Measuring and Preventing Supply Chain Attacks on Package Managers

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Abstract—Package managers have become a vital part of the modern software development process. They allow developers to reuse third-party code, share their own code, minimize their codebase, and simplify the build process. However, recent reports showed that hundreds of malware have sneaked into package managers, which have been downloaded millions of times, posing significant security risks to developers as well as end-users. For example, eslint-scope, a package with millions of weekly downloads in Npm, was compromised to steal credentials from developers.

To understand the attacks on package managers and the misplaced trust that makes them possible, we propose a comparative framework to study the package managers for interpreted languages. By systematically analyzing the recent attacks using our framework, we can identify security gaps and broken trust in the package manager ecosystem. Based on these insights, we propose and implement a vetting pipeline, MAI.OSS, to perform metadata, static and dynamic analysis on packages and flag the suspicious ones. Through iterative labeling, we identified and reported 339 malware to package manager maintainers. 278 (82 percent) of them have been confirmed and removed, and 3 of them with more than 100,000 downloads have been assigned CVEs. To help secure the ecosystem, we propose actionable security improvements for package manager maintainers and suggestions for other stakeholders.

I. INTRODUCTION

Many modern web applications rely on interpreted programming languages because of their rich libraries and packages. Registries (also known as package managers) like PyPI, Npm, and RubyGems provide a centralized repository that developers can search and install add-on packages to help in development. For example, developers building a web application can rely on Python web frameworks like Django [1], web2py [2], and Flask [3] to provide boilerplate code for rapid development. Not only have registries made the development process more efficient, but also they have created a large community that collaborates and shares open-source code. Unfortunately, miscreants have found ways to infiltrate these communities and infect benign popular packages with malicious code that steal credentials [4], install backdoors [5], and even abuse compute resources for cryptocurrency mining [6].

The impact of this problem is not isolated to small one-off web apps, but large websites, enterprises, and even government organizations that rely on open-source interpreted programming languages for different internal and external applications. Attackers can infiltrate well-defended organization by simply subverting the software supply chain of registries. For example, eslint-scope [4], a package with millions of weekly downloading in Npm, was compromised to steal credentials from developers. Similarly, rest-client [5], which has over one hundred million downloads in RubyGems, was compromised to leave a Remote-Code-Execution (RCE) backdoor on web servers. These attacks demonstrate how miscreants can covertly gain access to a wide-range of organizations by carrying out a software supply chain attack.

Security researchers [7] are aware of these attacks and have proposed several solutions to address the rise of malicious software in registries. Zimmermann et al. [8] systematically studied 609 known security issues and revealed a large attack surface in the Npm ecosystem. BreakApp [9], on the other hand, isolates untrusted packages, which addresses credential theft and prevents access to sensitive data, but does not stop cryptocurrency mining or backdoors. Additionally, many solutions [10]–[12] assume developers are benign which does not apply to malware. To make matters worse, some attacks are very sinister and use social engineering techniques [13], [14] to disguise themselves by first publishing a “useful” package, then waiting until it is used by their target to update it and include malicious payloads. Although, many security researchers are investigating attacks on registries and proposing solutions, very little is done to understand the root cause problem that makes these attacks easy to carry out.

For example, are attacks different across registries? What are the most common attacks observed in the past? Can we apply well-known security principles to solve these problems? Why is it difficult to analyze interpreted language packages and identify malicious intent? These questions motivate our work to study the software supply chain attacks on registries in depth and carry out a cross-language comparative analysis to answer our questions.

To this end, we propose a framework that highlights key functionality, security mechanisms, stakeholders, and remediation techniques to comparatively analyze different registry ecosystems. We use our framework to look at what features registries provide, what security principles are enforced, how is trust delegated between different parties, and what remediation and contingency plans registries have in place for post-attack. We leverage our findings to provide practical action items that registry managers can enforce using pre-existing tools and security principles that will make it difficult for attackers to subvert the software supply chain. We document a set of tools and techniques that we formalized into an analysis pipeline for the community to help analyze packages and identify
suspicious behavior.

Our vetting pipeline, MALOSS, leverages, metadata, static, and dynamic analysis to find suspicious packages in registries that can be manually verified. Initially, we assumed vetting techniques in the Google Play Store [15] and Apple’s App Store [16] can be reused, but we found that to be a naive assumption. One of the challenges for analyzing interpreted language packages is that they rely on other dependencies, which can differ by name and version making hard to pinpoint the specific malicious version. The nature of interpreted languages allows for dynamic typing and dynamic code generation, which cannot be accurately analyzed using static approaches. Our intention for MALOSS, is to give researchers and registry maintainers a modular pipeline that can be extended and support newly discovered malicious techniques.

Our comparative analysis identified common problems across the different registries that registry maintainers can remediate using existing practical changes. For example, PyPI and Npm can learn from RubyGems and add typo detection at the client-side to minimize accidental errors of developers. MALOSS analyzed over one million packages from PyPI, Npm, and RubyGems and identified 7 malicious packages in PyPI, 41 malicious packages in Npm, and 291 malicious packages in RubyGems. We reported these packages to registry maintainers and had 278 of them removed, over 82%. Three of the reported malicious packages had over 100K installs and they were assigned an official CVE number. We dive deep into a couple of packages to demonstrate the sophistication of these malicious packages and present their infection vectors, capabilities, and persistence. Lastly, we perform a passive-DNS measurement analysis to show how widely spread the infections are.

II. AN OVERVIEW OF REGISTRY ABUSE

We present a selected list of supply chain attacks in Figure 1, spanning across different types of registries (e.g. interpreted languages, system-wide). In 2016, Tschacher [7] demonstrated a proof-of-concept attack against package managers. The attack used typosquatting, which is a technique that misspells the name of a popular package and waits for users installing the popular package to typo the name (hence typosquatting) resulting in the installation of the malicious package instead. As of August 2019, there were more than 300 malicious packages reported and removed in different registries (PyPI, Npm, RubyGems, etc.). In Figure 2, we aggregate the number of malicious packages uploaded into registries and their corresponding download counts. We note that these counts are documented/detected attacks, which is a subset of all the attacks (known and unknown). Figure 2 shows that in 2018 alone there were more than 100 malicious packages that had more than a cumulative 600 million downloads.

Typosquatting is just one type of attack, a more recent report by Snyk [17], a vulnerability analysis platform, classified three types of attacks, namely typosquatting, account hijacking, and social engineering. Hijacking is account compromise through credential theft and social engineering is a deceptive tactic to trick owners of package repositories to transfer ownership. The report highlights that typosquatting is the most common attack tactic because most registries do not enforce any security policies as shown by Loden [18]. Account hijacking takes place because of weak credentials that attackers can guess and social engineering attacks exploit the collaborative nature of open-source projects as seen in many attacks [13], [14], [19]. Unfortunately, the focus of the community has been on finding bugs in package code through platforms like Synode [10], NodeCure [11], and ReDoS [12]. Recent efforts by BreakApp [9] use runtime isolation of untrusted packages, but suffers from practicality and cannot deal with cryptojacking attacks. Registry maintainers are aware of these issues and have taken initiative to implement some security enhancements such as package signing [20] and two-factor authentication [21]. Despite these commendable efforts, Figure 2 shows the number of malicious packages in registries is on the rise.

III. COMPARATIVE FRAMEWORK

This section presents our framework that enables a comparative analysis of three popular registries for interpreted languages. The framework is inspired by modeling the management and development process in the package management ecosystem and consists of four primary stakeholders. In the framework, we examine three aspects of registries, namely functional, review and remediation. Additionally, we outline threats that currently affect the ecosystem and show how it applies to our framework.

A. Stakeholders

Registries are platforms for code sharing and play an essential role in the software development process. Four primary stakeholders are involved in developing, managing and using packages from registries, namely Registry Maintainers (RM), Package Maintainers (PM), Developers (Dev) and End Users (EU). The simplified relationships among them are sketched in Figure 3. Note that the stakeholders described above can be thought of as roles, which can be assigned to a single person.

Registry Maintainers. Registry maintainers are responsible for running registries, which are centralized repositories that host packages developed by package maintainers. Registries provide search and install capabilities for developers (Dev) to help organize packages in a central repository. Registry maintainers require package maintainers to signup before they are allowed to publish (write) their package. On the other hand, developers (Dev) can query and install (read) from the registry with or without signup.

Package Maintainers. Package maintainers are responsible for developing, maintaining and managing packages. Package maintainers typically use a code hosting platform like GitHub to manage their development and collaborate with other contributors. They may receive pull requests from contributors interested in their projects, thus allowing community support for enhancement and maintenance.
Developers. Developers are consumers of published packages and are responsible for finding the right packages to use in their software and releasing their products to end-users. Dev focus on developing unique features in their software and reuse packages from registries for common functionalities. Also, Dev are responsible for addressing relevant issues arising from reused packages, such as known vulnerabilities and incompatibilities.

End Users. Although not directly interacting with registries, end users are still one important stakeholder in the ecosystem. EU are at the downstream and use services or applications from Dev via tools such as browsers, mobile devices or Internet-of-Things (IoT) devices. They usually have no control of software, but can be affected by them.

B. Registry Features

Registries are the core component of package manager ecosystems and provide features such as package hosting and account protection. Since different registries may implement different features, we, therefore, list three popular registries for interpreted languages in Table I, namely PyPI, Npm, RubyGems, and systematically compare their features. We classify registry features into three categories, namely functional, review and remediation.

Functional Features. As shown in Figure 3, PM, as suppliers, access accounts and publish and manage their packages on registries, and Dev, as consumers, select and install packages from registries as dependencies. Each registry has a different way of installing packages on Dev’s system and provides different capabilities to allow PM to ship code.

- **Access**: refers to how registries authenticate PM to publish a package. We look at account security-related features such as public-key authentication and multi-factor authentication (MFA).
- **Publish**: refers to how packages are packaged and released to registries. We look at release approaches such as upload by PM and reference through package development repository. We also look at packaging features such as signing and naming rules such as typo guard.

Fig. 1: Selected supply chain attacks on package managers sorted by date of reporting.

Fig. 2: The number of malware and their downloads aggregated by year of uploading as of August 2019.

Fig. 3: Simplified relationships of stakeholders and threats in the package manager ecosystem.

### Table I: Framework for comparison of registries.

| Features                  | PyPI          | Npm          | RubyGems        |
|----------------------------|---------------|--------------|-----------------|
| **Access**                 |               |              |                 |
| Password                   | ●             | ○            | ●               |
| Access Token               | ○             | ●            | ●               |
| Public Key Auth            | ○             | ○            | ○               |
| Multi-Factor Auth          | ○             | ○            | ○               |
| Upload                     | ○             | ●            | ●               |
| Reference                  | ○             | ○            | ○               |
| Signing                    | ○             | ○            | ○               |
| Typo Guard                 | ○             | ○            | ○               |
| Namespace                  | ○             | ○            | ○               |
| **Publish**                |               |              |                 |
| Tank Package               | ○             | ○            | ○               |
| Deprecate Package          | ○             | ○            | ○               |
| Add Collaborator           | ○             | ○            | ○               |
| Transfer Ownership         | ○             | ○            | ○               |
| Reputaion                  | ○             | ○            | ○               |
| Code Quality               | ○             | ○            | ○               |
| Security Practice          | ○             | ○            | ○               |
| Known Issue                | ○             | ○            | ○               |
| Typo Detection             | ○             | ○            | ○               |
| **Review**                 |               |              |                 |
| Hook                       | ●             | ○            | ○               |
| Dependency Locking         | ●             | ○            | ○               |
| Native Extension           | ○             | ●            | ●               |
| Embedded Binary            | ○             | ●            | ●               |
| Dependency Check           | ○             | ○            | ○               |
| Update Inspection          | ○             | ○            | ○               |
| Binary Inspection          | ○             | ○            | ○               |
| PM Account                 | ○             | ○            | ○               |
| Stylistic Lint             | ○             | ○            | ○               |
| Logical Lint               | ○             | ○            | ○               |
| Suspicious Logic           | ○             | ○            | ○               |
| **Remediation**            |               |              |                 |
| Install                    | ○             | ○            | ○               |
| Embedded Binary            | ○             | ○            | ○               |
| Import                     | ○             | ○            | ○               |
| Functional                 | ○             | ○            | ○               |
| Package                    | ○             | ○            | ○               |
| Publisher                  | ●             | ○            | ○               |
| Installed Package          | ○             | ○            | ○               |
| PM                         | ○             | ○            | ○               |
| Dependent PM               | ○             | ○            | ○               |
| Dev                        | ○             | ○            | ○               |
| Advisory DB                | ○             | ●            | ○               |

*unsupported - ○, optional - ●, enforced - ●*
• Manage: refers to how packages are managed and what controls are allowed on packages. Controls can include removing the package by version, deprecating the package, or adding authorized collaborators.

• Select: refers to rating or reputation score that helps Dev select which packages to trust and add as dependencies. We look at criteria related to the rating and reputation of repositories and authors.

• Install: refers to how packages are installed by Dev. We look at features such as install hooks which can run additional code, dependency locking which can specify secure dependencies, and if the package can contain native extensions or embedded binaries which may have proprietary code. Note that native extension compilation, which is supported in RubyGems, enables install hooks.

**Review Features.** We define review features that registries implement to proactively secure user access and detect vulnerable and malicious packages. We list three main categories of analysis, namely metadata, static and dynamic analysis. Unfortunately, none of them are currently supported.

• Metadata: refers to metadata analysis of a given package, which includes dependency analysis, author information, update history, and additional packaged components.

• Static: refers to performing lint for stylistic and logical code analysis. This can include finding vulnerable or malicious code. Also, it includes scanning binary components with anti-virus (AV) solutions.

• Dynamic: refers to analyzing behaviors of a package by installing it, executing the embedded binaries, importing its modules, and invoking exported functions. This process includes monitoring system behaviors, such as network calls, process operations and filesystem calls for suspicious activities such as access to sensitive files.

**Remediation Features.** Once RM have identified abnormal signals that warrant further investigation, a security team investigates the incident case and carries out removal and notification based on the findings.

• Remove: refers to how proactive RM are with removing a package based on a report. Basic operations include removing the affected package and disabling the publisher’s account, while proactive operations include removing from installed packages.

• Notify: refers to the mechanism in which RM notify the public of the offending package. This includes how do they notify. For example, RM can create an issue on the git repo to notify PM, or alternatively, contact PM via email. This also includes whom do they notify. For example, RM can notify public victims such as PM of the offending package and its dependents. More proactive notifications would seek to notify Dev and publishing advisories to inform other dependents and suggest fixes.

We manually evaluated each feature under the functional section in Table I. For the review and remediation features we contacted registry maintainers directly to report malicious packages that we identified with our pipeline. Based on our information exchange, we noted their responses such as what they have in place to detect or flag suspicious packages, and document them in the review and remediation section of Table I. Moreover, we collected information from presentations and blogs that disclosed the security practices of registries.

**C. Threat Model**

As highlighted in Figure 3, we consider supply chain attacks that aim at exploiting upstream stakeholders (i.e. PM and RM) in the package manager ecosystem, to amplify their impacts on downstream stakeholders (i.e. Dev and EU). We investigate existing reports of supply chain attacks and elaborate on their attack vectors and malicious behaviors.

**Attack Vectors.** Several threats subvert the package management supply chain ecosystem. We define them as follows and annotate them with attack numbers in Figure 3.

• Registry Exploitation ②: refers to exploiting a vulnerability in the registry service that hosts all the packages and modifying or inserting malicious code [22], [23].

• Typosquatting ②: refers to packages that have misspelled names similar to popular packages in hope that Dev incorrectly specify their package instead of the intended package [7], [18], [24]. This also includes squatting popular names across registries and platforms (also called package masking [25]), in the hope that Dev falsely assume their presence on a particular registry [26], [27].

• Publish ②: refers to directly publishing packages without expectation of typos. This can be used for bot tracking or malware-hosting [28].

• Account Compromise ③: refers to compromising PM accounts on the registry portal, allowing the attacker to replace the package with a malicious package or release malicious versions [4], [5], [29]–[31].

• Infrastructure Compromise ①: refers to the compromise of development, integration and deployment infrastructure of PM, allowing the attacker to inject malicious code into packages [32].

• Disgruntled Insider ④: refers to authorized PM that insert malicious code or attempt to sabotage the package development [33].

• Malicious Contributor ④: refers to a benign package that receives a bug fix or an improvement that includes additional vulnerable or malicious code [14].

• Ownership Transfer ③④: refers to packages that are abandoned and reclaimed or the original owner transfers responsibility to new owners for future development [13], [19]. The transfer can happen both at code hosting sites and registries.

**Malicious Behaviors.** In supply chain attacks, we consider victims as downstream stakeholders such as Dev and EU in Figure 3. Dev can be exploited to steal their credentials or harm their infrastructure. Dev can also be exploited as a channel to reach EU through their applications or services. When EU use applications or services provided by compromised Dev, they can also be exploited to steal their
credentials or harm their devices. We refer to descriptions of existing malware in advisories and blogs and summarize their malicious behaviors into the following list.

- **Stealing**: refers to harvesting sensitive information and sending them back to attackers. Various types of information can be collected or stolen, ranging from less-sensitive machine identifiers which can be used for tracking sensitive information [34] including secret tokens [4], cryptocurrencies [14], passwords and even credit cards which may lead to further compromise or financial loss.

- **Backdoor**: refers to leaving a code execution backdoor on victim machines. The backdoor can be implemented in various ways. It can be code generation (e.g. eval) of a specific attribute (e.g. cookie) [30], a specific payload [5], or a reverse shell that allows any command [35].

- **Sabotage**: refers to the destroying of system or resources. This is less severe in the browser due to isolation, but critical on developer infrastructure and end-user devices. This can be done for profit and fun. The common thing is to destroy the system by removing or encrypting the file system and ask for money (ransomware) [28].

- **Cryptojacking**: refers to exploiting the computing power of victim machines for crypto-mining. The cryptojacking behavior [6] is a rising family of malware that is also seen in browsers [36] and other platforms [35], [37].

- **Virus**: refers to spreading malware by leveraging the fact that a person can be Dev and PM at the same time to infect packages maintained by him [38].

- **Proof-of-concept**: refers to packages without real harm, but rather proof-of-concept that aims at demonstrating something malicious can be done [38].

## D. Broken Trust and Security Gaps

### TABLE II: Trust model changes for stakeholders in the package manager ecosystem.

| SH/T | C | PM | RM | Dev | EU |
|------|---|----|----|-----|----|
| PM   | $\rightarrow$ | $\bullet$ | $\bullet$ | $\bullet$ | $\bullet$ |
| RM   | $\bullet$ | $\rightarrow$ | $\bullet$ | $\bullet$ | $\bullet$ |
| Dev  | $\bullet$ | $\bullet$ | $\rightarrow$ | $\bullet$ | $\bullet$ |
| EU   | $\bullet$ | $\bullet$ | $\bullet$ | $\bullet$ | $\bullet$ |

| no trust - $\bigcirc$, majority trust - $\bullet$, complete trust - $\bullet$ |

We further analyze the enumerated threats in §III-C under the supply chain model in Figure 3. Registry exploitation is caused by the implementation errors of RM, but it is hard to launch and rarely seen. Typosquatting and publish are caused by the implicit trust in PM by RM to act benignly. Account compromise is caused by careless PM and missing support of MFA and abnormal account detection by RM. Infrastructure compromise, disgruntled insider and malicious contributor are caused by insufficient security mechanism of PM and implicit trust in PM by RM to secure their code and infrastructure. Ownership transfer is caused by the implicit trust in new owners by PM and RM to act benignly.

The security gaps require enhancement to the ecosystem and are straightforward to fix. To better understand the broken trust, we listed the trust model changes for stakeholders in Table II. RM are central authorities in the ecosystem, so PM and Dev would have to trust RM to act benignly and responsibly. But on the contrary, although RM can still trust the majority of PM and Dev as a community, RM should not trust all of them due to potential attackers. PM interact with contributors and other PM and should also weaken their trust to the majority of them, due to potential malicious contributors and disgruntled insiders. Dev and EU, as downstream users in the ecosystem, would have to trust the benign intent of upstream stakeholders, although they may add some security mechanisms for protection. On the other hand, Dev interact with EU from all over the Internet and have no trust in them.

### E. Challenges For Vetting Packages

RM, as central authorities in the ecosystem, are responsible and capable of improving the ecosystem. Inspired by vetting and review processes of mobile stores [15], [16], we anticipate that an automated vetting pipeline, namely MALOSS, which can be adopted by RM, would reveal suspicious and malicious behaviors of packages. However, to design such a pipeline for package managers, there are several unique challenges.

First, packages in registries may have a large number of dependencies. For example, eslint and electron both reuse over 100 packages on Npm, including indirect dependencies. Directly applying static analysis to them not only incurs significant time and space overhead, but also wastes computing resources in repeatedly analyzing commonly used packages. Inspired by StubDroid [39], MALOSS addresses this challenge by proposing modularized static analysis to summarize dependencies into formats that can be directly reused for further static analysis. Second, the nature of interpreted languages allows for dynamic typing and dynamic code generation, indicating that static analysis algorithms such as type inference and points-to analysis are inaccurate. To account for such inaccuracies, MALOSS employs hybrid analysis, which includes metadata, static, and dynamic analysis, to flag suspicious packages: MALOSS checks anomalies and aggregate similar packages in metadata analysis; reports suspicious APIs and information flows in static analysis; installs, executes, imports and interacts with packages to reveal their behaviors in dynamic analysis. The reported suspicious packages are then iteratively checked for their maliciousness.

### IV. Package Analysis Tools

In this section, we provide details about implementing the MALOSS vetting pipeline. Figure 4 is an overview of the workflow and internal components of MALOSS. We divide the implementation into four components, namely metadata analysis, static analysis, dynamic analysis, and iterative labeling. Packages from registries are processed by the three analysis components to generate intermediate reports which highlight suspicious activities. The iterative labeling component filters suspicious packages using heuristic rules and employs a semi-automated labeling process to flag malware.
A. Goals and Assumptions

We envision MALOSS as a pipeline that performs automated analysis to flag suspicious packages, followed by iterative labeling to check malicioussness and improve heuristic rules. In the package manager ecosystem, the automated analysis can be adopted by RM, and the iterative labeling process can be offloaded to RM and Dev, the majority of whom can still be trusted as highlighted in Table II.

We begin the design of MALOSS by setting goals and assumptions. In this work, we focus on vetting public packages in three package managers for interpreted languages in Table I, namely PyPI for Python, Npm for JavaScript and RubyGems for Ruby. Figure 5 explains interactions between packages and the underlying system, including the runtime environment, libraries, and operating system. In MALOSS, metadata analysis focuses on correlating packages based on various information such as releases and authors, which allows identification of packages similar to known malware; static analysis focuses on checking interactions between packages and the runtime environment, which allows identification of suspicious API invocations and information flows such as code generation using data from network; dynamic analysis focuses on running packages and tracing system calls and their arguments during execution, which allows tracing of sensitive operations such as read of /etc/passwd. The three analyses unveil different views of packages and are combined to flag suspicious packages for iterative labeling. Using the MALOSS pipeline, we aim at identifying malicious in the wild, as well as understanding their attack vectors and malicious behaviors. We assume registry maintainers are trusted, implying that any malware reported can be attributed to one of the attack vectors in §III-C. We assume packages are installed, imported and used by developers, rather than installed for further development, implying that only runtime dependencies need to be considered.

B. Metadata Analysis

Metadata analysis focuses on collecting auxiliary information (e.g. package name, author, release, downloads, and dependencies) of packages and aggregating them based on different criteria. All information are directly retrieved from registry APIs. Note that, for Npm, we collect downloads for the past three years, since Npm API only allows range queries for downloads. Metadata analysis can flag suspicious packages, as well as identify packages similar to known malware. For example, using edit distance of package names, metadata analysis can group packages based on their names, allowing pinpointing of typosquatting candidates of popular packages. Using author information, metadata analysis can group packages based on authors, allowing identification of packages from known malicious authors.

C. Static Analysis

The static analysis focuses on analyzing source files of the corresponding interpreted language for each package manager and skips embedded binaries and native extensions. The analysis consists of three components, manual API labeling, API usage analysis, and taint flow analysis. To allow efficient processing of packages with a large number of dependencies, we perform modularized analysis using package summaries.

Manual API Labeling. As highlighted in Figure 5, we focus on four types of runtime APIs in the static analysis, namely, network, filesystem, process, and code generation. Network APIs allow communication over various protocols such as socket, HTTP, FTP, etc. They have been used to leak sensitive information [40], fetch malicious payload [5], etc. Filesystem APIs allow file operations such as read, write, chmod, etc. They have been used to leak ssh private keys [40], infect other packages [33] etc. Process APIs allow process operations such as process creation, termination and permission change. They have been used to spawn separate malicious processes [6]. Code generation APIs allow runtime code generation and loading. This includes the infamous eval and others like vm.runInContext in Node.js, which have been used to load malicious payload [5], [31].

For the runtime of each registry, we manually go through their framework APIs and check if they belong to any of the above categories. To allow taint flow analysis, we further label them as data sources if they can return sensitive or suspicious data and data sinks if they can perform suspicious operations on inputs. Note that an API can be both a source and a sink, e.g. https.post in Node.js can both retrieve suspicious data and send out sensitive information. Also, some sink APIs do not have to be used with a source to perform malicious behaviors. For example, fs.rmdir in Node.js is a sink and raises a warning if its argument comes from user input. But even without a source, fs.rmdir can be used to sabotage user machines by hardcoding the input path to the root folder. Hence, we need to identify both suspicious APIs and their flows.

API Usage Analysis. We parse source files of packages into Abstract Syntax Trees (AST) using state-of-the-art libraries [42]–[45] and search for usage of manually labeled APIs in AST. For APIs in the global namespace (e.g. eval
try{
  var https=require('https');
  https.get({'hostname':'pastebin.com',path:'/raw/XLeVP82h',headers:{'User-Agent':'Mozilla/5.0 (Windows NT 6.1; rv:52.0) Gecko/20100101 Firefox/52.0',Accept:'text/html,application/xhtml+xml,application/xml;q=0.9,*/*;q=0.8'}},(r)=>{
    r.setEncoding('utf8');
    r.on('data',(c)=>{
        eval(c);
    });
    r.on('error',()=>{});
    }));
} catch(e){}

Listing 1: eslint-scope [4] downloads malicious payload via https.get and executes via eval.

const request = require('request');
...
login(token = this.token) {
  try {
    request({
      ...,
      form: { 'token': token }
    }, (err, res, body) => {
      if (err) {};
    });
  } catch(e){}
}

Listing 2: discord.js-user [41] steals discord tokens via its dependency request.

for Python), we match them against function calls using their names. For APIs that are static methods of classes or exported functions of modules (e.g. vm.runInContext for Node.js), we identify their usage by tracking aliases of classes or modules and matching their full names. For APIs that are instance methods of classes, since identifying them in dynamically typed languages is an open problem, we make a trade-off and identify their usage in two ways: method name only and matching their full names. For APIs that are static methods of classes or exported functions are indirect sources which return values derived from known sources, or indirect sinks whose arguments propagate into sinks, or propagation nodes which return values derived from arguments. As we walk up the dependency tree of all packages, we output identified flows, as well as indirect sources, indirect sinks and propagation nodes, which are merged into the customized configuration for subsequent analyses. For example, we can first summarize the request to find that its exported function request invokes network sinks such as https.post and then analyze code in Listing 2 to identify the malicious flow of leaking token through the network.

D. Dynamic Analysis

Dynamic analysis focuses on executing packages and tracing their interactions with the underlying operating system. In comparison to static analysis, dynamic analysis considers source files, as well as embedded binaries and native extensions, but it does not have visibility into the runtime environment (e.g. cannot track eval). The analysis consists of two parts, package execution within Docker [49] containers for sandboxing and dynamic tracing using Sysdig [50] for efficiency and usability.

Package Execution. Packages can be used in various ways, such as standalone tools or libraries, which should be considered in dynamic analysis. We, therefore, execute packages in four ways, namely, install, embedded binary, import and functional. For install, we run the installation command (e.g. npm install <name>) to install packages, which triggers customized installation hooks if any and allows attackers to
act at the user’s privilege. For embedded binary, we run embedded binaries and executable scripts from packages, since attackers can include prebuilt binaries or obfuscated code to obstruct the investigation. For import, we import packages as libraries to triggers initialization logic where attackers can tap into. For functional, we fuzz exported functions and classes of libraries to reveal their behaviors. The current prototype invokes exported functions, initializes classes with null arguments, and recursively invokes callable attributes of modules and objects. We perform the above operations for a package, on Ubuntu 16.04. We leave advanced fuzzing strategies and support for other operating systems as future work. While executing packages, we use Docker [49] containers as sandboxes to protect the underlying system from malware like destroyer-of-worlds in Listing 3 which abuses system resources.

**Dynamic Tracing.** While executing packages, we aim at capturing their interactions with the underlying system to flag suspicious behaviors. There are three popular tools, namely Strace [51], Dtrace [52] and Sysdig [50], to capture system call traces in Linux-based systems. After cross-comparison, we choose Sysdig as the tracing tool due to its high efficiency and good usability. To fully leverage the computing resources, we analyze multiple packages in parallel, each in a separate Docker container whose name encode package information such as name, version etc. Sysdig captures system call traces and correlates them with userspace information such as container names, thus allowing us to differentiate behaviors from different containers and packages. While prototyping, we track system calls related to four types of information, namely IP, DNS queries, files, and processes and dump them into files to allow further processing. Note that, Sysdig can only see system calls and cannot handle suspicious behaviors within runtime environment such as dynamic code generation.

### E. Iterative Labeling

Iterative labeling is semi-automated and includes an automated process to flag suspicious packages based on heuristic rules and a manual process to check maliciousness and update rules. The updated rules are used to iteratively filter and narrow down suspicious packages. By learning from existing supply chain attacks and other malware studies [53], we specify an initial set of heuristic rules.

**Metadata Analysis Rules.** First, inspired by behaviors such as typosquatting, we flag packages whose names are similar to popular ones in the same registry or the same as popular ones in other registries but with different authors. Second, inspired by the idea of leveraging malware seeds to find new ones, we flag packages if they depend on known malware or have similar authors and release patterns.

**Static Analysis Rules.** First, inspired by that malware usually execute malicious code during installation, we flag packages with customized installation logic. Second, inspired by that account compromise-based malware usually keep existing benign versions and release new malicious versions, we flag packages if recently released versions use previously unseen network or code generation APIs. Third, inspired by that malware exhibiting stealing and backdoor behavior usually involves network activities, we flag packages with certain types of flows, such as flows from filesystem sources to network sinks and from network sources to code generation sinks.

**Dynamic Analysis Rules.** First, inspired by behaviors such as stealing and backdoor need network communication, we flag packages that contact unexpected IPs or domains, where expected ones are derived from official registries (e.g. pypi.org) and code hosting services (e.g. github.com). Second, inspired by malicious behaviors usually involve access to sensitive files, we flag packages if they write to or read from such files (e.g. /etc/sudoers, /etc/shadow). Third, inspired by that cryptojacking usually spawn a process for cryptomining, we flag packages with unexpected processes, where expected ones are initialized to registry clients (e.g. pip).

Nevertheless, to provide evidence for RM or PM to take action, we have to manually investigate suspicious packages to confirm their maliciousness or label them as false positives to help update heuristic rules. To avoid re-computation when rules are updated, we cache the output of metadata, static and dynamic analysis. We iteratively perform the automated filtering process based on rules and the manual labeling process, to report malware.

### V. FINDINGS

#### A. Experiment Setup

**Environment.** We use 20 local workstations running Ubuntu 16.04 with 64GB memory and 8 x 3.60GHz Intel Xeon CPUs to download and analyze all packages and their versions from the PyPI, Npm and RubyGems. We use network-attached storage (NAS) server with 60TB disk space to provide shared storage to all the workstations. We use the NAS server to mirror packages and their metadata from registries and store analysis results. The registry mirrors allow us to obtain copies of malware even if they are taken down.

**Tools and Data Sets.** For metadata analysis, we collect auxiliary information for packages and their versions from official registry APIs. For static analysis, we rely on open source projects for AST parsing [42]–[45] and taint flow analysis [46]–[48], [54]. To perform modularized analysis, we build a dependency tree for each registry and schedule analysis of packages in dependency trees using Airflow [55], which is capable of scheduling directed acyclic graphs (DAGs) of tasks. For dynamic analysis, we rely on Docker [49] for sandboxing and Sysdig [50] for a deep system-level tracing. We use Celery [56] to schedule analyses of packages.

#### B. Package Statistics

We use the MALOSS pipeline to process over one million packages from PyPI, Npm and RubyGems as presented in Table III. Through an iterative labeling process, we identified 7 malware in PyPI, 41 malware in Npm and 291 malware in RubyGems. We reported these 339 malware respectively.
TABLE III: Statistics of analyzed packages in registries.

|                        | PyPI   | Npm    | RubyGems |
|------------------------|--------|--------|----------|
| # of Packages          | 186,785| 997,561| 151,783  |
| # of Package Versions  | 809,258| 4,388,368| 629,116  |
| # of Package Maintainers† | 67,552 | 284,009| 51,505   |

† The number of package maintainers may not match the number of users in registries as not all users publish packages.

(a) Distribution of the number of downloads per package in Figure 6a. The distribution of the number of downloads shows that packages have more than 100K downloads, indicating a large number of users. Therefore, we requested CVEs (CVE-2019-13589, CVE-2019-14282, CVE-2019-14281) for them, in the hope that the potential victims can get timely notifications for remediation.

Metadata Analysis. For all the packages in registries, we present the distribution of the number of versions and downloads per package in Figure 6a. The distribution of the number of versions shows that 80% of packages have less than 7 to 9 versions and different registries have similar distribution, implying a similar release pattern across registries. In comparison, the distribution of the number of downloads varies among registries, with 20% of RubyGems and PyPI packages being downloaded more than 13,835 times and 678 times respectively, indicating that packages distributed on RubyGems are more frequently downloaded and reused.

We also present the distribution of dependency count for the top 10K downloaded packages in Figure 6b, including both direct and indirect dependencies. 80% of these packages have 2 or fewer direct dependencies, which inflates to 20 or fewer indirect dependencies, implying an implicit trust for PM to ensure quality of reused OSS and RM to vet packages for maliciousness. The maximum number of indirect dependencies in Figure 6b reaches more than 1K, implying a significant amplification when frequently reused packages get compromised.

Static Analysis. We ran API usage analysis for all package versions in registries, followed by taint flow analysis for packages using suspicious APIs. To allow modularized static analysis, we build a dependency tree for all packages in each registry and walk up the tree to find suspicious APIs and flows, as well as summarize packages for subsequent analyses. We present the percentage of top 10K downloaded packages using suspicious APIs in each registry, as well as summarize packages for subsequent analyses. We dynamically analyzed all packages in registries, following by taint flow analysis for packages using suspicious APIs. We present the timeline of the number of packages exhibiting unexpected dynamic behaviors in Figure 7a. Contrary to the intuition that code generation APIs such as `eval` are dangerous and rarely used, Figure 7a shows that 7% of PyPI packages and 10% of RubyGems packages use code generation APIs. Such code generation APIs are not only frequently used in supply chain attacks, but also can lead to code injection vulnerabilities if their inputs are not properly sanitized.

Performance. We present the timeline of the number of new packages and package versions published each month in Figure 8a. Overall, the timeline shows that the number of newly published packages has been increasing, implying the need of analyzing packages at scale in MALOSS. In Figure 8a, RubyGems spikes around 2010 because the registry moved from `gems.rubyforge.org` to `rubygems.org` and all timestamps were reset. As for the other spikes of RubyGems around 2015, no public explanation has been found. The timeline also indicates that the PyPI and Npm community have been growing recently, while the RubyGems community has plateaued.

Therefore, to quantify the benefit of using modularized static analysis, we randomly select 1K packages from the top 10K PyPI packages and present the processing time and speedup ratio of analysis with summary versus without summary in Figure 8b. The measurement shows that modularized analysis achieves more than 5 times and 18 times of speedup ratios in API usage analysis and taint flow analysis respectively for 20% of the analyzed PyPI packages. We argue that other registries would follow a similar pattern of speedup.

Dynamic Analysis. We dynamically analyzed all packages in registries by sandboxing them in Docker containers [49] and tracing their behaviors with Sysdig [50]. Figure 7b shows the number of packages exhibiting unexpected dynamic behaviors in each registry according to the initial heuristics in §IV-E.
The figure reveals that Npm and PyPI have more packages with unexpected network activities (i.e. IPs and DNS queries) than RubyGems. It is important to note that unexpected behaviors during the installation phase are amplified by dependent packages, resulting in a seemingly large number of flagged packages in Figure 7b. We remove such redundancy by checking with the dependency tree.

C. Supply Chain Attack Details

Starting from the initial set of heuristic rules in §IV-E, we iteratively label suspicious packages, update rules and end up finding 339 malware. In addition, we have been tracking supply chain attacks since Jan 2018, and collected 312 malware samples reported by the community, consisting of 67 malware in PyPI, 230 malware in Npm and 15 malware in RubyGems. To this end, we systematically summarize this 651 malware, using the framework and terminologies proposed in §III. We analyze them in multiple dimensions, including attack vectors, malicious behaviors, persistence, impact, and infection. While presenting, we use Overall to refer to malware reported overall, Community for ones reported by the community and Authors for ones reported by the authors.

**Attack Vectors.** We categorize malware by their attack vectors in Figure 9a, which shows that typosquatting is the most exploited attack vector, followed by account compromise and publish. It is intuitive that typosquatting and publish would dominate, since attackers tend to use low-cost approaches. However, the popularity of account compromise implies a lack of support by RM and awareness of PM to protect accounts. Though not significant, other attack vectors such as malicious contributor and ownership transfer are exploited by attackers, indicating that each stakeholder in the package manager ecosystem should raise awareness and be involved in fighting supply chain attacks.

**Malicious Behaviors.** We categorize malware by their malicious behaviors in Figure 9b, which shows that stealing is the most common behavior, followed by backdoor, proof-of-concept and cryptojacking. We further investigate the dominating category, stealing, and find that around three quarters of them are collecting less sensitive information, such as usernames, IPs etc., posing less harm to developers and end users. The rest of stealing packages collects various sensitive information, such as passwords, private keys, credit cards etc. As for backdoor and cryptojacking, their popularity indicates that attackers are targeting not only end users, but also developers and infrastructure of enterprises, implying an urgent need for developers and enterprises to take action.

**Persistence.** We present the distribution of number of persistence days and number of downloads for each malware in Figure 10, which shows that 20% of them persist in package managers for over 400 days and have more than 1K downloads. As of August 2019, none of the three registries has claimed to deploy analysis pipelines or manual review processes, but instead rely on the community to find and report malware, thus leading to the long persistence of malware. To better understand the distribution of malware in terms of persistence and popularity, we show the correlation between number of persistence days and number of downloads in Figure 11. The scatterplot reveals that popular packages are likely to persist for fewer days, possibly due to their larger user base. As highlighted in Figure 11, 18 malicious packages were identified with more than 100K downloads. We (i.e. the authors) reported 4 of these 18 packages. Three of our reported malicious packages, i.e. paranoid2, simple_captcha2 and datagrid, were confirmed and removed by registry maintainers and are assigned CVE-2019-13589, CVE-2019-14282 and CVE-2019-14281 respectively. The fourth identified malicious package, rsa_compat, unfortunately still remains online. It collects information regarding the package, Node.js runtime and operating system, and is being investigated by Npm maintainers due to lack of policies defining user tracking versus stealing.

**Impact.** Besides malware characteristics, we also measure their impact. In particular, we answer whether these malware are affecting developers and end users. From Figure 10b, we select malware with more than 10 million downloads.
The combined downloads for the most popular malicious packages (event-stream - 190 million, eslint-scope - 442 million, bootstrap-sass - 30 million, and rest-client - 114 million) sum to 776 million. In addition to threats imposed by direct downloads, we emphasize that unlike mobile stores where apps are user-facing, the packages in registries are developer-facing, thus amplifying their impact by their dependents. Moreover, by walking up the dependency tree in Figure 6b to compute reverse dependencies, we find that event-stream has 3,905 dependents, eslint-scope has 15,356 dependents, bootstrap-sass has 546 dependents and rest-client has 4,722 dependents. By measuring their dependents for benign purposes, such as pastebin.com contacted domains. Followed by exclusion of commonly used domains for notification channels. Additionally, victims may not be aware of this issue, implying the need for notification channels. Additionally, ptpb.pw, a domain used in acroread [19], permanently shutdown in Mar 2019 [57] due to service abuse from cryptominers, implying possibility of correlating malware campaigns using DNS queries and necessity for online services to be abuse-resistant.

D. Anti-analysis Techniques

While manually checking malicious payloads, we notice that malware have been evolving and leveraging various anti-analysis techniques to defeat detection. Inspired by previous works on evasive malware [58]–[62], we enumerate and categorize techniques used in these supply chain attacks, to raise the community’s attention and aid future analyses.

Listing 5: fast-requests [63] uses code obfuscation to defeat analysis.

def _! begin yield rescue Exception end end

Listing 4: rest-client [5] uses anti-analysis techniques such as benign service abuse, multi-stage payload, logic bomb and non-latest release.

var _0xb3f3={"\x64\x69\x73\x63\x6f\72\x64\x6a\x73","\x72\x65\x71\x75\x65\x73\x74","\x6f\x6e","\x63\x74\x72\x69\x6e\x67","\x6f\x6e","\x63\x74\x72\x65\x73\x74","\x6f\x6e","\x63\x61\x74\x69\x6e\x67"};

Listing 3: Resist [27] uses code obfuscation to defeat analysis.

Infection. Although downloads and reverse dependencies can be an indirect measure of malware popularity, it is still unclear whether malware made their way to Dev and EU and got executed. Inspired by the observation that many of these malware involves network activity in their malicious logic, we collaborate with a major Internet Service Provider (ISP) to check malware related DNS queries. We start with manually checking malicious payloads and extracting contacted domains. Followed by exclusion of commonly used domains for benign purposes, such as pastebin.com and google-analytics.com. We query the remaining domains against the passive DNS data shared by the ISP and present their volume aggregated by month in Figure 12. The data contains queries from Jan 2017 to Sep 2019, with the exception from Jun 2017 to Dec 2017 due to data loss. As shown in Figure 12, mironanoru.zzz.com.ua, a domain used in rest-client [5], has 10 hits in Aug 2019, but drops to almost zero in Sep 2019. This matches the fact that rest-client is uploaded and removed in Aug 2019, which shows effectiveness of supply chain attacks and validates our intuition that a large user base can help timely remediate security risks. ncdn-radar.com, a domain used in AndroidAudioRecorder [27], has hits until Sep 2019, showing infection even after its removal in Dec 2018. Further inspection reveals that no CVE or public advisory is created for this incident and the
DNS tunneling to leak sensitive information, abusing the DNS service which is usually allowed by intrusion detection systems (IDS). From DNS query point of view in Figure 12, pyconau-funtimes [64] successfully hides the attacker among normal users of 0.tcp.ngrok.io, a service for establishing secure tunnels.

**Multi-stage Payload.** Since AV tools are mostly based on signatures, malware tend to hide their logic and footprint for fingerprinting by segmenting malicious logic into multiple stages and including minimal code snippets. For example, Listing 4 contains only payload fetching, code generation and error handling, and hides its malicious logic such as stealing environment variables and backdooring infected hosts in the second-stage payload from pastebin.com.

**Code Obfuscation.** Existing studies [65], [66] classify malware obfuscation techniques into categories such as randomization obfuscation, encoding obfuscation, logic structure obfuscation etc., and point out that malware can obfuscate code to hide malicious logic from both manual inspection and automatic detection. We find supply chain attacks are no different. For example, both getcookies [31] and purescript [33] use encoding obfuscation. Similarly, fast-requests [63] in Listing 5 uses randomization obfuscation and encoding obfuscation to defeat analysis.

**Logic Bomb.** TriggerScope [67] defines a logic bomb as malicious application logic that is executed, or triggered, only under certain (often narrow) circumstances. Logic bombs can be used to defeat both static and dynamic malware analysis approaches. For example, dynamic analysis of rest-client [5] would never execute the malicious payload if it isn’t executed in a production environment (Line 8 in Listing 4).

**Older Version.** Several malware [5], [30] published through account compromise utilize unique techniques to defeat analysis. Rather than publishing the malicious payload to the latest version of a package (i.e. maximize the volume of victims, which in turn increases the probability of being caught), attackers instead publish these payloads to older versions of the package to target a smaller number of victims. We imagine the attacker’s intuition is that developers using older versions are less cautious about security, thus maximizing attack persistence and minimizing detection probability.

**Security Analysis Hurdles**

While iteratively labeling suspicious packages, we encountered several seemingly malicious behaviors which turned out to be benign. We enumerate them to increase awareness in the research community and help avoid pitfalls, while hoping that RM will specify policies to define and regulate such behaviors.

**Installation Hook.** During installation, some packages fetch data from online services and locally evaluate or write them to sensitive locations. For example, stannp uses cdoverserter.com to convert its README to RST format, and meshblu-mailgun tries to skip the build process by checking availability of pre-built binaries at cdn.octoblu.com. Such behaviors are similar to malicious activities and would confuse automated analyses.

**Dynamic Code Loading.** Loading code at runtime is considered as suspicious by mobile stores, since it can be abused to inject unknown code into apps. However, some benign packages locally evaluate payloads from network. For example, net_http_detector in Listing 6 evaluates payload from github.com.

**User Tracking.** PM may want to track users for improving user experience or increasing business, but the boundary between information stealing and user tracking is unclear without well-defined policies. For example, rsa-compat, one of the packages under investigation due to lack of user tracking policies (Figure 11), collects Node.js runtime and operating system metrics, and sends them back to https://therootcompany.com.

VI. Mitigation

The goal of our study was to not only bring attention to this overlooked problem, but also to provide guidance to stakeholders in the package manager ecosystem for detecting and mitigating supply chain attacks. In this section, we discuss the general mitigation strategies for each stakeholder and the limitations of the MALOSS pipeline which RM may extend on, and help improve the security posture of the ecosystem.

**A. Mitigation Strategies**

**Registry Maintainers.** RM are the central authorities in the ecosystem. We elaborate their mitigation strategies based on the three types of features presented in Table I, i.e. functional, review and remediation.

(1) **Functional Feature:** RM can significantly improve account protection by providing MFA and code signing, blocking weak or compromised passwords and detecting abnormal logins. They can also combat typosquatting by detecting typos at the registry client side and preventing typos of popular packages from publishing. In addition, RM can publish policies to guard ownership transfer, to regulate package behaviors such as tracking users without notification in rsa-compat, and to rule out unwanted packages such as restclient which claims to be a typo-guard gem without proof of their own innocence.

(2) **Review Feature:** RM can extend MALOSS to identify packages with (i) names similar to existing popular packages or related to existing attacks using metadata analysis, (ii) suspicious API usages and taint flows using static analysis, (iii) unexpected runtime behaviors using dynamic analysis. The iterative labeling process in MALOSS can be scaled by crowdsourcing manual reviews. Since the package manager ecosystem is an open source community with stakeholders such as PM and Dev, they can be involved to secure the ecosystem. In particular, when RM detects a suspicious package version, it
can broadcast this information to the corresponding developers or publish its analysis results for “social voting”.

(3) Remediation Feature: Since RM hold the central authority, they can not only remove malicious packages and publishers from the server, but also installed packages from the client by comparing against blacklists. Moreover, RM can also employ various notification channels such as emails, security advisories and client-side checks to inform stakeholders about security incidents. Notification targets include both Dev and PM of affected packages and their dependents. For example, the infection of AndroidAudioRecorder after removal shown in Figure 12 highlights the importance of notification-based remediation.

**Package Maintainers.** Attack vectors targeting PM include account compromise, infrastructure compromise, disgruntled insider, malicious contributor and ownership transfer. PM can protect their accounts by adopting techniques such as MFA, code signing and strong passwords. PM can protect their infrastructure through firewall, timely patches and IDS. PM need to be cautious about both new contributors and disgruntled insiders, and manually inspect small packages or employ a code review system for larger packages. In addition to enhancements, PM can help improve the ecosystem by reporting security issues to advisories, updating dependencies to avoid known issues, joining “social voting” and avoiding security analysis hurdles.

**Developers.** Although Dev cannot control upstream packages, they can follow best practices to remediate security issues. Dev can host private registries with known secure package versions to avoid supply chain attacks from upstream stakeholders. Dev can periodically check security advisories and timely update to remain secure. For untrusted packages, Dev can manually check, deploy MALOSS to vet code and isolate them at runtime [9], [10] to avoid potential hazards. In addition, Dev can join “social voting” to improve security analyses.

**End Users.** Despite no control of any provided service and software, EU can leverage AV tools to secure their devices and protect themselves. In addition, EU can raise their security awareness and access only official and reputable websites.

**B. MALOSS Limitations**

**Scope of Analysis.** While prototyping MALOSS, we only consider files written in the corresponding language for each registry in static analysis, excluding native extensions, embedded binaries and files written in other languages. We only consider Linux platform in dynamic analysis, in particular Ubuntu 16.04, excluding other Linux distributions, Windows and MacOS environments. We only consider runtime dependencies, thus ignoring development dependencies.

**Inaccurate Static Analysis.** MALOSS relies on existing AST parsing and taint analysis tools in static analysis, which can be inaccurate due to dynamic typing. In addition, programming practices such as reflection and runtime code generation add to the problem, and lead to inaccurate results. However, we argue that more accurate tools and algorithms can be developed and integrated into MALOSS when available.

**Dynamic Code Coverage.** MALOSS currently performs four types of dynamic analyses on Ubuntu 16.04, but may have limited code coverage. Possible improvements include environment diversification (e.g., Windows, browser), force-execution [68], symbolic execution [69] etc.

**Anti-analysis Techniques.** As discussed in §V-D, attackers have evolved and adopted anti-analysis techniques. We expect more sophisticated techniques such as intentional vulnerable code and heavy obfuscation to appear in the future. We solicit the future researchers to combat evolving attackers.

**VII. Related Work**

**Software Supply Chain Attacks.** The earliest software supply chain attack is the Thompson hack in 1983, in which he left a backdoor in the compiler, and could compromise a program even if its source code is benign. Following that, similar attacks [70]–[74] are launched, targeting various supply chain components such as infrastructure, operating systems, update channels, compilers and cryptographic algorithms. Recent years witness an increasing trend of supply chain attacks targeting package managers [4], [5], [7], [13], [19], [30], [32], [35], [37], which host prebuilt packages for benefits such as code sharing. Our work studies supply chain attacks against three popular package managers to identify root causes, scan new threats and suggest improvements.

**Package Management Security.** Previous works studied the design and implementation of package managers and proposed attacks [75], [76] and defenses [77]–[79]. These works focus on designing a more secure package manager with properties such as compromise-resilience and supply chain integrity. In addition, due to the rising number of vulnerabilities and malware in the Npm ecosystem, various works [8]–[12], [80], [81] have been proposed to find new vulnerabilities, isolate untrusted packages, evaluate risks and remediate issues. Our work differs from prior work by studying a corpus of real-world supply chain attacks against package managers and proposing actionable improvements and suggestions.

**Security Tools.** MALOSS is an extensible framework and more tools can be added to the pipeline to generate better results. For example, static analysis tools for various languages [39], [82]–[88] and binaries [89], [90] can possibly generate more accurate and comprehensive results. Dynamic analysis tools [51], [52], [68], [91]–[95] can increase dynamic code coverage and provide support for various platforms and environments.

**VIII. Conclusion**

To systematically study the recent supply chain attacks in the package manager ecosystem, we propose a comparative framework, which reveals relationships among stakeholders. We pinpoint the root causes and summarize their attack vectors and malicious behaviors. We propose MALOSS, the first large scale analysis pipeline at package manager level, to detect
malicious packages. We identified and reported 7 malware in PyPI and 41 malware in Npm and 291 malware in RubyGems, out of which, 278 (82 percent) have been removed and 3 have been assigned CVEs.

We will provide the collected malware samples for research purpose on request, to aid future research on improving security of package managers. We envision this work as a first step towards securing the package manager ecosystem, and solicit more work on detecting advanced malware, as well as protecting developers and end users.

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