Malware Detection Using Machine Learning (Case Study)

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Abstract- Currentantivirus software's are effectiveagainst known viruses, if a malware with new signature is introduced then it will be difficult to detect that it is malicious. Signaturebased detection is not that effective during zero-day attacks. Till the signature is created for new (unseen) malware, distributed to the systems and added to the anti-malware database, the systems can be exploited by that malware. Research shows that over the last decade, malware has been growing exponentially, causing substantial financial losses to various organizations. Different anti-malware companies have been proposing solutions to defend attacks from these malware. The velocity, volume, and the complexity of malware are posing new challenges to the anti-malware community. Current state-of-the-art research shows that recently, researchers and anti-virus organizations started applying machine learning and deep learning methods for malware analysis and detection. Machine learning methods can be used to create more effective anti malware software which is capable of detecting previously unknown malware, zero-day attack etc. We propose an approach that various machine learning methods such as Support Vector Machine (SVM), Decision tree, Random Forest and XG Boost will be used.

I. INTRODUCTION

Idealistic hackers attacked computers in the early days because they were eager to prove themselves. Cracking machines, however, is an industry in today's world. Despite recent improvements in software and computer hardware security, both in frequency and sophistication, attacks on computer systems have increased. Regrettably, there are major drawbacks to current methods for detecting and analysing unknown code samples. The Internet is a critical part of our everyday lives today. On the internet, there are many services and they are rising daily as well. Numerous reports indicate that malware's effect is worsening at an alarming pace. Although malware diversity is growing, anti- virus scanners are unable to fulfil security needs, resulting in attacks on millions of hosts. Around 65,63,145 different hosts were targeted, according to Kaspersky Labs, and in 2015, 40,00,000 unique malware artefacts were found. Juniper Research (2016), in particular, projected that by 2019 the cost of data show that script-kiddies are generating more and more attacks or are automated. To date, attacks on commercial and government organisations, such as ransomware and malware, continue to pose a significant threat and challenge. Such attacks can come in various ways and sizes. An enormous challenge is the ability of the global security community to develop and provide expertise in cybersecurity. There is widespread awareness of the global scarcity of cybersecurity and talent. Cybercrimes, such as financial fraud, child exploitation online and payment fraud, are so common that they demand international 24-hour response and collaboration between multinational law enforcement agencies.

breaches will rise to \$2.1 trillion globally. Current studies

MALWARE DETECTION

In such a way, hackers present malware aimed at persuading people to install it. As it seems legal, users also do not know what the programme is. Usually, we install it thinking that it is secure, but on the contrary, it's a major threat. That's how the malware gets into your system. When on the screen, it disperses and hides in numerous files, making it very difficult to identify. In order to access and record personal or useful information, it may connect directly to the operating system and start encrypting it Detection of malware is defined as the search process for malware files and directories. There are several tools and methods available to detect malware that make it efficient and reliable.

II. NEED FOR MACHINE LEARNING IN MALWARE DETECTION

Machine learning has created a drastic change in many industries, including cybersecurity, over the last decade. Among cybersecurity experts, there is a general belief that AIpowered anti-malware tools can help detect modern malware attacks and boost scanning engines. Proof of this belief is the number of studies on malware detection strategies that exploit machine learning reported in the last few years. The number of research papers released in 2018 is 7720, a 95 percent rise over 2015 and a 476 percent increase over 2010, according to Google Scholar,1. This rise in the number of studies is the

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product of several factors, including but not limited to the increase in publicly labelled malware feeds, the increase in computing capacity at the same time as its price decrease, and the evolution of the field of machine learning, which has achieved ground- breaking success in a wide range of tasks such as computer vision and speech recognition. Depending on the type of analysis, conventional machine learning methods can be categorised into two main categories, static and dynamic approaches. The primary difference between them is that static methods extract features from the static malware analysis, while dynamic methods extract features from the dynamic analysis. A third category may be considered, known as hybrid approaches. Hybrid methods incorporate elements of both static and dynamic analysis. In addition, learning features from raw inputs in diverse fields have outshone neural networks. The performance of neural networks in the malware domain is mirrored by recent developments in machine learning for cybersecurity.

INTERFACE REQUIREMENT

The section gives an overview of the functionality of the product. It describe the informal requirement and is used to establish a context a context for the technical requirement specification

HARDWARE REQUIREMENT

processor type : Intel i5 (10gen) Speed :4.0ghz Ram: 8 Hard disk:300 gb Keyboard:101/102 standard keys Mouse:Scroll mouse

SOFTWARE REQUIREMENTS

Language	Python
IDE	Anaconda
Packages	Pandas
	OS
	Numpy
	Sklearn

SOURCE CODE

importos import pandas importnumpy

importsklearn.ensembleasek

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fromsklearnimport tree, linear_model fromsklearn.feature_selectionimportSelectFromModel fromsklearn.naive_bayesimportGaussianNB fromsklearn.metricsimportconfusion_matrix fromsklearn.pipelineimportmake_pipeline fromsklearnimportpreprocessing fromsklearnimportsvm fromsklearn.linear_modelimportLinearRegression dataset =pandas.read_csv('MalwareData.csv',sep='|',

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III. PROPOSED SYSTEM

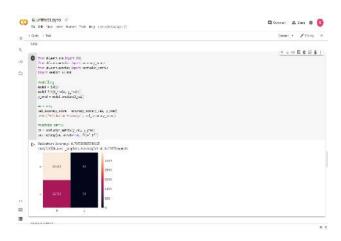
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DECISION TREE





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IV. CONCLUSION

We have proposed a malware detection module based on advanced data mining and machine learning. While such a method may not be suitable for home users, being very processor heavy, this can be implemented at enterprise gateway level to act as a central antivirus engine to supplement antiviruses present on end user computers. This will not only easily detect known viruses, but act as a knowledge that will detect newer forms of harmful files. While a costly model requires costly infrastructure, it can help in protecting invaluable enterprise data from security threats, and prevent immense financial damage.

This paper presents the survey about existing literature on malware analysis using different machine learning algorithms. Table 1 defines the different literature of existing works with what are the tools used in their work, what are the machine learning algorithms they used in their work, from what sources dataset is collected, what are parameters they consider to reach their goal and the corresponding experimental results and what are the future works are proposed all are listed in the table form. In the discussion, it clearly identifies thatmachine

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