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Research Article

Adaptive Cybersecurity Systems: Leveraging Real-Time Data For Threat Mitigation

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ABSTRACT

A self-adaptive anomaly detection system for IoT traffic, including unknown attacks, is proposed. The proposed system consists of a honeypot server and a gateway. The honeypot server continuously captures traffic and adaptively generates an anomaly detection model using real-time captured traffic. The gateway uses the generated model to detect anomalous traffic. The proposed system can adapt to unknown attacks to reflect pattern changes in anomalous traffic. Results of all experiments show that the detection model with the dynamic update method achieves higher accuracy for traffic anomaly detection in comparison to the pre-generated detection model. Experimental results indicate that a system adaptable in real-time to evolving cyberattacks is a novel approach that ensures the comprehensive security of IoT devices against both known and unknown attacks. Adaptive cybersecurity systems leverage real-time data to mitigate threats. With the continuous growth of internet-of-things (IoT) devices, an increase in cyberattacks that exploit vulnerable devices infected with malware has been observed. This tendency can lead to massive device infection, impacting the operations of an entire organization if the infected devices are connected to the organization's network. Among the IoT devices, network-enabled home appliances, such as air conditioners, refrigerators, and heaters, have recently garnered attention due to their convenience, inefficiency, and vulnerabilities to various cyberattacks. To eliminate vulnerabilities and quickly handle unknown cyberattacks, it is essential for both the vendors and users of such devices to continue updating the firmware of the devices. However, this is a challenging task that usually requires a long time after identifying such vulnerabilities. Therefore, in the meantime, a system must adapt autonomously to changes in cyberattacks.

Keywords: Adaptive Cybersecurity, Real-Time Data, Threat Mitigation, Cyber Threat Detection, Dynamic Security Systems, Data-Driven Security, Threat Intelligence, Cyber Defense Strategies, Real-Time Analytics, Adaptive Threat Response, Cyber Risk Management, Incident Response.

1. Introduction

Big Data from Social Scenarios or Environments (BDSSE) involves various types of actors and is characterized by uncertain, vague, imprecise, and incomplete data. Traditional knowledge discovery and data mining (KDD) approaches designed for Big Data containing static numerical or symbolic data cannot deal with such challenges. In response, a new type of BDSSE KDD, termed Big Data Mass Knowledge Discovery, is developed, which processes a huge amount of uncertain, vague, imprecise, and incomplete data to discover mass relevant knowledge or mass observations, that compactly summarize the behavior of the associated complex system. The BDSSE KDD is characterized by Branches 1-3 of Big Data Mining, by types of KDD, by types of mass discovery, by multi-granularity mass models, and by types of mass mining and knowledge. The increased simultaneous presence of people and robots in our living environment demands collaborative and socially acceptable roles. A relatively large number of robots performing similar or complementary tasks will likely engage with the same individuals. In this case, the involved robots must be aware of each other's presence and activities. They should furthermore share a common understanding of who is responsible for which action, and who can use which mutual support. While some of these requirements can be guaranteed by task design, mutual

awareness amongst robots may not be ensured and robot-robot interactions aim at addressing this gap. It is suggested that the type of robot-robot interactions varies according to the degree of autonomy and the importance of mutual awareness regarding the task that is executed. A taxonomy of robot-robot interactions is proposed, together with hypotheses on the interaction type that is preferred based on these two considerations.[3]

Fig 1: Cyber Security Presentation

1.1. Background and Significance

The fortification of computer systems and detection of vulnerable/compromised machines in the network through probing and monitoring are valuable tools for the cybersecurity engineer. The purpose is to develop a system that builds a picture of an organization's network and activities using built-in queries, calculated metrics, and third-party tools. Such a system can make use of many data sources: altmetric sources like Blocked Exits (BE) API that track the behavior of large Classless Inter-Domain Routing (CIDR) block networks, and end-user reported events from ZeuS Tracking System (ZTS), Domaintools, and others. Using these data sources, models of normal behavior can be developed, including spikes or shifts in traffic increase to/from countries on the watch, and abnormal presence, duration, or frequency of the sensor activity. Such a model can track sources of Internet traffic anomalies, closing with the global observatory of Internet security. Malware allows intruders to alter, release, or destroy sensitive data, either personal, commercial, or governmental. In March 2015, the US Office of Personnel Management was hacked, with the breach of millions of personal files related to employees in sensitive governmental positions. The insurance company Anthem was hacked in 2015, exposing the health records of about 80 million clients. In the early 2000s, Code Red and the SQL Slammer worm caused service disruptions across the delay. A DOS attack against the Estonian Government blocked access to social media, banks, and media websites and disrupted the function of public services. This attack is deemed the first cyber war. In the past 25 years, the world has witnessed the extraordinary development of cyberspace and a perceptible shift in the way businesses are conducted. The rise of e-commerce and social media has spurred the rapid growth of online products and services, which has unchanged the way people communicate and share ideas. However, this growth has been accompanied by an incalculable number of businesses and governments becoming the target of malicious software (malware) diseases and Internet Protocol (IP) address abuses. Infections with malware, such as viruses, trojans, worms, etc., are probably the most familiar form of cyber threats aimed at compromising the security of computers and networks.

1.2. Research Objectives

Adaptive cybersecurity systems are capable of learning, evolving, and adapting over time to cater to an unknown threat landscape, thus enhancing the overall cyber resilience of an organization. In the adaptive cybersecurity context, intelligent and real-time cyber threat monitoring and mitigation systems can leverage the exponentially growing and continuously changing real-time data, which are driven by advanced technologies such as big data, cloud computing, and IoT. With the advancement in smart and self-driving technologies such as AI, ML, and DL algorithms, the adaptive cybersecurity systems will also autonomously evolve, react, and act on the exponentially growing real-time threat situations as human expertise intervention would be minimal and impractical on a large corpus of threat data. Nevertheless, it is imperative to realize how these abilities can be implemented in the adaptive cybersecurity context, specifically the unknown threats detection, classification, and mitigation problems. The proposals to develop adaptive cybersecurity systems that will intelligently leverage the continuous and instantaneous threat data to adaptively design and tune the required cyber monitoring and mitigation systems will improve an organization’s cyber resilience. Moreover, the utilization of real-time data from cyber monitoring systems to continuously change the design of cyber

security will improve the effectiveness and efficiency of multi-layered cyber monitoring and mitigation capability against advanced and unknown threats to the data, systems, and networks in an organization.[9]

Fig 2: Adaptive security Architecture

2. Foundations of Cybersecurity

Cybersecurity is about the protection of digital devices, systems, networks, and data from unauthorized access, theft, or damage. Capturing, providing, or maintaining access to and understanding the system configuration, operational procedures, security controls put in place, failure scenarios, planning, and their characteristics (attackability/radiality), complex contagion, and resilience of information and communication technology (ICT) systems collectively is called Cyber Situational Awareness (CSA). Cyber Kill Chain is a seven-phase approach (reconnaissance, weaponization, delivery, exploitation, installation, command and control, and execution) for understanding how to foresee, detect, and hole incidents of cyberattacks on computer networks. Other important terms include cyber threat, cyberattack, threat vectors, malware, logical isolation, backup, jumping to the conclusion, distributed denial-of-service (DDoS), cross-site scripting, SQL injection, man-in-the-middle, honeypots, and cybersecurity intelligence. Recent developments in big data and streaming data analytics bring fresh opportunities to more timely uncover, visualize, and construct scenarios, and ultimately impede evolving outside-as-a-whole threats. Cybersecurity is a domain at the confluence of several disciplines, striving to protect and defend from multiple forms of threats. With the rapid deployment of information and technology, including the Internet of Things, smart grid, critical infrastructure, and cloud and multi-cloud computing services, the cybersecurity attack landscape has metamorphosed. Mobile malware, victim data breaches, ransomware, cryptojacking, Internet hijacking, and information leakage via social media are widely reported in the world every day. To variably visualize, analyze, and overcome evolving security concerns, it is imperative to understand the fundamental concepts first. Cybersecurity is about the protection of digital devices, systems, networks, and data from unauthorized access, theft, or damage. Capturing, providing, or maintaining access to and understanding the system configuration, operational procedures, security controls put in place, failure scenarios, planning, and their characteristics (attackability/radiality), complex contagion, and resilience of information and communication technology (ICT) systems collectively is called Cyber Situational Awareness (CSA). Cyber Kill Chain is a seven-phase approach (reconnaissance, weaponization, delivery, exploitation, installation, command and control, and execution) for understanding how to foresee, detect, and handle incidents of cyberattacks on computer networks. Other important terms include cyber threat, cyberattack, threat vectors, malware, logical isolation, backup, jumping to the conclusion, distributed denial-of-service (DDoS), cross-site scripting, SQL injection, man-in-the-middle, honeypots, and cybersecurity intelligence. Recent developments in big data and streaming data analytics bring fresh opportunities to more timely uncover, visualize, and construct scenarios, and ultimately impede evolving outside-as-a-whole threats.

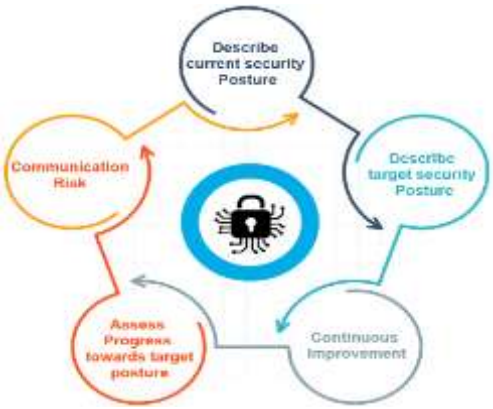

Fig 3: Top Cyber Security Frameworks

2.1. Basic Concepts and Terminology

The dynamic interactions need to be modeled to leverage data. Many methods have been proposed to model evolution and changes depending on the application context. Bi-level optimization problems are devised to model defender and attacker plans as mixed-integer and continuous decisions. Markov Chain Monte Carlo (MCMC) models researchers capture complex multi-dimensional dynamics from data through probabilistic simulation and sampling techniques. A stochastic partial differential equation (PDE) approach models the spatial-temporal evolution in the context of mine production. Deep learning is explored to capture temporal evolution. Game theoretic constructs can be integrated to describe evolution. However, the methods have significant drawbacks in trust, capability of modeling complex dynamics, applicability, and performance. Adaptive cybersecurity systems are resilience mechanisms that can mitigate concerns created by threats to vulnerabilities exploited by attackers. Recently, data-driven methods harnessing the online availability of data have grown as attractive techniques for a range of applications. In the formulation, threats to vulnerabilities are discovered and analyzed by defenders, who then exploit detected threat-vulnerability pairs to take preemptive defensive measures. Attackers form plans to exploit defender reactions. By learning from data, systems adaptively mitigate concerns created by threats and vulnerabilities. However, there are challenges in collecting broad and representative data describing the dynamic interactions in the evolving threat landscape. Oftentimes, real-time dynamic data is sparse, high-dimensional, uncertain, and incomplete.[14]

2.2. Common Threats and Attack Vectors

Cybersecurity, referring to the process and technology that protects networks, computers, and data from unauthorized access or damage, has been the most disputed and highly important issue, especially with the explosion of the Internet. Over time, hackers have continually learned and adjusted their strategy and attack type relative to the defensive measures implemented by their target. As a result, many conditions like DoS attacks, man-in-the-middle attacks, Web attacks, password/ denial of service attacks, etc. emerged as threats to the security of any computer devices connected to the Internet. DoS attack is an insertion of unwanted traffic to the network to pass the saturation point of the network and severely disrupt the packet delivery. A specialized version of the DoS attack is the DDoS or Distributed Denial of Services. The attacker composes a huge botnet of zombies or slaves and uses these to wage the attack against the victim making it difficult for the concerned authorities to trace back the source of the attack.

3. Real-Time Data in Cybersecurity

In a world where organizations rely on information technology to conduct their daily operations, it is paramount that a defense mechanism or cybersecurity system is in place to protect the integrity of that network. Continuous 24/7 monitoring of a network alone is insufficient to protect against known and emerging threat vectors, as hackers and cybercriminals are motivated, driven, and creative in finding potential weaknesses that can be exploited.

Therefore, it is imperative that how cybersecurity systems utilize data be as close to immediate as possible, leveraging technologies that gather and analyze up-to-the-minute recorded information about a situation to discover events and conditions as they occur — in any field, this is often referred to as “real-time”. An organization that does not leverage real-time data in its cybersecurity systems and protocols could be seen as negligent, as thousands if not millions of potential security breaches go undetected every minute. Filtered through the lens of adaptive cybersecurity systems, several techniques rely on real-time data that facilitate multi-faceted defense protocols capable of identifying potential security breaches and stopping them before any malice is realized.

Those techniques are Continuous Monitoring, Threat Intelligence Sharing, and Machine Learning.At its most elementary level, real-time data in cybersecurity refers to the use of “now” information, or data that is very current because it is continually updated and available in real-time. In many situations, real-time data is referred to as “near real-time” data, or data that is also consistently updated, but not necessarily in real-time. Cybersecurity in its simplest definition is the level of protection or defense an organization has against unauthorized access or attack to its components, groups, or systems that make up the information technology network.

Cybersecurity deals mostly with an organization's information technology assets and defense against such threats as confidential information theft, disabling access to an organization's computer networks, or intentional release of malicious software or malware. Combined, real-time data in cybersecurity could refer to the current surveillance measures of a network and the continual upgrading of that data to take immediate action against harmful attempts to compromise or penetrate the parts of that network, using new information to do so. Adaptive cybersecurity systems rely on real-time data to effectively detect, transmit, and mitigate threats.

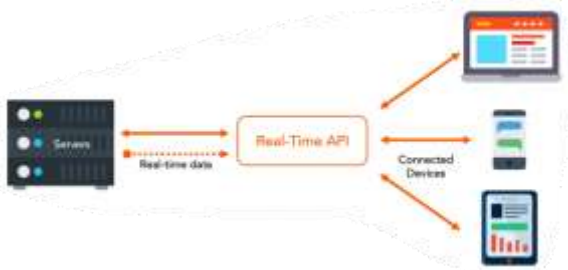

Fig 4: Real Time Data

3.1. Sources of Real-Time Data

Self-induced attacks are caused by network security detectors and the architecture adds too much noise for a machine learning-based global model. This overhead depletes CPU cycles and network bandwidth as well. Organizations such as Managed Security Service Providers (MSSP) have an interest in developing scalable learning tools to address common problems experienced in many networks (e.g. brute-force attacks on public servers). In stakeholder communities that share similar threat and contextual capabilities, it is desirable to learn and share concepts depicting recurring insider or outsider attackers, common types of attacks, or unique network traffic signatures. In other communities, such as organizations in the healthcare industry or universities, there is an extreme sensitivity of network data due to HIPAA regulations. Further investigations into threat neutralization are required to build tools and programs that achieve these capabilities. Adaptive cybersecurity systems aim to monitor real-time data from various sources to allow organizations to understand potential threats that may harm their business and respond with executable mitigation actions. There is a continuous evolution of threat vectors related to insider attacks, vulnerable devices, social engineering, and new attack pathways such as cloud providers, remote workers, BYOD devices, and IoT devices. The volume and sensitivity of network log data prevent long-term retention and sharing across organizations. Barriers to entry prevent small or more vulnerable organizations from adopting complex or expensive technology. For many organizations, existing cybersecurity solutions are overly complex, resulting in overly complicated management, burdensome staffing needs, and ineffective technologies. Continuous feedback from network security operators is important to identify novel attacks and mitigate them as quickly as possible.[19]

3.2. Challenges and Opportunities

In a future full cyberwar context, threats to vulnerable small computer systems/organization networks should also be expected to exert a sudden increase in blindness levels, no matter how sophisticated and complex defender systems and approaches may be. Such total blindness scenarios may induce some initial/raw identification (such as region, country, and industrial sector), which in a more sophisticated analysis may discover and evaluate the most probable attacks and propose response options. It is in this second aspect of analysis that the utilization of automatic systems could also help to update knowledge on a more diverse attack vector taxonomy. Considering the extreme imbalance of blind understanding systems on both sides, a defense and anticipatory understanding side could be created at zero cost and time considering many fractions of systems under attack. Reducing very sophisticated attack knowledge to simple and easily reproducible procedures is a major effort broadly anticipated by the hacker community, which is extremely organized and efficient compared to the predicted capabilities of their potential defenders. Because of this consideration, AI-based automatic understanding and defense responses should act on an equivalent/comparable time scale. At present, such an organization is yet absent from the cyber defense side. With this approach, human security specialists on the defender side would lack the unbiased information needed to understand realistic conditions and the evolution of complex and hidden computer systems under attack. The continuous increase in size and complexity of protected systems is accompanied by disproportionate validation time and the inability to properly check system behavior on modest and seemingly evident perturbations of normal operational conditions. Hence, the defender systems strive to diagnose and anticipate the evolution of internal online points of view and states of a system to understand expected deviations from the norm.The systematic and very sophisticated increase of computer angles of attack, which has occurred during the last two decades, has deeply complicated their online defense systems. Every day, computers and networking systems become more crucial for personal, financial, governmental, military, and business functions as they enable great efficiency improvements. Because of the inevitable occurrence of programming errors or vulnerabilities in poorly designed computer systems, there will always be opportunities for malicious exploitation. Thus far, detection, prevention, and response systems for online computer protection have been based on early and rather rudimentary statistical techniques, heuristics, or brute-force rule-based systems.

4. Adaptive Cybersecurity Systems

The architecture of an ACSS may be defined as being composed of several interconnected components. The first component, referred to as the "monitor" component, is responsible for the real-time acquisition of threat intelligence, be it raw or processed data, concerning recent security incidents. Such monitoring is generally

seen as passive, meaning that such gathering occurs regardless of ongoing attacks or any state of the monitored systems. Such intelligence may come from external and internal sources alike. An external source may be one or more third-party threat intelligence information providers, which calculate and publish the intelligence gathered regarding threat information on a subscription basis, for example. Internal sources generally include log data of security products deployed on the monitored systems, detailing the activity on these systems over time. Engagement in monitoring or collection of threat intelligence data on one specific information source at a time is generally referred to as "slow" monitoring. A second ACSS component, referred to as the "prevention" component, is responsible for the execution of real-time adjustments on the deployed security measures based on the intelligence gathered in the prior component.[24]

Fig 5: Key Components of Adaptive Cybersecurity Systems

4.2. Machine Learning and AI in Adaptation

Machine learning, in this context, encompasses various data-driven and statistical techniques to build models based on sampled data from the real world. Such models can then be exploited to, generally speaking, estimate, predict, classify, or simulate future behavior of previously unseen observations from the application domain. Appropriately trained machine learning models can thereby assist cybersecurity systems in deciding on relevant adaptations based on real-time data. More specifically, by keeping an eye on, i.e., monitoring, environmental data, machine learning models can estimate changes in the environment that matter for adaptation, such as the emergence of new vulnerabilities or significant modification in the operational profile of the monitored system. In the same vein, models can assist in deciding on the most relevant adaptation strategies based on predicted change severity or costs. Moreover, machine learning models can be fine-tuned to continuously monitor the timeliness, accuracy, and impact of implemented adaptation strategies. By filtering the relevant data to consider, machine learning models can readily help to address scalability issues involving large amounts of high-velocity data. In this sense, machine learning can help cybersecurity systems proactively adjust the behavior and processes through which they monitor environmental changes.Adaptive cybersecurity systems continuously adapt their development, deployment, and run-time behavior to improve threat mitigation capabilities. This is achieved by monitoring changes in the systems themselves, their environments, and the threats they face, and translating the findings to adaptations. By adjusting the design and configuration, adaptive systems can improve both the effectiveness and efficiency of the deployed cybersecurity measures. However, human perception and ability to timely process surveillance data is limited, especially in large, complex environments with a plethora of potentially relevant information being generated at high velocity. In this context, machine learning and, more generally, artificial intelligence can assist adaptations to environmental changes by automatically leveraging relevant real-time data.

5. Case Studies and Applications

The learned lessons indicate the multi-faceted nature of the threat and fast evolution of issues in the cyber landscape. Nevertheless, the defense was more organized and prepared than likely assumed initially. Despite rapid evolution and lethal danger, well-tested adaptive approaches to remediation, dusted resilience and assurance templates, procedures of decision-making under uncertainty, and continual cooperation with involved organizations turned out to be decisive for mitigation.A special case of incidence agent Red13M in the focus of the defense is described. In the given case, the defense was challenged to mitigate after the attack was already known, thus persistence and available means of the adversary to follow the goal were underestimated. Nevertheless, wild and intensive attacks indicated continuous lateral scanning of the whole environment, which includes identification of unprotected endpoints and compromise inclusive system intrusion once a suitable exploit is found. The presented investigation and remediation path cover diverse fields such as identification of exposed, unprotected legacy network connections, obscure line modem and communication devices, zero-day vulnerability disclosure, code intrusion incident outbreaks, persistence and cleaning tasks, adaptation of security posture toolkit settings, and further asset hardening recommendations.To meet the challenge of almost real-time detection of zero-day attacks, machine learning, and stochastic modeling techniques are employed in the anti-pattern recognition modules of the ecosystem. Different asset groups of one company may behave similarly, but, at the same time, each of them is unique due to the types of applications running, different operating systems in use, software vendors, configurations applied, historical incidents, cultural

aspects of computer usage, and types of cyber threats that environment have encountered in the past. Thus, building a simple standard model to be used for all assets in the company is not an option. All detection models should be tuned for particular groups of assets. In the case of EoTM, each group of assets operating similarly is vented into Arthat, an independent adaptive ecosystem of surveillance and threat mitigation systems.A representative case of an adaptive cyber-physical ecosystem is the EoTM/SA intelligent malware solution. It consists of tens of thousands of appliances globally and protects local installations across enterprises in diverse fields such as telecommunications, military, and banking. The core assets of the solution are big data analytics modules that ingest, across locally installed appliances, alerts notified by the intrusion detection system and various system tread logs, including service processes, resource statuses, software, network configurations, historical patterns, and vulnerability assessments. By combining unsupervised clustering and supervised classification, such data is analyzed in almost real-time, as new data come in, and convert either zero-day attacks or vulnerabilities that may have been exploited to reach a successful attack.[29]

Fig 6: Artificial Intelligence in Cybersecurity

6. Conclusion

In conclusion, leveraging real-time data for threat mitigation is crucial for effective adaptive cybersecurity systems. By continuously monitoring and analyzing real-time data, organizations can rapidly identify and respond to emerging threats, reducing the risk of cyber attacks. This approach empowers cybersecurity teams to stay ahead of evolving threats and protect their data, systems, and networks more effectively. Embracing real-time data and leveraging advanced technologies is essential for staying resilient against the ever-changing cybersecurity landscape.

6.1. Future Directions

Adaptive Cybersecurity Systems: Leveraging Real-Time Data for Threat Mitigation In light of the threats and opportunities brought about by emerging technologies, researchers and businesses must consider how the defensive capability of adaptive cybersecurity systems might be improved in the future. For instance, to produce adaptive systems that mitigate threats in real-time, defensive agents might manipulate and cooperate with various real-time data. Connectivity in smart cities and the Internet of Things can lead to attacks from malicious drones, tampering with smart traffic lights, and bio-data leaks from smart health devices. To limit the damage, detection and the enactment of mitigation strategies must take place in real time. Such technologies as edge computation, temporal coherence, federated learning, and reinforcement learning would be used to collect and process data from multiple sensors and integrate this information with the knowledge of the defensive agents and the historical data produced by both the targets and the attacks. With this comprehensive picture of the cyber-attacks, mitigation strategies that party a threat would be executed instantly by autonomous defensive agents.

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