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TITLE: DETECTING WEB ATTACKS WITH END-TO -END DEEP LEARNING

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DETECTING WEB ATTACKS WITH END-TO-END DEEP LEARNING

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ABSTRACT

Web applications are often the target of cyberattacks because of their frequent vulnerabilities and network accessibility. An intrusion detection system monitors online applications and notifies users when an attempt at an attack is made. Current implementations of intrusion detection systems frequently extract qualities from input strings or network packets that are explicitly chosen as relevant to attack analysis. However, selecting characteristics by hand requires a great deal of effort and in-depth knowledge of the security area. Moreover, in order to classify normal and abnormal actions, supervised learning algorithms need large volumes of labelled legitimate and attack request data, which are usually prohibitively expensive or difficult to obtain for live online services. Three new perspectives are added to the field of autonomic intrusion detection systems study by this paper. First, we evaluate the practicality of an unsupervised/semi-supervised approach.

Keywords: Web security, Deep learning, Application instrumentation.

1. INTRODUCTION

Emerging trends and challenges. Web applications are attractive targets for cyber attackers. SQL injection [1], cross site scripting (XSS) [2] and remote code execution are common attacks that can disable web services, steal sensitive user information, and cause significant financial loss to both service providers and users. Protecting web applications from attack is hard. Even though developers and researchers have developed many counter-measures (such as firewalls, intrusion detection systems (IDSs) [3] and defensive programming best practices [4]) to protect web applications, web attacks remain a major threat. For example, researchers found that more than half of web applications during a 2015–2016 scan contained significant security vulnerabilities, such as XSS or SQL Injection [5]. Moreover, hacking attacks cost the average American firm \$15.4 million per year [6]. The Equifax data breach in 2017 [7, 8] (which exploited a vulnerability in Apache Struts) exposed over 143 million American consumers' sensitive personal information. Although the vulnerability was disclosed and patched in March 2017, Equifax took no action until four months later, which led to an estimated insured loss of over 125 million dollars. Conventional intrusion detection systems do not work as well as expected for a number of reasons, including the following: large demand and relatively low barrier to entry into the software profession, however, many developers lack the necessary knowledge of secure coding practices.

2. LITERATURE SURVEY

large demand and relatively low barrier to entry into the software profession, however, many developers lack the necessary knowledge of secure coding practices. Many intrusion detection systems rely on rule-based strategies or supervised machine learning algorithms to differentiate normal requests from attack requests, which requires large amounts of labeled training data to train the learning algorithms.

It is hard and expensive, however, to obtain this training data for arbitrary custom applications. In addition, labeled training data is often heavily imbalanced since attack requests for custom systems are harder to get than normal requests, which poses challenges for classifiers [10]. Moreover, although rule-based or supervised learning approaches can distinguish existing known attacks, new types of attacks and vulnerabilities emerge continuously, so they may be misclassified.

3. EXISTING METHOD

As discussed, different attacks have different characteristics and traditional feature engineering approaches lack a unified solution for all types of attacks. RSMT bypasses these attack vectors and instead captures the low-level call graph. It assumes that no matter what the attack type is (1) some methods in the server that should not be accessed are invoked and/or (2) the access pattern is statistically different than the legitimate traffic. RSMT operates as a late-stage (post-compilation) instrumentation-based toolchain targeting languages that run on the Java Virtual Machine (JVM)

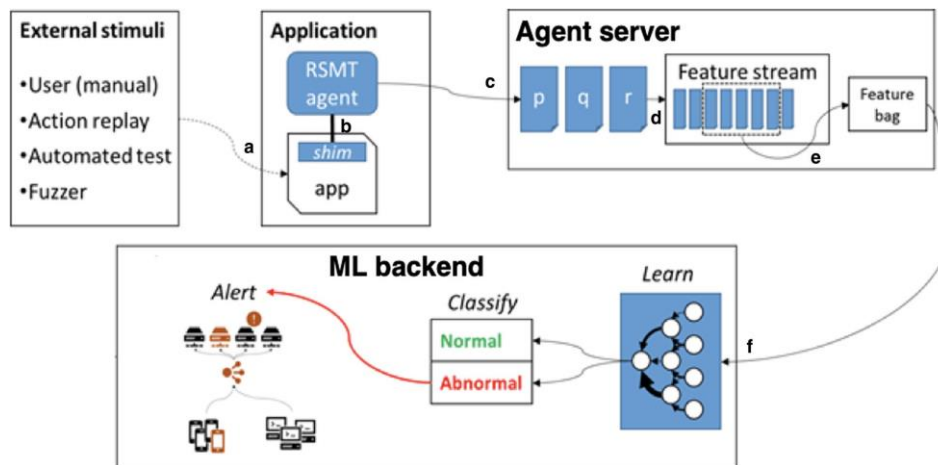


Fig. 1: arbitrarily fine-grained traces of program execution

Figure 1 shows the high-level workflow of RSMT's web attack monitoring and detection system. This system is driven by one or more environmental stimuli (a), which are actions transcending process boundaries that can be broadly categorized as either manual (e.g., human interaction-driven) or automated (e.g., test suites and fuzzers) inputs. The manifestation of one or more stimuli results in the execution of various application behaviors. RSMT attaches an agent and embeds lightweight shims into an application (b). These shims do not affect the functionality of the software, but instead serve as probes that allow efficient examination of the inner workings of software applications. The events tracked by RSMT are typically control flow-oriented, though dataflow-based analysis is also possible.

As the stimuli drive the system, the RSMT agent intercepts event notifications issued by shim instructions. These notifications are used to construct traces of behavior that are subsequently transmitted to a separate trace management process (c). This process aggregates traces over a sliding window of time (d) and converts these traces into "bags" of features (e). RSMT uses feature bags to enact online strategies (f), which involve the following two epochs:

4. PROPOSED METHOD

To train our stacked autoencoder we use a pretraining step involving greedy layer-wise training. The first layer of encoder is trained on raw input. After a set of parameters are obtained, this layer is used

to transform the raw input to a vector represented as the hidden units in the first layer. We then train the second layer on this vector to obtain the parameters of second layers. This process is repeated by training the parameters of each layer individually, while keep the parameters of other layers unchanged.

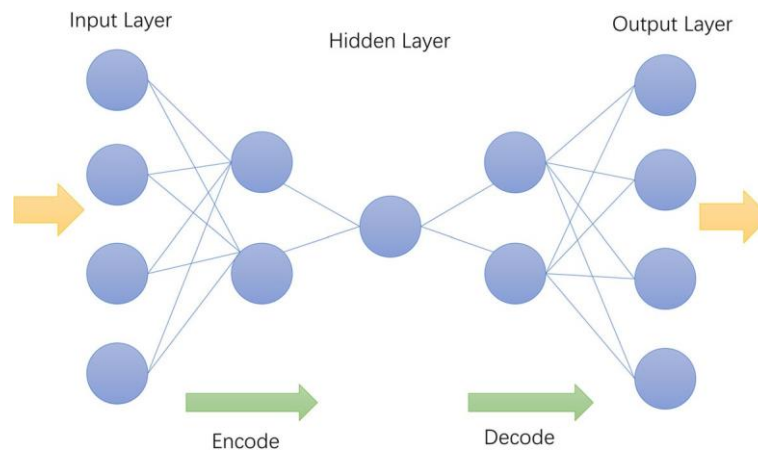


Fig. 2: T-SNE Visualization of Normal and abnormal requests

5. CONCLUSION

This paper describes the architecture and results of applying a unsupervised end-to-end deep learning approach to automatically detect attacks on web applications. We instrumented and analyzed web applications using the Robust Software Modeling Tool (RSMT), which autonomously monitors and characterizes the runtime behavior of web applications. We then applied a denoising autoencoder to learn a low-dimensional representation of the call traces extracted from application runtime. To validate our intrusion detection system, we created several test applications and synthetic trace datasets and then evaluated the performance of unsupervised learning against these datasets. While cross validation is widely used in traditional machine learning, it is often not used for evaluating deep learning models because of the great computational cost. We needed to compare autoencoder approaches with other machine learning methods. To enable a fair comparison, we didn't use cross validation in our experiments.

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