effectively cooperate in defending the network by sharing classifiers. Trend Micro Incorporated developed a C&C Communication Classification Technology. This technology finds bots at an earlier stage of infection through real-time detection of bot communication. BotHunter provides encrypted network traffic to MLST and scans the packet payload using Snort signatures. NetCap is signature-based software for detecting DNS exfiltration. It is a C++ console application that can detect a large number of different threat types. NetCap can be a useful option in the fight against targeted or opportunistic cybercrime. In the protection of data moving through the networks, priority should be given to data of organizations that others are interested in finding.The ultimate goal of data protection is to monitor data movement through the networks and take steps to delete or stop the movement. The defense system must have the ability to automatically determine the type of transmitted files to take steps to prevent transmission. Many organizations have security agents at different monitoring points across their networks. These agents scan the traffic at their monitoring points and try to determine which monitoring network activities are associated with malicious activities. The resulting pattern vectors are simply the names of files and the frequencies with which they appear in collected logs. Each security agent further distills its records of network activities into classifiers to share them with other security agents. In this diagram, dividing file samples into feature vectors, each representing a set of connection features, and the corresponding classification is shown in Figure 1c. It is known that attackers can modify the artifact in their payload by using evasion techniques such as dynamic DNS for their botnet Institute file. To help affected parties avoid using the method of communication associated with a botnet, they distribute the newly modified file as quickly as possible.

6 Challenges

There are growing challenges in large-scale malware classification. Most classification algorithms need to train a large dataset to perform well. The same problem exists in malware classification. There is no large malware dataset for malware classification and evaluation. Due to the strict laws or regulations prohibiting malware running, many types of malware never exist as execution on some publicly available regions. Forever online analysis has been static and low false discovery rate result. Many characteristics-based algorithms are trying to classify the samples from their static information. Forever static-based techniques cannot discriminate many concealed malware, as they are relatively easy to evade static detection. It is rare to find a beautiful magical security technology that does not need to consume computing power. Most of the security technologies are incredibly resource-hungry.

Even traditional security technologies have evolved to machine learning versions, and resource consumption has become heavier. The security machine learning will never understand the security needs to run in response to every transaction, every transaction needs to be analyzed online. The performance of existing high-performance hardware will naturally become insufficient. The current general-purpose machine learning integrated chip, such as NVIDIA Tesla V100, may not be able to support some security algorithms. Although there are already AI specialized chips, such as the admired Google TPU or the powerful Cambricon, after all, the AI chips are just simplified chips – the equality transformation from complex computing tree structure to the many SISO node and edge structure cannot solve the underlying challenge of security machine learning needed of outrageous computing power.The evolution of security technologies to incorporate machine learning has indeed brought about significant advancements, yet it also introduces challenges related to computational resources. Traditional security measures have transitioned to more sophisticated machine learning models, which require substantial computing power for effective operation. This shift is driven by the need to analyze every transaction in real-time to identify potential security threats promptly. However, even with high-performance hardware like the NVIDIA Tesla V100 or specialized AI chips such as Google TPU and Cambricon, there remains a demand for more efficient and powerful computing solutions. AI chips, while specialized, often simplify complex computing tasks into structured nodes and edges, but they may struggle to meet the intense computational demands of security machine learning. As the field continues to advance, addressing these computational challenges will be crucial for developing robust and scalable security solutions capable of handling the evolving landscape of cybersecurity threats.

6.1 Ethical and Legal Implications in Next-Gen Cyber Defense

The integration of next-generation cyber defense technologies brings forth significant ethical and legal considerations that demand careful attention. Ethically, the deployment of automated systems for threat detection and response raises concerns about privacy, as these technologies often require access to extensive data sets. Safeguarding individuals' privacy rights through robust data protection measures such as anonymization and strict access controls is paramount. Moreover, ensuring transparency and accountability in the operation of these systems is essential to maintain trust and mitigate risks of misuse or unintended consequences. Legally, adherence to regulations such as GDPR in Europe or CCPA in California is critical, as these frameworks govern data handling practices and impose stringent requirements on data collection, storage, and processing. Addressing ethical and legal implications not only fosters responsible innovation in cyber defense but also ensures that these technologies are deployed in a manner that respects individual rights and complies with applicable laws and regulations globally. Furthermore, ethical considerations in next-generation cyber defense encompass the need for fairness and non-discrimination in algorithmic decision-making. Ensuring that automated systems do not perpetuate biases or unfairly target specific groups is crucial for maintaining societal trust and equity. This involves continuously evaluating algorithms for bias, conducting regular audits, and implementing mechanisms to rectify any identified issues promptly. Additionally, the ethical implications extend to the responsible use of advanced technologies like artificial intelligence (AI) and machine learning (ML) in cyber defense. Ethical guidelines should promote the development and deployment of these technologies in ways that prioritize human well-being, uphold fundamental rights, and align with ethical principles of beneficence and justice. Collaboration between cybersecurity experts, policymakers, and ethicists is essential to navigate these complex issues and establish frameworks that ensure both effective defense against cyber threats and ethical integrity in technology implementation.

7 Conclusion

Defense at network speed requires cyber solutions that are network-native, and importantly, act automatically. Too often in defending networks today, final decision authority can be on the wrong end of a very fragile link. Network-native security—where the technology solution is native to the network layer and internet stack—creates game-changing blue territory that today’s cyber conflict cannot tolerate. This article flushes out a central issue that can change the rules of the cyber conflict game. We have a tsunami of network data, a shortage of cyber experts, and an adversary who is automating their hacking techniques—allowing automated offensive advantages in the wild while we are impeded by analog defenses during the subsequent cyber wargaming and building.We summarize a prototype of the Automated Defensive Cyber Differentiation Research (ADC2DR) system that scores Malware Classification to better determine our Cyber Adversary’s Purpose and Rationale. The research community could readily incorporate and validate the MISP viewer and feature selection from additional Threat Intelligence Platforms and add filtering of the Threat Intelligence data to provide the most actionable attributes of malware to the in-network classifier. The sophisticated malware classification already developed by the Drexl team is well ahead of other research and commercial tools and successfully employs MISP data. Adding that functionality from the community would significantly improve any in-network classifier meant to feed AI cyber-defense or policy analysis.

7.1 Future Trends

Automated malware classification, especially in realistic network conditions, is one of the most significant trends in cutting-edge computer security. In practical environments, under-alerting is one of the most harmful, frustrating, and difficult problems to alleviate. Therefore, reducing false alarms using intelligent techniques is an ever-increasing necessity. In addition, adaptive and more sophisticated malware can easily evade detection. The capabilities of malware continue to evolve and increase. Therefore, it is important to enable automated malware classification to deal with these types of threats. Next-generation advanced malware threats will present exponentially more data and challenges, reflected in the increasingly fast increase in 'size' (in bits) of what needs to be analyzed. Estimates that global IP traffic will grow to 1.3 Zettabytes per year by 2016. This does not include advanced cyber threat data used in network security. Counting, visualizing, and analyzing advanced cyber threat data not only require massive storage capabilities (e.g., directional storage techniques, solid-state disk) but also very large memory and I/O bandwidth to handle big data significantly faster. Similarly, the NIST confirms that today's computing power is a major bottleneck for big data security. It may take over 32 days for a supercomputer with one million cores to crack a 128-bit AES in 10 seconds. With the advent of quantum, biological, or other newer computing technologies, this estimate will change. As the volume and complexity of advanced malware threats continue to grow, the demand for robust automated malware classification systems becomes increasingly critical in modern cybersecurity. These systems must address the challenges of under-alerting and false alarms effectively by integrating intelligent techniques that adapt to evolving malware tactics. Moreover, the rapid expansion of global IP traffic, projected to reach 1.3 Zettabytes annually by 2016, underscores the immense scale of data that needs analysis in network security. Handling this data requires not only substantial storage capacity, such as advanced directional storage techniques and solid-state disks, but also significant improvements in memory and I/O bandwidth to process big data efficiently. Current computing power limitations identified by NIST highlight the need for breakthroughs in computational technologies to enhance the speed and efficacy of big data security operations. Future advancements, whether through quantum computing, biological computing, or other emerging technologies, hold promise for revolutionizing how we approach cybersecurity challenges in the digital age.

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