Siren - Advancing Cybersecurity through Deception and Adaptive Analysis

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Abstract-Siren represents a pioneering research effort aimed at fortifying cybersecurity through strategic integration of deception, machine learning, and proactive threat analysis. Drawing inspiration from mythical sirens, this project employs sophisticated methods to lure potential threats into controlled environments. The system features a dynamic machine learning model for realtime analysis and classification, ensuring continuous adaptability to emerging cyber threats. The architectural framework includes a link monitoring proxy, a purpose-built machine learning model for dynamic link analysis, and a honeypot enriched with simulated user interactions to intensify threat engagement. Data protection within the honeypot is fortified with probabilistic encryption. Additionally, the incorporation of simulated user activity extends the system's capacity to capture and learn from potential attackers even after user disengagement. Siren introduces a paradigm shift in cybersecurity, transforming traditional defense mechanisms into proactive systems that actively engage and learn from potential adversaries. The research strives to enhance user protection while yielding valuable insights for ongoing refinement in response to the evolving landscape of cybersecurity threats.

Index Terms—Cybersecurity, Deception, Machine learning, Honeypot, Threat analysis, Adaptive security, Threat detection, Dynamic analysis

I. INTRODUCTION

The ongoing transformation of cyber threats underscores the critical need for adaptive and innovative defense strategies. Confronted with an expanding attack surface and increasingly sophisticated threat vectors, the traditional reactive measures often prove inadequate. Recognizing this imperative for state-of-the-art cybersecurity solutions, this research introduces the Siren system as an inventive and proactive defense mechanism. By integrating deception, machine learning, and real-time threat analysis, Siren seeks to contribute to the ongoing discourse on cybersecurity, offering insights and solutions tailored to the dynamic challenges posed by the ever-changing threat landscape.

Reactive strategies, while foundational, inherently operate in response to known threats, leaving organizations vulnerable to novel and evolving attack vectors. The escalating sophistication of cyber threats necessitates a paradigm shift toward proactive defense mechanisms. Proactive approaches enable anticipation and mitigation of potential threats before they materialize, offering a more robust and adaptive defense posture.

This shift is imperative to stay ahead of adversaries, addressing vulnerabilities in advance and minimizing the impact of unforeseen and rapidly evolving cyber threats. The research presented here underscores the critical need for proactive cybersecurity measures.

Existing defensive paradigms predominantly hinge on reactive methodologies, responsive to known threats but lacking preemptive capabilities against unforeseen risks. The motivation to bridge this gap stems from the imperative to cultivate a cybersecurity approach that is not merely responsive but anticipatory, affording organizations the ability to proactively thwart potential threats. By introducing a proactive system, the Siren project aspires to revolutionize cybersecurity protocols, minimizing the lag time between threat emergence and defensive response. This research endeavors to address the critical need for anticipatory cybersecurity measures, aiming to contribute to the ongoing discourse in the field and fortify organizations against the ever-evolving landscape of cyber threats.

The aim is to create an environment where attackers are lured into controlled spaces by simulating vulnerabilities, facilitating an analysis of their behaviors. This unique approach seeks to leverage the power of deception to proactively engage with and understand potential threats, marking a departure from conventional cybersecurity methodologies. This involves the seamless integration of deception, adaptive machine learning, and real-time threat analysis within the Siren system. The research seeks to contribute empirically validated insights into the efficacy of proactive cybersecurity, examining its potential to preemptively identify and neutralize emerging threats.

Furthermore, the project aims to enhance the current understanding of adversary behaviors by meticulously analyzing their responses within controlled environments. By achieving these objectives, the Siren project aspires to establish a novel benchmark in cybersecurity practices, redefining the industry's approach to threat mitigation and contributing substantively to the evolution of proactive defense strategies. The foundational strategy of the Siren system involves a cohesive integration of deception, adaptive machine learning, and real-time threat analysis. This approach leverages the dynamic interplay between these core components to create a proactive defense mechanism. The Siren system is meticulously designed to

anticipate and respond to emerging cyber-threats, offering a comprehensive solution that transcends the limitations of reactive cybersecurity approaches.

Distinctive attributes define the Siren system, setting it apart in the realm of cybersecurity. An adaptive machine learning model forms the cognitive backbone, ensuring continuous evolution in response to emerging threats. The inclusion of a link monitoring proxy adds an additional layer of scrutiny, while the honeypot, fortified with probabilistic encryption, creates a secure and controlled environment. Furthermore, the incorporation of simulated user activity enhances the system's capacity to engage and learn from potential threats, marking a paradigm shift in cybersecurity strategies.

The envisioned outcomes of the Siren research project are twofold. Firstly, the system aims to elevate user protection by proactively identifying and mitigating potential threats. Through empirical validation and real-world application, Siren endeavors to demonstrate the efficacy of its approach in enhancing overall cybersecurity resilience. Secondly, the research anticipates contributing valuable insights to the broader cybersecurity domain. By analyzing adversary behaviors within controlled environments, this system aims to provide nuanced perspectives that contribute substantively to the ongoing discourse on proactive defense strategies. This research paper unfolds systematically, beginning with an introduction that establishes the context of the current cybersecurity land-scape and underscores the importance of proactive defense mechanisms.

The subsequent section provides a detailed overview of the Siren system's approach, elucidating its core components and their integration. A dedicated segment highlights the unique features of Siren, emphasizing the adaptive machine learning model, link monitoring proxy, honeypot with probabilistic encryption, and simulated user activity. The outcomes section provides a glimpse into the expected impact of the research on user protection and its contribution to cybersecurity insights. Finally, the paper concludes with a summary and recommendations for future research, providing a comprehensive roadmap for readers to grasp the significance and implications of the Siren project.

II. RELATED WORKS

In this paper, the possibilities of imbuing machine learning and probabilistic encryption with one another to strengthen security are explored. The current state of honeypots is that they are currently used as a secondary method to firewalls as a largely reactionary method according to M.Nawrocki.[1]. Honeypots, even if interacted with, generally just serve as a deterrent for attackers to waste time but can become a vulnerability if exposed for too long or largely interacted with. A honeypot design can be loosely based off a scanning tool, a fingerprinting device, and a few other tools from L.Kuwatly. [2]. However, far more novel methods such adding an additional layer with user reconfirmation from Li and Schmitz[11] present far more security even with relatively prolonged interactions as well with very minimal if

any leakage at all. This not only encourages the attacker to interact with the honeypot entity as a whole but can in fact keep the attacker from exploiting the vulnerability detected altogether.

The main feature that makes honeypots a weak point is their easy access and vulnerability due to features such as encryption. However, the encryption itself can be strengthened if made probabilistic as put by J.Benaloh [6]. The probabilistic encryption scheme can be made using the standard encryption function of input and cipher but with a third variable that is random in nature.

Harn and Kiesler [5] presented a fairly efficient probabilistic scheme based on the concept of using a randomized variable to simplify functions such as Rabin's 4-1 scheme with randomized variables to ensure that the complexity of the encryption is retained but there is gain in speed. A probabilistic scheme does however pose the challenge of choosing the random variable as well and that in itself would need to be addressed in its entirety.

Lastly, deep learning frameworks to further protect the honeypot without making changes to the vulnerability itself can also be used. The model, according to Tang et al. [3], can extract most of the detail using RNN-GNU models for decently engineered precision and some speed as well. Xuan, Nguyen, and Nikolaevich [4] also further present that the URL can be sent to the machine learning model from the website itself to give near instant recognition to the user and administrator as part of the whole security of the organization. Matin [7] further enhances this using the honeypot itself to lure a phisher to come to the vulnerability it creates. Yet none of the papers have managed to address the consistent vulnerability that the honeypot creates with the prolonged interaction of the phisher. Detection alone may not be entirely feasible on its own.

III. METHODOLOGY

A. Overview

The work proposes a framework that uses a deep learning model in order to learn the nature of the URL by training on a dataset of malicious URLs so that it can identify and differentiate malicious and non-malicious URLs from one another. If the malicious URL has been identified, the honeypot to the server gets activated along with the probabilistic encryption scheme which can further re-encrypt the already encrypted data adding another layer of protection to it.

This helps to overcome the major bottleneck of keeping honeypots open for long periods of time due to security risks as the honeypot here is fairly isolated while also having files be fairly inaccessible due to the repeated probabilistic encryption usage.

B. Dataset And Feature Extraction

The dataset consists of two main columns, one for the specific URLs and the type of URL that they are. There are 4 main types of URLs in the dataset – benign, defacement,

phishing and malware. The objective here is to simply classify the data based on the given link after extracting all possible features from it.

Features are extracted based on a few different categories from the URL itself. Firstly, the protocol, host, path, parameters, query and fragment are all separately extracted from the URL itself and placed into different columns of the dataset. This allows us to parse each component down to its most basic units and decide which features can be retained and which do not need retention later on. Any URL that does not have such features like query or fragment will be stored as null values. There is a clear imbalance in features with a majority of the URLs provided belonging to the benign category. Even within the malevolent links, the majority of links belong to the category of defacement with phishing having a few lesser and barely any belonging to malware.

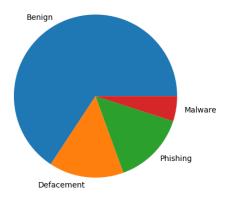


Fig. 1. Feature Distribution Of Dataset

• URL Features: Those columns with predominant null values are subsequently removed as they do not have much effect on the model itself. Here, the values removed were parameters, query and fragment. Any columns with remaining null values were then extracted and the null values were removed. Regular expressions were then used to extract IP addresses that were valid, considering IPv4, IPv4 with port, IPv4 in hexadecimal and IPv6 addresses. The regex used for the extractions are given below:

IPv4:

- (([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\. ([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\. ([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.
- $([01]?\d\d?[2[0-4]\d]25[0-5])\)$

IPv4 With Port:

- (([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.
([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.
([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.|
- ([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\/)|

IPv4 Hexadeceimal:

- $((0x[0-9a-fA-F]\{1,2\})\\\\(0x[0-9a-fA-F]\{1,2\})\\\\\\$ F]\{1,2})\\\. $(0x[0-9a-fA-F]\{1,2\})\\\\\$

IPv6:

- (?:[a-fA-F0-9] $\{1,4\}$:) $\{7\}$ [a-fA-F0-9] $\{1,4\}$ |
- $-([0-9]+(?:\.[0-9]+)3:[0-9]+)|$
- ((?:(?:\d|[01]?\d\d|2[0-4]\d|25[0-5])\.){3}(?:25[0-5]|2[0-4]\d|[01]?\d\d| \d)(?:\/\d{1,2})?)

URLs with special symbols were then extracted and stored in specific columns to check if any predominant symbol was used in the making of the URL itself. The length of each URL was also extracted as a feature to check for correlations on possible addon domains in malicious websites. Shortening services such as bit.ly tinyurl and such were also considered for the usage of URLs to not exclude links that have been shortened and put them in their own category for classification. URL characteristics such as digit count, email addresses, letter counts, vowel counts and top-level domain counts were also considered. Only top-level domain counts were retained as a prominent feature. Any possibilities of a server client being mentioned for purposes of classification were also used to make sure that fake malicious copies of real websites could be identified.

- <u>Path Features:</u> The first feature that extracted on path were special symbols, the same as in URLs. Similarly extracted length, digit counts, letter counts and vowel counts were also extracted.
- Host Features: Here too the special symbols, length, digit counts, letter counts and vowel counts were extracted.
- Final Feature Engineering: Due to the presence of several zeroes, the columns with very low mean values are removed. Columns such as some special symbols for path and host and protocol were removed. The remaining columns were merged together. All the symbols for path, URL and the HTTPS and FTP columns were merged together. The labels are then extracted from the data and categorically numbered to make all of them into values between 0 and 3, inclusive using one-hot encoding.

To ensure that the data can allow for easier gradient descent, the data was scaled using a standard scale to have all columns with a mean of 0 and a standard deviation of 1. The labels are then added back to the data for the purpose of further feature engineering.

The data is first split into training, validation and testing data using Stratified K-Fold algorithm and shuffling. This ensures a balanced mean value to be present in each set by allowing an equal percentage of labels in each set for higher model accuracy. Around 65% of the data in training with 30% for validation and 5% for

testing will be used. The data split ensures that a good chunk of data can be used for training while maintaining a sizable amount of data for validation and testing.

C. Model

The model that is used is a basic perceptron for classification using a 68 dimensional input to make sure all the features extracted thus far can be input into the neural network. The hidden layers have a dimension of 300, 200 and 100 respectively. To ensure the highest possible chance of generalization, two dropout layers to the model with a probability of 0.2 and a batch normalization layer have been added before it is fed to the output, assuming a softmax activation. The hidden layers are all activated using the Scaled Exponential Linear Unit or SELU activation to ensure that gradients are fed back properly and account for any chances of the activation function dying or causing the gradient to vanish or explode.

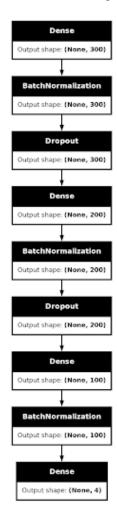


Fig. 2. Model Architecture

D. Honeypot

The honeypot is made using a standard architecture with the intention of giving the attacker a method of trying to access the system under the guise of being a dummy that simply serves no purpose in and of itself other than bait. The honeypot needs to being able to sustain itself to make sure that the attacker remains within the honeypot itself for as long as the attacker's belief on the fact that the system is a real vulnerable system that can be exploited can be maintained.

The honeypot itself also needs to ensure a sort of detachment from the main systems to make sure the attacker cannot use the honeypot as a breaching point very easily. The main methodology suggested here is the use of a one-way connection to connect the mainframe to the honeypot so that some communication is possible.

The one-way further allows encryption commands to be sent to the honeypot so that the files can be encrypted before access just to make sure the attacker cannot gain access to the files very easily, even if they are dummy files so as to waste the attacker's time and effort.

This further enables the study of the attacker's patterns if monitoring the honeypot is added so that the attack patterns can be learnt with time as the attacker is executing them.

The main stalling feature that will be used is a probabilistic key generation algorithm on the RSA encryption to prevent cryptanalysis of any sorts between texts. The major architecture of the honeypot is shown in the diagram below.

E. Probabilistic RSA Encryption

Probabilistic RSA encryption is an enhancement of the traditional RSA encryption algorithm that introduces randomness into the encryption process to bolster security against certain types of attacks. RSA encryption, named after its inventors Rivest, Shamir, and Adleman, is an asymmetric encryption scheme widely used for securing communications and data transmission.

In traditional RSA encryption, plaintext is encrypted using the recipient's public key, and the resulting ciphertext can only be decrypted with the corresponding private key. However, this basic scheme is susceptible to certain vulnerabilities, particularly when encrypting small or predictable plaintexts. Probabilistic RSA encryption addresses these vulnerabilities by incorporating randomness during encryption.

The fundamental principle behind probabilistic RSA encryption is to introduce randomness into both the plaintext and the encryption process itself. This randomization helps thwart attacks that exploit regularities or patterns in the plaintext data. Unlike deterministic encryption schemes, where the same plaintext always encrypts to the same ciphertext, probabilistic encryption ensures that each encryption operation produces a different ciphertext, even for the same plaintext.

The process of probabilistic RSA encryption using weather data without padding can be summarized as follows:

• Key Generation:

- Take 2 random numbers between 1 and the total number of cities being considered.
- Find the city associated with the first number.

- Take the maximum and minimum temperature for that day in Kelvin.
- Find the difference of the two temperatures.
- Multiply it by an arbitrary number x to get a value and find the nearest prime to that value.
- Repeat the above process to get the two primes needed for the encryption.
- Once the primes have been received, product, totient of the product, public and private key can be generated.
- The public key and product are sent to the sender of the ciphertext.

Sender:

- The sender receives the public key and encrypts his plaintext using modular exponentiation by raising the text to the value of the public key modulo product.
- The ciphertext can be sent to the receiver.

· Receiver:

- The receiver can decrypt the ciphertext by raising to the value of the private key modulo product.

IV. IMPLEMENTATION:

The model was implemented on the Tensorflow library on the Python programming language. All the data preprocessing was done on the same language as well. All weight and kernel initializations were done using Lecun to make sure that samples were drawn from a standard Gaussian curve of mean 0 and standard deviation 1.

The loss function used for this is a Categorical Crossentropy loss function with a Nesterov-accelarated Adaptive Moment Estimation optimizer (NAdam) to ensure adequate change in learning rate depending on the time. The metrics used for the model are Recall and Loss.

All training was done on a quad-core intel CPU and an NVIDIA T4 GPU. The model will also be early stopped at the best epoch and saved on callback to make sure that the best point of training and validation can be taken for evaluating links.

The honeypot was engineered using the Cowrie library on Ubuntu to emulate a honeypot-like architecture on Ubuntu itself which can be attacked using tools such as the Nmap scanner on Kali Linux and thus tested for security and to verify whether or not the data is secure or compromised within the honeypot.

The probabilistic encryption was made using weather data provided by the OpenWeather API to generate the keys from the weather data of 371 cities and considering the decimal places of the weather for primes of 4 digits or higher allows us to get a minimum probability of getting the exact right number as given by us as:

$$\frac{1}{3710000}$$

A. Results

The model was saved at epoch 28 due to the closeness of the precision and recall itself with recall differences being limited

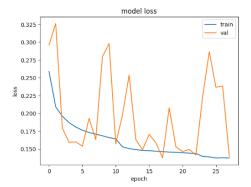


Fig. 3. Model Loss

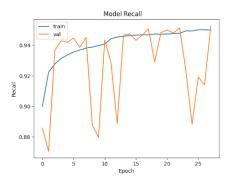


Fig. 4. Model Recall

to around 0.0028 for training and validation recall and 0.0032 for training and validation loss. The model can now be used for detection of fraudulent or malevolent links being clicked within the framework so as to activate the honeypot and check if any intruder has entered within the given time frame.

Cowrie had further proven to be successful at emulating the honeypot itself with proper file access and the ability to add and remove files from the honeypot as we please.

The probabilistic encryption also worked as expected returning different strings for each encryption take done at any given point in time. Assuming the test string to be Hello World:

The ASCII representation of Hello World in numbers: 72, 101, 108, 108, 111, 32, 87, 111, 114, 108, 100

• Time 1:

Encrypted: 553, 582, 330, 330, 777, 106, 87, 777, 595, 330, 618

Decrypted: 72, 101, 108, 108, 111, 32, 87, 111, 114, 108, 100

• Time 2:

Encrypted: 901, 640, 823, 823, 777, 483, 725, 777, 102, 823, 676

Decrypted: 72, 101, 108, 108, 111, 32, 87, 111, 114, 108, 100

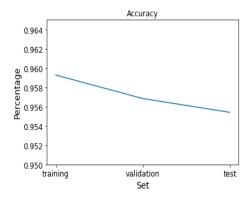


Fig. 5. Accuracy On Data Split

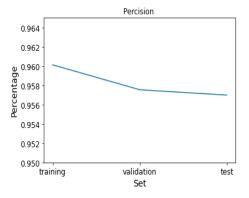


Fig. 6. Precision On Data Split

B. Conclusion

This paper presents research on Siren, a proactive cybersecurity protection mechanism that combines machine learning, deception, and real-time threat analysis. Siren makes it easier to analyze prospective attacker activity and gives the system the ability to proactively stop threats by deliberately luring them into controlled surroundings. The fundamental principle of Siren is its capacity to detect and react to new threats, presenting a major departure from reactive cybersecurity techniques.

A link monitoring proxy for increased scrutiny, a honeypot strengthened with probabilistic encryption to ensure data security, an adaptive machine learning model that constantly adapts in response to new threats, and the addition of simulated user activity to increase the system's ability to learn from potential threats are some of Siren's unique features.

By adding randomness to the encryption process, probabilistic RSA encryption improves the honeypot's security posture and increases its resistance to different types of cryptographic attacks.

There's a good chance that this research will significantly advance cybersecurity. User protection will be strengthened by the empirical evaluation of Siren's effectiveness in proactively recognizing and reducing potential threats. Moreover, studying how adversaries behave in controlled settings will provide

insightful information that will significantly influence the creation of proactive defensive plans in the future.

The results of this study highlight how urgent it is to advance beyond reactive cybersecurity strategies. Organizations may fortify their defenses and remain ahead of the constantly changing threat landscape by implementing proactive solutions like Siren. Subsequent research endeavors encompass the extensive implementation and assessment of Siren in realworld settings, in conjunction with constant enhancement of the system's constituent elements to guarantee its effectiveness against innovative and intricate cyber hazards. Siren clears the path for a day where cybersecurity is strengthened and proactive rather than reactive, protecting digital assets and reducing the dangers associated with persistent cyberattacks. The results of this study highlight how urgent it is to advance beyond reactive cybersecurity strategies. Organizations may fortify their defenses and remain ahead of the constantly changing threat landscape by implementing proactive solutions like Siren. Subsequent research paths involve the extensive implementation and assessment of Siren in real-world settings, in addition to constant improvement of the system's elements to guarantee its effectiveness against new and complex dangers from cyberspace. Siren clears the path for a day where cybersecurity is strengthened and proactive rather than reactive, protecting digital assets and reducing the dangers associated with persistent cyberattacks.

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