Artificial Intelligence Techniques for Security Vulnerability Prevention

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Abstract
Computer security has been a concern for decades and artificial intelligence techniques have been applied to the area for nearly as long. Most of the techniques are being applied to the detection of attacks to running systems, but recent improvements in machine learning (for example, in natural language processing) have enabled the opportunity to process software and specifications to detect vulnerabilities in a system before it is deployed. This paper presents a survey of artificial intelligence techniques (including machine learning) to detect or repair security vulnerabilities before product introduction. In the surveyed papers, techniques are presented for using NLP to analyze requirements documents for security standard completeness, performing neural fuzz testing of software, generating exploits to detect risk, and more. We categorize current techniques into 3 groups: vulnerability detection, vulnerability repair, and specification analysis. Generally, while AI techniques have become quite useful in this area, we show that AI techniques still tend to be limited in scope, providing a collection of tools which can augment but not replace careful system development to reduce vulnerability risks.

Keywords: artificial intelligence, machine learning, security, vulnerabilities, software

1. Introduction
Machine learning has been expanding in scope in recent years to the point where meaningful natural language processing (NLP), automated testing, and code analysis can be utilized. Additionally, more tradition artificial intelligence (AI) techniques such as support vector machines, genetic algorithms, and inference engines can be applied to code before it is used in a setting where it may be attacked. Using artificial intelligence techniques to prevent vulnerabilities from being introduced is a broad field and warrants an updated survey paper to identify promising avenues of research in this area.

According to Cybersecurity Ventures, 111 billion lines of new software code are created annually worldwide (Ventures, 2017). By utilizing automated mechanisms to aid in detecting vulnerabilities before system deployment, a product team can focus more on feature development and performance. The large number of devices and applications being deployed today both increases the risks of vulnerabilities to a networked system and also provides a large collection of training data to use with artificial intelligence techniques. As we discuss papers in this survey, we will consider which areas of security vulnerability reduction are most likely to benefit from further artificial intelligence advances in the near future.

The broadest recent survey in this area reviews papers from 2008-2015 and explored how machine learning techniques were being applied to broad security domains (Jiang et al., 2016). Our survey differs from that work in 3 primary ways. First, we will be including papers published as recently as 2018; second, we will be considering all artificial intelligence approaches, not limiting to machine learning; and third we will be focussed on vulnerability detection and prevention, not attack detection or other security issues. Another recent survey paper is a student paper available on arXiv and discusses the DARPA sponsored Cyber Grand Challenge to detect, exploit, and/or repair vulnerabilities in software (Brooks, 2017). We will discuss the results of these surveys in more detail in sections 2 and 3. In our survey we include some references that are not peer-reviewed (such as the student survey but also publications from companies). These references are provided in the spirit of giving a broad understanding of the current work in this area.

There are many ways to organize an algorithm to use AI with security, but figure 1, taken from one of our surveyed papers (Wang et al., 2015), is useful for understanding many common components. The figure identifies the input data as audit logs, existing security access policies, and known
access patterns. The learning algorithm in the figure uses a nearest-neighbor classifier along with other components to learn when policies should be loosened or tightened based on the audit log information. The output of the system refines the policies. This format of using training data to develop an AI system which can then be applied to new inputs is a general approach used by many of the papers cited.

This paper is organized into 3 sections. Section 2 covers techniques to detect vulnerabilities in source code or binary code. Section 3 covers techniques to automatically repair vulnerabilities in source code. Section 4 discusses techniques to analyze security specifications to insure the future code is correct or to check that access permissions match the documentation. For each of the 3 areas, we will assess what we consider the most promising avenues of research.

2. Vulnerability detection

Vulnerability detection is the problem of identifying vulnerable code sequences by analyzing source code prior to deployment. Table 1 shows papers which use AI techniques for vulnerability detection. Two of the papers focus on Android apps and this highlights a primary reason for machine learning in the security space (Peng et al., 2012) (Rasthofer et al., 2014). Companies whose reputation depends on their software quality are also making platforms available to which large numbers of coders can contribute. The ability to automatically process submitted applications greatly reduces the overhead of quality assurance by trained professionals.

Yamaguchi, one of the authors cited in the table, wrote further about his techniques in his PhD thesis (Yamaguchi, 2015). His work combines a new parsing strategy with a joint data structure of program syntax, control flow, and data flow into a code property graph. This graph is embedded into a vector space for use with machine learning algorithms and mined for instances of vulnerable program patterns. For his application, he found that supervised training for security was not as valuable as unsupervised training based on clustering. Yamaguchi was able to reduce the code needing human review by 95% by focussing on dimensionality reduction, anomaly detection, and clustering.

Two of our references in this category deal with Android applications (Peng et al., 2012) (Rasthofer et al., 2014). Given the large number of applications submitted for use on Android platforms, automating any part of the security problem is valuable. One of these papers includes data showing that malicious software frequently requests many more permissions than valid software (for example, only 2-3% of valid applications request the READ_SMS permission, but almost 60% of malware requests it) (Peng et al., 2012). By training a system to recognize the malware request patterns, the 2-3% of valid applications are mostly classified as safe, while the malware is detected. The other Android reference compares their technique for detecting unsafe data leaks to other dynamic taint analysis tools like Fortify SCA and TaintDroid (Rasthofer et al., 2014). In taint tracking, one monitors the flow of data between resources such as the file system or network. The approach uses supervised training to learn when privacy information such as location information or address book data is leaked to risky destinations such as certain web domains. Their code was able to find new
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<tr>
<td>(Richardson et al., 2010)</td>
<td>Limits of automated fingerprinting for OS</td>
<td>Decision tree, rule learner, SVM-SMO, instance-based clustering</td>
<td>ML tended to overfit on unimportant differences in variants. Training data was fuzz testing with candidate queries feeding into a classifier.</td>
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<td>(Peng et al., 2012)</td>
<td>Score and rank risks of Android apps</td>
<td>Naive Bayes, Probabilistic generative model</td>
<td>Analyzes GooglePlay apps and a Malware dataset based on permissions requested (READ_SMS, ACCESS_WIFI_STATE, etc) to create single risk score to simplify user interactions.</td>
</tr>
<tr>
<td>(Rasthofer et al., 2014)</td>
<td>Identify sources and sinks from code of any Android API</td>
<td>Linear SVM</td>
<td>Recognizes sensitive data sources and potentially untrustworthy data sinks which might leak data by analyzing source code.</td>
</tr>
<tr>
<td>(Mokhov et al., 2014)</td>
<td>Identify bad coding practices</td>
<td>NLP, Modular A* Recognition Framework</td>
<td>Analyze CVE code base for training examples of weak code and use model to identify risk areas in source code.</td>
</tr>
<tr>
<td>(Yamaguchi et al., 2015)</td>
<td>Infer vulnerability search patterns in C code</td>
<td>Complete-linkage clustering</td>
<td>Detect attacker-controlled data attack to a sensitive data sink. (Heartbleed is an example). Constructs code property graph and uses ML to reduce amount of code needed to audit by 95%.</td>
</tr>
<tr>
<td>(Liu et al., 2015)</td>
<td>Predict future data leak instances from network logs</td>
<td>Random Forest</td>
<td>Predict future organization breaches by analyzing externally measurable network features (misconfigured DNS, phishing sourced from organization, etc).</td>
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<tr>
<td>(Blum et al., 2017)</td>
<td>Improve fuzzing of inputs</td>
<td>Neural network</td>
<td>Fuzzing is a technique to provide crafted malicious input to test a program for vulnerabilities. This paper uses neural networks to learn which areas in programs to attack to test for vulnerabilities.</td>
</tr>
<tr>
<td>(Shoshitaishvili et al., 2018)</td>
<td>Discover vulnerabilities in binary code</td>
<td>Symbolic execution and fuzzer</td>
<td>Searches for tainted input vulnerabilities. Avoids path explosion of symbolic execution by intelligently combining it with fuzzing techniques.</td>
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Table 1. Artificial Intelligence techniques addressing automatic detection of software vulnerabilities
data destinations used by malware (sinks) in the Android application set which were not previously on lists of sinks for the ecosystem.

Microsoft has an enormous code base that must be maintained and developed with attention to security vulnerabilities. Fuzzing is a dynamic program technique which mutates program inputs to find vulnerabilities that cause crashes, buffer overflows, memory errors, and exceptions. Long Short Term Memories (LSTMs) are used in recurrent neural networks to facilitate learning patterns in time as well as syntax structures in human or computer languages. Microsoft researchers used neural networks including LSTMs to learn patterns from past fuzzing explorations to guide future fuzzing mutations efficiently (Blum et al., 2017). Crashing a system is a key measurement of fuzzing efficacy and using their LSTM guided fuzzing technique Rajpal et al., were able to find 37% more unique crashes than the benchmark fuzzing technique they compared against.

Automating the processes of checking code for vulnerabilities is important. DARPA sponsored the Cyber Grand Challenge to detect, exploit, and/or repair vulnerabilities in software; and the Mayhem and Mechanical Phish (Shoshitaishvili et al., 2018) programs were the top 2 ranked submissions. Both used symbolic execution to aid in the search for vulnerabilities (Brooks, 2017). Symbolic execution is a technique where input values are tracked symbolically through a program, as opposed to running multiple test cases with specifically chosen values for input parameters. Both Mayhem and Mechanical Phish are designed to discover exploitable vulnerabilities in binary code. Their techniques can help uncover buffer overflow vulnerabilities, format string vulnerabilities, and general memory corruption vulnerabilities. However, neither winner is yet ready to be used for large, complex systems and so further research in this area is warranted.

Using NLP techniques on code has shown interesting results (Mokhov et al., 2014). Mokhov et al. show how to teach a language model what bad code looks like using CVE and CWE cases and then use the trained model to identify sections of source code that match given vulnerabilities. They build their system on top of MARFCAT, a machine learning code analysis application they also developed (Mokhov et al., 2015). Their core NLP methodology includes 2 character n-grams with smoothing techniques, which means the language is analyzed using these 2 character patterns but with some adjustment made to smooth out the probabilities for rarely seen tuples. With appropriate training their model can work on binary code or source code in various languages. MARFCAT learns known weaknesses by computing various language models from the CVE-selected test cases and then can compare these models to unseen code fragments for vulnerability discovery.

We conclude this section with reference to a cautionary paper. Remote operating system fingerprinting in order to identify different OS versions usually requires manual effort. Richardson et al. (Richardson et al., 2010) tested a previously published promising technique to eliminate manual intervention. The new technique used an approach similar to fuzz testing. They found that when tested on 329 different machine instances the results with the new technique were poor. They suspected the system overfitted to behavioral differences that were not OS-specific and concluded that manual expertise would still be needed for OS fingerprint generation. In general, many of the AI techniques that show initial promise need to be tested in larger production environments before being broadly deployed.

3. Vulnerability repair

The next step beyond detecting vulnerabilities is to attempt automatic repairs with artificial intelligence techniques. The goal of code repair is to learn from examples how to transform vulnerable code into non-vulnerable code. As this field progresses, millions of lines of legacy code could be scrubbed to improve security very broadly. Even early progress in this area can be very valuable. If a new class of vulnerability is found (such as Spectre), training examples of changing vulnerable code to protected code can often be generated quickly (for Spectre, compiling Visual C++ with older vs latest MSVC can create training cases (Microsoft, 2018)). Creating an automated system that can transform code with the vulnerability to clean code can allow large software repositories to be repaired efficiently.

Klieber and Snively (Klieber & Snively, 2016) use code transformations to repair common types of bugs. For example, access control is one of the top ten vulnerabilities in the OWASP list (OWASP, 2017) and falls under CWE-285; their approach uses a first order logic solver to prove access controls are safe and will add appropriate conditions if it is not. They analyze the code to determine the intended (implied) access controls that should be available to the user and can repair functions to limit access to only this implied set. As an example from the paper, consider a collaborative document viewing/editing system which allows documents to be viewed by members of a team but only edited by the author given normal UI access options. The approach taught how to compute the intended access control policy as well as the policy available to an attacker without restriction to the normal UI interface. When an attacker’s access exceeds the intended access, the codebase is repaired to provide the proper limitation.

Another approach to program repair is to search for code changes which pass security test cases (Le et al., 2017). Le et al. use a domain-specific language for input along with test cases and sets up a search space to find quality repairs to bugs in code. The code is analyzed to find likely lines at risk for bugs, adjust those lines to use symbolic execution, and analyzes the symbolic execution given the inputs and outputs provided for quality assurance. Bugs which are found can then often be repaired to produce the correct output given the input.
One of our references is an example of a more specific yet widely applicable use of AI for improving mandatory access control (MAC) for Android (Wang et al., 2015). The system uses audit logs from existing applications and semi-supervised learning to train a network to generate improved MAC policies as well as improved audit logs. The improved audit logs can then be used to improve the MAC policies further. Figure 1 is from this paper and shows how the components of this system interact.

As an example of ongoing work in industry, we include an article by Draper in this table (Draper, 2017). Heartbleed is a famous security bug from 2014 involving buffer overflow in the OpenSSL cryptography library. Using a neural network trained on 170,000 C/C++ projects from GitHub, their DeepCode architecture found and fixed Heartbleed bugs when run on previously unseen programs.

4. Specification analysis

Advances in natural language processing have given researchers the opportunity to automatically process vulnerability descriptions or product specifications to assess security risks. In 2017, CVE logged almost 300 vulnerabilities per week (CVE, 2018), which puts enormous burden on system administrators to evaluate, prioritize, and patch critical vulnerabilities. Bozorgi et al. (Bozorgi et al., 2010), use machine learning to digest the CVE vulnerability labels and descriptions and produce a single score that summarizes both the exploitability of the vulnerability and its severity. The goal is that the single score can be used by system administrators to prioritize work on patches for new vulnerabilities. Their technique relies on an NLP technique known as 'bag-of-words'. For example they record whether particular tokens like "buffer", "heap", or "DNS" appear in specific text fields like "title", "solution", or "product name". Their classifier is about 90% accurate, much more so than the 'Exploitability' score provided by CVSS.

To help address risk assessment in new mobile applications, WHYPER has been trained to recognize sentences in a smartphone application description to infer the permissions an application should need (Pandita et al., 2013). For example, if the application description includes "You can share the yoga exercise to your friends via Email and SMS", then this indirectly implies the application should have the READ_CONTACTS permission on the smartphone. Applications which ask for permissions not implied in the description to the customer could be classified as suspicious.

Our final paper in this category addresses the goal of finding vulnerability issues in product specifications before code is being written. Figure 2 shows the traditional cost of change curve during software development. As discussed in the introduction, many artificial intelligence techniques applied to computer security are being applied at the production stage - detecting attacks to running system by monitoring traffic or logs. This paper aimed to highlight artificial intelligence techniques that can be applied earlier in the design cycle. In order to find security vulnerabilities before code is even written, some researchers have looked at analyzing security requirements documents (Malhotra et al., 2016) (Hayrapetian & Raje, 2018). The earlier paper (Malhotra et al., 2016) is structured as a proposal for an approach to the problem. That paper notes that previous work to detect requirement document problems focussed on 'weak phrases' and 'linguistic defects'. The paper proposes training a neural network on ISO security standards and using the General Architecture for Text Engineering (GATE) to detect problems. The paper proposes creating concept graphs and comparing the ISO standards to the document in question. For example, if the standards expect authentication to require a user ID and a password and the document only refers to a user ID, then the graph comparison would detect the missing password requirement and detect the error. The later paper is by some of the same authors as the first paper (Hayrapetian & Raje, 2018) and this paper provides results of the approach comparing security documents to ISO and OWASP standards. They were able to reach 89% accuracy in determining the completeness of standard statements, indicating a technique which could be a valuable tool for a specification reviewer, but not yet a replacement for careful review.

5. Future work

As computer hardware continues to improve and more powerful artificial intelligence techniques are created, more such techniques will be applied to the problem of software security. To stay abreast of new developments, we recommend watching for future publications by the authors and companies sited in this paper. Several of the frameworks proposed yield promising but not yet productizable results, so further work in the areas discussed is likely to be fruitful.
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<td>(Wang et al., 2015)</td>
<td>Semi-supervised learning for Android MAC</td>
<td>Nearest neighbors (metric: semantic connectivity between known and unknown subjects)</td>
<td>Analyzes access patterns from system usage to improve Mandatory Access Control policies.</td>
</tr>
<tr>
<td>(Klieber &amp; Snavely, 2016)</td>
<td>Repair Missing Function-Level Access Control</td>
<td>First order logic solver</td>
<td>Uses first order logic solver to prove access controls are safe and, if not, add the appropriate condition. This vulnerability type is one of top 10 on OWASP list (OWASP, 2017).</td>
</tr>
<tr>
<td>(Le et al., 2017)</td>
<td>Repair vulnerable code using programming by examples</td>
<td>Inductive Synthesis, Symbolic Execution</td>
<td>Sets up search space to find quality repairs to code and tests candidate fixes using test cases.</td>
</tr>
<tr>
<td>(Draper, 2017)</td>
<td>Uses ML to eliminate found vulnerabilities</td>
<td>Neural network</td>
<td>This is not a scientific paper, but their approach is described more in (Jagannathan, 2017). Learn over large code corpus how to repair programs.</td>
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Table 2. Artificial intelligence techniques aimed at automatically repairing vulnerabilities

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<tr>
<td>(Bozorgi et al., 2010)</td>
<td>Predict possibility and timing of vulnerable exploits</td>
<td>Bag-of-words, Linear SVM</td>
<td>Assess impact and exploitability of new CVE and OSV vulnerabilities using bag-of-words and numerical ML techniques from vulnerability descriptions.</td>
</tr>
<tr>
<td>(Pandita et al., 2013)</td>
<td>Identify permission sentences in mobile apps</td>
<td>Part-of-speech(POS) tagging, phrase and clause parsing, named entity recognition, semantic graph, typed dependency</td>
<td>Uses NLP on application descriptions and determines if permissions given to app are justified. Bridges gap between user expectations and app functionality to reduce risk assessment of apps.</td>
</tr>
<tr>
<td>(Hayrapetian &amp; Raje, 2018)</td>
<td>Evaluating security features in software requirements</td>
<td>NLP, Neural Network</td>
<td>Continuation of (Malhotra et al., 2016) work learning concept graphs from OWASP, OSI, and PCI specs and checks software documents for alignment to specs.</td>
</tr>
</tbody>
</table>

Table 3. Artificial intelligence techniques aimed at discovering vulnerability risks in specifications
6. Conclusion

While the field of applying artificial intelligence to security vulnerabilities is rather narrow, there is a lot of interest as shown by the diversity of papers we have discussed in this survey. Some of the most intriguing results surveyed include the ability to detect vulnerabilities in code and specification for new smartphone applications, a widely visible area of risk to the consumer community. The potential to automatically repair vulnerable code by learning the appropriate code transformation could be very useful when enormous amounts of code need to be reviewed due to the discovery of a new vulnerability. Also promising is the ability to analyze an English language specification for security risks with reference to security standards documents. Advances in natural language processing and code transformation techniques from fields outside security are creating approaches which can be applied to security problems. Given the estimated 111 billion lines of software being generated annually in the world today, automated security techniques which can be applied before systems are deployed will be critical for technology to continue to be safely used by consumers, corporations, and governments.

References


