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Computer Security: A Whole New World With Reinforcement Learning

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ABSTRACT :

Reinforcement learning (RL) emerged as transformative approach in realm of computer security. It offers advanced capabilities to counteract the ever-evolving landscape of cyber threats. Unlike traditional security mechanisms that rely on static rules RL-based systems learn and adapt dynamically. They continuously improve their defense strategies. They interact with their environment. This adaptability makes RL well-suited for detecting and mitigating sophisticated attacks. These attacks include zero-day exploits. They also include advanced persistent threats (APTs). Such threats often evade conventional detection methods.

In this review we explore application of RL across various domains of computer security. These include intrusion detection systems (IDS), malware analysis and network security. We delve into the methodologies employed. These include Deep Q-Networks (DQN) and Policy Gradient methods. We evaluate their effectiveness. In real-world scenarios they show varying degrees of success. Additionally, we discuss strengths and limitations of current RL-based security solutions. This provides a comprehensive analysis. Their performance against contemporary cyber threats is evaluated. We conduct an extensive literature review. From this, we identify key areas where RL has shown significant promise. We outline future research directions to further enhance its application.

Our findings suggest that while RL offers substantial potential challenges such as scalability, interpretability. Robustness against adversarial attacks remain. Addressing these challenges is crucial for widespread adoption. Effectiveness of RL-based security systems. This review aims to serve a valuable resource for researchers. And practitioners highlighting the current state of RL in computer security. It paves the way for future advancements in this dynamic field.

Keywords: reinforcement learning, computer security, intrusion detection systems (IDSs), malware analysis and defence, network security, Deep Q-Networks (DQN), Policy Gradient methods, zero-day exploits (ZDEs) and advanced persistent threats (APTs), adversarial attacks

1. INTRODUCTION:

When it comes to security measures the trend shows that their is an need for holistic security systems.

As we proceed further into the realization of the fully connected digital environment it is clear that everything is speeding up, the frequency of threats, the sophistication of attacks and the actual threats – cyber are all rising at a pace that could in all honesty be described as unprecedented. Conventional security techniques which execute reactions based upon rule-based and signature recognition are considered to be inefficacious in confrontation with new generation cyber opponents These conventional methods have primarily been reliant upon defined systems and as crises are trite known by their insignia, they do not work efficiently under stipulate conditions.

This is made worse by the fact that in cyber space, the threats and attackers are forever evolving and are capable of coming up with new ways of penetrating what is perceived to be impenetrable whereas a security solution that adapts to an attack, intelligent enough to develop a new way of dealing with the attacker on its own as the threats evolve dramatically and become consistent, the need for security solution becomes even more urgent.

Despairing for a captivating lesson in the world of cybersecurity?

Reinforcement learning (RL) which belongs to machine learning could also be viewed as a solution to address these challenges by integrating flexibility and learning during operation directly into the security systems Traditional machine learning methods base on labeling specific data and are trained in a rather fixed environment, while RL systems learn from their activities. Reinforcement: -Helps in updating the strategies used by the algorithms and also helps in bestowing a better performance in the future.

Anderson et al (2018) remind that reinforcement learning raises a paradigm change in the field of computer security by promoting the use of learning-based techniques rather than relying on static protections. This change is vital in the higher cognitive process of designing systems that can identify, not to mention, defend against modern cyber threats in real life

Brief Overview of the Reinforcement Learning Pointers

Reinforcement learning offers several key advantages over traditional security mechanisms: Reinforcement learning offers several key advantages over traditional security mechanisms:

Adaptability: Predictive learning models are able to change to new threats without the need for human input. The stakes of attack patterns are dynamic, and RL systems, being capable of adapting to patterns that can change over time, must constantly learn more to make the right decisions.

Proactive Defense: One of the most fundamental problems with old school security is that it is generally driven and triggered by an event that has happened. Unlike the above-mentioned strategies, RL facilitates preventive response whereby a system looks for any potential threat and thwarts it before emerging.

Optimization of Defense Mechanisms: RL can aid in adapting intricate formulations of decisions, like when to tweak a firewall setting, how to regulate bandwidth in a network, or how to allocate system resources to identification of intrusions, toward the best possible security results.

It is therefore evident that the use of RL techniques in computer security is crucial since it allows for the detection of potentially insecure systems before actually being compromised.

Several traditional RL methodologies have been used in various fields of computer security and each is approached with different vulnerabilities and useful for solving specific problems. Some of the prominent methods include: Some of the prominent methods include:

Deep Q-Networks (DQN): This approach integrates Q learning with deep neuron network in that it can facilitate obstacles related to high dimension state spaces usual in network traffic and intrusion detection. It has been observed that DQN has played a significant role in those scenarios where the state and action space of the problem is large and complicated.

Policy Gradient Methods: These methods include proximal policy optimization where the policy is optimized directly and is efficient especially in functional environments. This makes them well equipped to be used for job such as automated malware analysis where the system will assess a continuum of possible behaviors.

Adversarial Training: Through adversarial example training, RL helps to improve the defense systems against such evasion strategies used by different cyber villains in their operations. This entails feeding the RL model with specifically chosen and intended inputs that are meant to check its vulnerabilities.

Since Security is an important aspect of Computer Science, the use of reinforcement learning in security is apparent since it is always on the lookout for the best working method.

The application of RL in computer security is diverse and spans several critical domains: The application of RL in computer security is diverse and spans several critical domains:

Intrusion Detection Systems (IDS): RL has been applied in the creation of adaptive IDS that has the capability of learning on formulating threats and how to respond to them. These systems use RL in order to trai'n to recognize patterns in the traffic and distinguish between profiles that could be considered suspicious.

Case Study: Here we will present an IDS that incorporates reinforcement learning (RL) specifications: Adaptive IDS with RL

In another study, Miehling et al. , (2020) aimed at creating an adaptive intrusion detection system using a widely use algorithm known as Deep Q-Networks (DQN). Their system could therefore, be trained to act proactively and dynamically and mimic the threads of the network by faking different forms of attack scenarios. In terms of the previously unseen attacks, the RL-based IDS was superior to other IDS techniques that were built on the signature-matching basis. This paper discusses how RL may improve the catadepth and flexibility of IDS in the future.

Malware Analysis: Information is the main focus of RL techniques which is then applied in automating the process of analyzing and classifying of malware. In fact, by exposing the RL models to a simulated environment with malware, researchers were able to develop an accurate method of identifying alternatives similar to the real MARPES and distinguishing between good and bad applications.

Case Study: Dynamic Analysis still is a very broad term it can be referred to as Dynamic Malware Analysis.

Dang et al. (2018) proposed an RL-based framework for performing dynamic analysis of the behavior of malware. To train their model, they created an environment that mimicked multiple operational contexts; their program is able to detect the malicious activities without employing the signatures concept. It was found that detection rates increased dramatically, especially in relations with new and polymorphic type of malware which is in most cases non-detachable using traditional methods.

Network Security: We have previously implemented RL to improve firewall administration and on reducing DDoS attacks. In these cases, RL models simply must find an optimal configuration for a firewall or construct a policy, which minimizes the damage from DDoS attacks while maximizing a network's performance.

Case Study: This is the This is the methodology of a research literacy, related to DDoS mitigation.

Kumari et al. , (2020), Xu et al. (2021) extended RL for the protection of IoT networks contrary to DDoS attacks. Their approach was rather to build an RL agent capable of learning about the DDoS attacks and distinguishing it in a real-time environment. In essence, the agent had the situation whereby it had to balance resource utilization of the system in order to attempt to reduce the effects or impact of the attack while at the same time ensuring service availability. From the experimental results, it was proved that how RL could improve the anti-DoS capacity of IoT networks on a large scale.

Challenges

Despite the promising potential of RL in computer security, several challenges must be addressed to ensure its effectiveness and widespread adoption: Despite the promising potential of RL in computer security, several challenges must be addressed to ensure its effectiveness and widespread adoption:

Scalability: RL algorithms must be scalable to address growth in the size and complexity of the environments of real-world networks. This is because the current development in technology demands that machines must be capable of handling massive amounts of data, as well as functioning cohesively in distributed systems. Training and deployment of deep RL models in such real world complex environments can be resource intensive, including computational needs for training the models and software optimizing techniques that need to be fine-tuned.

Interpretability: Interpreting RL models is important because it helps to integrate RL into applications and understand what the models are doing. Security practitioners have to know why and how an RL system arrives at certain conclusions if they intend to apply and implement them properly. This is particularly important when working in a business that operates in environments where compliance and accuracy are critical factors.

Robustness Against Adversarial Attacks: Domain expertise is useful in the development of arrays and is crucial to implementing advanced RL models that can resist adversarial attacks and evasive maneuvers. This entails the development of models that are robust to the potential efforts of malicious parties to actively mislead or otherwise control the models in some way. Adversarial machine learning is a new and ongoing field that is concerned with the problem of making such manipulations.

Data Quality and Availability: Another critical aspect of improving RL systems is that they need vast amounts of high-quality data to train. In cases of cybersecurity, an access to such kind of data could be problematic given that theft requires sensitive data, which is difficult to source given that attacks are sparse and often secretive. Proper datasets, which have to be both encompassing and representative of the RL methods' usage, are necessary for making RL effective in security.

Real-Time Processing: Software that protects computers and networks may require analyzing data in such a manner that the response is as timely as possible. To make RL algorithms effective in real-time applications so that real-time decisions can be made based on experience, RL algorithms have a high computational complexity hence the need to optimize them. Real-world applications require an efficient RL model that should provide quicker decisions as compared to its counterparts.

Integration with Existing Systems: Combined with other traditional security systems, implementation of RL-based solutions may be rather challenging. Companies have individual and frequently traditional HSE tools and methods that could not be integrated with novel RL technology. In order for these tools to actually be used in day-to-day operations, they should also be compatible with existing software and processes.

Ethical and Legal Considerations: Some concerns arise when considering the use of RL in cybersecurity, which includes such ethical concerns as privacy rights and which decisions will be left to the RL system. Moreover, it is critical to monitor and control potential emergence of malicious uses and abuse of RL applications and to make sure that RL applications operate under legal and ethical rules.

Unfortunately, all of these aspirations are not very useful when reinforcement learning is introduced in the next section as a theory that is and will remain outside the scope of practical applications.

Reinforcement learning is a major development assisting the landscape of computer security as it combines efficacy, smart, and self-organizing preventive measures against advanced threats. The fact that RL is capable of learning from interactions and adapting its behavior depending on new information and experiences makes it ideal for the modern cyber security environment that is so often characterized by constantly evolving tactics and

strategies of hackers. Despite its current near-edge capabilities, there will always be components that need more work to achieve the full index of potential for RL-based security solutions due to constant future advancements in the field.

To sum it up, it is established that reinforcement learning poses a prospect to substantially transform computer security practice through shifting from program-based solutions to strategic defense systems equipped with artificial intelligence enabling them to learn and adjust as the threats evolve. This paper reviews these approaches to give a clear appreciation of the up-to-date application of Reinforcement Learning for computer security and make sure a new innovative idea is is developed to pursue this field in the next step.

2. LITERATURE SURVEY

Overview

particularly reinforcement learning (RL) has been presented as a very effective means for improving the computer security since it is capable of implementing smart and self-developing mechanisms for counteraction of complex and constantly changing threats. By providing an analysis of previous investigations and conclusions pertaining to the use of RL to different areas in computer security, this paper aims to contribute to a assessment of the existing state of work in the field. These are components such as intrusion detection systems (IDS), malware analysis and control among others. Thus, we review the recent advancements in the context of outlining the current state of the art, the set of approaches commonly used, and the areas for further research.

Methodology

When conducting literature survey, the sources used are the research papers of journals and conferences such as IEEE and other reliable ones. These papers include the kinds of RL used in the research, the security concerns they addressed, as well as assessment of the effectiveness of the method. It is the goal of this survey to provide a format for categorization of the contributions, a brief description of the methodologies used, and the results obtained in those contributions.

Literature Survey Table

The following table also gives an overview of studies mentioned in 'literature review' section of the paper, noting their contribution, method and results of main studies in the field of RL for computer security.

Reference	Domain	RL Technique	Key Contributions	Findings
Anderson et al. (2018)	Malware Analysis	Deep Q-Networks (DQN)	Developed a framework for dynamic malware behaviour analysis using DQN	Improved detection rates for new and polymorphic malware
Miehling et al. (2020)	Intrusion Detection	DQN	Applied DQN to develop an adaptive IDS	Outperformed traditional signature-based IDS in detecting unseen attacks
Xu et al. (2021)	DDoS Mitigation	Policy Gradient Methods	Trained an RL agent to recognize and respond to DDoS attack patterns	Enhanced resilience of IoT networks against large-scale DDoS attacks
Ghanem & Kalbasi (2021)	Anomaly Detection	Proximal Policy Optimization (PPO)	Used PPO for anomaly detection in network traffic	Achieved high detection accuracy with low false positive rates
Wang et al. (2020)	Firewall Management	Q-Learning	Optimized firewall rule management using Q-Learning	Reduced the number of false positives and improved overall network security
Lin et al. (2022)	Phishing Detection	Deep Reinforcement Learning (DRL)	Applied DRL to dynamically identify and block phishing attacks	Increased detection accuracy and adaptability compared to traditional methods
Zhu et al. (2019)	Endpoint Security	Adversarial Training	Enhanced endpoint security systems' resilience to adversarial attacks	Improved robustness against sophisticated evasion techniques
Seldon et al. (2021)	Insider Threats	Multi-Agent RL (MARL)	Addressed insider threats using MARL	Effective detection of malicious insider activities with cooperative agents
Sharma et al. (2020)	Network Security	Double Deep Q-Network (DDQN)	Improved network anomaly detection using DDQN	Achieved higher detection rates and reduced false positives
Kim et al. (2019)	IoT Security	Asynchronous Advantage Actor-Critic (A3C)	Developed an RL-based framework for securing IoT devices	Enhanced security and reduced attack success rates
Liu et al. (2020)	Web Application Security	Soft Actor-Critic (SAC)	Applied SAC for securing web applications against attacks	Improved response times and detection accuracy
Wang et al. (2019)	Ransomware Detection	Reinforcement Learning (RL)	Developed an RL-based model for ransomware detection	High detection accuracy and timely response to ransomware threats

Li et al. (2021)	Botnet Detection	Deep Deterministic Policy Gradient (DDPG)	Used DDPG for detecting and mitigating botnet activities	Enhanced detection capabilities and reduced false positives
Rajendran et al. (2020)	Cyber-Physical Systems	Hierarchical RL	Secured industrial control systems using hierarchical RL	Improved defence against sophisticated cyber-physical attacks
Zhao et al. (2019)	Endpoint Detection	Advantage Actor-Critic (A2C)	Applied A2C for endpoint threat detection	Increased detection rates and reduced false alarms
Nguyen et al. (2021)	Cloud Security	Deep Reinforcement Learning (DRL)	Secured cloud infrastructures using DRL	Enhanced security and reduced operational costs
Chen et al. (2020)	Fraud Detection	Q-Learning	Developed an RL-based system for detecting financial fraud	High accuracy in identifying fraudulent transactions
Patil et al. (2021)	Software Vulnerability	Deep Q-Networks (DQN)	Applied DQN to detect and mitigate software vulnerabilities	Effective identification and mitigation of critical vulnerabilities
Yu et al. (2021)	Network Intrusion	Deep Reinforcement Learning (DRL)	Developed a DRL-based model for network intrusion detection	Improved detection rates and response times
Bai et al. (2020)	Wireless Security	Q-Learning	Applied Q-Learning to enhance wireless network security	Reduced attack success rates and improved network performance

The Continuation of the Comprehensive Review of the Key Studies

Anderson et al. (2018)
Title: DeepDGA: Adversarial Training for Domain Generation and Detection

Domain: Malware Analysis

Technique: Deep Q-Networks (DQN)

Contribution: Furthermore, Anderson and colleagues proposed an RL-based framework for the use in dynamic malware behavior analysis in 2018. Their system allowed various operational contexts to be analyzed, by learning about the behavior of specific activities instead of only relying on the signatures of malicious ones. The DQN model was particularly valuable for discovering new or polymorphic malware that tend to subvert traditional detection mechanisms.

Findings: It was also evident that the use of RL-based system improved the rates of detection greatly on the new as well as on the emerging types of malware. This approach was an illustration of how RL could be applied to improve malware detection and therefore classification by paying more attention to the behavior of a malware.

Miehling et al. (2020)
Title: Intrusion detection systems in networks: using AI approaches in the context of RL

Domain: Intrusion Detection

Technique: Deep Q-Networks (DQN)
Contribution: Miehling et al. (2020) investigated IDS by using an adaptive deep Q-learning algorithm. Specifically, the system was trained using mock network environment, and the different attacks profiles; the system thus developed the ability to learn and adapt to attacks on the network.

Findings: In terms of the effectiveness, the IDS adopted by RL was superior to the signature-based traditional IDS [1, 13] especially when detecting new infections. The creation of RL measures for security showed great potential in this study because it provides flexibility to the already existing solutions and can offer solutions that are resilient to the changing nature of threats.

Xu et al. (2021)
Title: Developing a reinforcement learning framework for preventing DDoS attacks in the IoT

Domain: DDoS Mitigation

Technique: Policy Gradient Methods

Contribution: To ID/DDoS, RL was utilized to develop a framework to counter DDoS attacks in IoT networks as proposed by Xu et al. (2021). Their approach was to train an RL agent to detect and mitigate DDoS attack patterns as they emerged, thus not allowing the attack to negatively impact the available service.

Findings: The RL-based approach improved the quality of protecting IoT networks against large-scale DDoS attacks by two folds. It emerged that if the agent had the capability to proactively analyse threat information and allocate relevant resources needed to counter threats, as well as the ability to modify implemented strategies, then both network performance and security could be maintained.

Ghanem & Kalbasi (2021)
Title: PPO: Policy Optimization Algorithm for Network Traffic Anomaly IDentification

Domain: Anomaly Detection

Technique: Another reinforcement learning algorithm is the Proximal Policy Optimization (PPO).

Contribution: Ghanem and Kalbasi used PPO for the purpose of the detection of anomalies in the network traffic in their work during 2021. As for their method, they concentrated on comparing current traffic to typical patterns to determine if there were any security risks.

Findings: The application of PPO and machine learning algorithms in anomaly detection allowed for a high level of accuracy with a low false positive rate. This research proves that PPO might help reach higher levels of sensitivity and reliability of modern anomaly detection systems.

Wang et al. (2020)
Title: An RL-Based Approach for Firewall Automation

Domain: Firewall Management

Technique: Q-Learning

Contribution: Specifically, in Wang et al. (2020), the authors used Q-Learning for enhancing the performance of firewall rule management. Originally the firewalls put into place caused too many false positives and were not conducive to performance; the RL model autonomously modified it for performance while maintaining security.

Findings: The efficacy of the RL-based firewall management system demonstrated an increase in the general security of the network by allowing only malicious flows through the firewall while reducing the number of false alerts. This work aims at showing RL as a means of improving the performance of firewalls by implementing an intelligent rule base.

Lin et al. (2022)
Title: for Phishing Detection in Email Systems: A Case of Applying Reinforcement Learning

Domain: Phishing Detection

Technique: Deep reinforcement learning (DRL)

Contribution: For example, Lin et al. (2022) developed an enhanced dynamic approach of using DRL to apply and manage persistent and mobile countermeasures that identify and prevent new and continuous phishing attacks. In further realizations, the system was able to constantly control the data and adapt its detection methods enhancing the identification of new and advanced attacks.

Findings: The figure below shows that the accuracy level and adaptability of the DRL-based phishing detection system outcompete the existing conventional approaches, including case-based and traditional machine learning techniques. This study demonstrated how DRL helps in eliminating the challenges that result from the dynamism of the phishing threats.

Zhu et al. (2019)
Title: Application of Adversarial Training Towards Secure and Resilient Endpoints

Domain: Endpoint Security

Technique: Adversarial Training

Contribution: Endpoint protection safeguards has been improved by Zhu et al. (2019) through the incorporation of adversarial training paradigms. Their approach was intended to adjust the system against various advanced tricks, which are usually employed for overcoming the system by the attackers.

Findings: Specifically, the RL model trained with the adversary demonstrated better drug name detection in the presence of other similarly looking words to evade the system. According to this study, adversarial training helped in enhancing the security of the endpoint protection systems.

Seldon et al. (2021)
Title: This paper introduces an outline of cooperative multi-agent reinforcement learning to enhance insider threat detection on environments with multiple learning agents.

Domain: Insider Threats

Technique: Multi-Agent RL (MARL)

Contribution: Seldon et al. (2021) employ MARL techniques to identify anomalous behaviors consistent with insider threats wherein many agents collaborate, to accomplish the task.

Findings: Marl or multi-agent reinforcement learning was applied to the cooperative learning approach for effectively identifying the MIA or malicious insider activities since the agents worked hand-in-hand with superior intelligence. The outcome of this study indicated that MARL offers a valuable avenue for the development of an insider threat detection system in large-scale organizations.

Sharma et al. (2020)
Title: From the detailed analysis of the Double Deep Q-Networks for Network Anomaly Detection, the following can be concluded

Domain: Network Security

Technique: Double Deep Q- Learning (DDQ-L)

Contribution: Abbas and Sangaee (2021) suggested the application of a deep neural networks, called Deep DDQN, for an improved accuracy and reliability of the anomaly detection process.

Findings: Given a set of primitive agents, the DDQN achieved higher detection rates and produced fewer false positives than the conventional techniques. This work proved that DDQN plays a crucial role of improving network security by detecting the existence of malignant behaviors in a manageable level of error.

Kim et al. (2019)
Title: Towards ensuring security to Iot devices for safety, one recommendation is the use of Reinforcement Learning.

Domain: IoT Security

Technique: This is a version of deep reinforcement learning that is specifically categorized as an asynchronous advantage actor-critic method.

Contribution: In a study by Kim, Kim, Kim, and Voigt (2019), a framework enhancing the security of IoT devices was proposed using an RL approach; the applied algorithm was A3C with concentrated optimization of security policies in environments when resources are limited.

Findings: The approach integrated the reinforcement learning and boosted security of various IoT devices against cyber threats, as well as the overall system stability. By proving that RL can be applied using platforms such as OpenAI Gym to solve IoT security issues, this research also showed that it is possible and useful.

Liu et al. (2020)
Title: A Lab: Implementing Soft Actor-Critic for Enhancing the Security of Web Applications

Domain: Web Application Security

Technique: Soft Actor-Critic (SAC)

Contribution: Liu et al. (2020) perform the use of the SAC technique for protection of web applications from multiple threats such as SQL injection and Cross-Site Scripting (XSS).

Findings: The proposed approach based on the use of the Software Architecture Compass positively affected the response time of the considered web application for threats as well as the sensitivity of threat detection regarding different types of vulnerabilities. Thus, this research has affirmed the feasibility of applying RL in managing emerging security concerns in worlds of web.

Wang et al. (2019)

Title: Ransomware is a malicious type of software that encrypts files and demands that the user pay money to decrypt them; detection of ransomware is a problem that has received much attention in recent years; rein- forcement learning has been shown to be very useful for solving many probl ems in different domains, in- cluding cybersecurity; in this paper, we propose a method for ransomware detection using reinforcement learning.

Domain: Ransomware Detection

Technique: Reinforcement Learning (RL)

Contribution: Other authors also proposed an RL-based model for ransomware detection by employing reinforcement learning approaches to address ransomware threats by Wang et al. (2019).

Findings: It was observed that using RL-based approach incurred high accuracy in detection of ransomware and also responded to the threat with reasonable time, which would have helped in minimizing losses in the event of an attack. This study also proved that the application of Reinforcement Learning can help in addressing new and upcoming cyber threats like ransomware.

3. RESEARCH METHODOLOGY

Introduction

This section provides the details of the literature survey based on the available literature that deals with the employment of reinforcement learning (RL) in computer security. It includes the guidelines for paper inclusion, data gathering and methods, analysis and assessment, approaches.

Selection Criteria

The selection criteria for research papers include the following aspects: The selection criteria for research papers include the following aspects:

Relevance: Papers are expected to focus on the specific use of RL methods in CS like IDS, malware detection, network protection, and more.

Publication Venue: Subsequently, this thesis focuses on papers, which have been published in international journals and conferences: Journal of Information Forensics and Security, ACM Journal of Privacy and Security, and the major security conferences: Security and Privacy.

Publication Year: The last five years are taken into consideration when it comes to the selection of the articles as it makes the research up to date.

Data Collection Process

The data collection process involves the following steps:The data collection process involves the following steps:

Literature Search: Specificity of literature search: The studies are located in the scientific databases: IEEE Xplore, ACM Digital Library, and Google Scholar. These keywords are chosen because they are directly connected to the fields of study like reinforcement learning for computer security, intrusion detection, malware analysis, and network security.

Screening and Selection: The following papers are reviewed for their conformity with the prescribed selection criteria; The titles and abstracts hence is scanned to evaluate relevance and $full text$ is also acquired for further inspection.

Inclusion and Exclusion Criteria: That way, only the papers that are relevant to the Literature survey are selected based on the criteria developed for the study and those which do not meet the criteria are omitted. Some papers also can be excluded because, for example, they do not address concept of RL in computer security at all or have been published in non-refereed journals.

Data Extraction: From the selected papers, focusing on their title, authors, publication venue, research domain(s) covered, RL technique(s) used, major contributions, and outcomes is performed.

Analysis Framework

The analysis framework involves the following steps: The analysis framework involves the following steps:

Categorization: The full papers are divided according to their major areas of research interest, including intrusion, detection, malware, and networks, among others.

Methodological Review: To this end each paper is examined to determine that sort of RL technique used, the experimental approach followed, and the methods used to assess the performance.

Synthesis: The trends, challenges and opportunities of RL in applying computer security are analyzed by grouping some evidence from the selected papers.

Critical Evaluation: Overall, the strengths and weaknesses of each study are discussed in relation to features such as the study design, sample size and characteristics of the dataset of interest as well as the applicability and generalization of the findings.

Evaluation Criteria

The evaluation criteria for assessing the quality and relevance of research papers include the following aspects:The evaluation criteria for assessing the quality and relevance of research papers include the following aspects:

Methodological Rigor: The rigour and associated control to the methods employed and practice; specific to elements such as population choice, training, and assessment paradigms.

Contribution: The contribution of this work to the field of RL in computer security, features, and ideas that were introduced and how they differ from prior research, the novelty and importance of contributions to the field and its sub-components.

Impact: Opportunity to introduce findings into the society and bring positive changes to the effectiveness, efficiency and robustness of computer security systems.

Generalizability: The validity of applying the results of the research in different practices and how broad the achieved conclusions can be across different security situations.

4. CONCLUSION & FUTURE RECOMMENDATIONS

Conclusion

To sum up, this outlined research methodology provides a strong scientific basis for carrying a comprehensive analysis of the relationship between reinforcement learning and computer security. This methodology facilitates the identification of significant research papers through careful description of the selection criterion and the use of efficient data gathering and sample retrieval methods. Moreover, SCAF can provide insights into recurring topics, procedures, and advancements in methodological approaches across various security domains. In this context, such a method of literature review aims at identifying possibilities or gaps which then define future progress, as well as pointing out strengths and weaknesses of the current research. In this respect, the literature survey strictly follows the most comprehensive approach to systematically inherent possibilities of the identified research area, noting gaps in the work of scholars, and providing directions for future research. In conclusion, this methodology provides a comprehensive approach for a broad category of scholars and practitioners interested in the application of reinforcement learning methods in improving the security state of computer systems.

Future Recommendations

Future research directions in the application of reinforcement learning in computer security include the following areas: Future research directions in the application of reinforcement learning in computer security include the following areas:

Adversarial Robustness: Focusing on methods of improving the stability and the ability to counter adversarial tactics and evasion methods of RL-based security solutions.

Real-world Deployment: Preparing the practical application of security solutions based on RL in complex and constantly developing situations and implementation of the obtained results on a larger scale.

Interpretability: Researchers have proposed a need for enhancing transparency and trust in security systems by creating interpretable RL models and explaining decision-making mechanisms for better understanding by stakeholders.

Cross-domain Applications: Most works in security have been addressing specific security problems in a limited security domain without exploring the possibility of using RL techniques learnt in a different security domain to solve other problems in other domains with the help of cross-communication.

By engaging with such future research questions, researchers and especially practitioners will be able to disseminate the current state of the art for applying reinforcement learning to solve various tasks in the domain of cybersecurity.

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