



Practical Automated Detection of Malicious npm Packages

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ABSTRACT

The npm registry is one of the pillars of the JavaScript and TypeScript ecosystems, hosting over 1.7 million packages ranging from simple utility libraries to complex frameworks and entire applications. Each day, developers publish tens of thousands of updates as well as hundreds of new packages. Due to the overwhelming popularity of npm, it has become a prime target for malicious actors, who publish new packages or compromise existing packages to introduce malware that tampers with or exfiltrates sensitive data from users who install either these packages or any package that (transitively) depends on them. Defending against such attacks is essential to maintaining the integrity of the software supply chain, but the sheer volume of package updates makes comprehensive manual review infeasible. We present AMALFI, a machine-learning based approach for automatically detecting potentially malicious packages comprised of three complementary techniques. We start with classifiers trained on known examples of malicious and benign packages. If a package is flagged as malicious by a classifier, we then check whether it includes metadata about its source repository, and if so whether the package can be reproduced from its source code. Packages that are reproducible from source are not usually malicious, so this step allows us to weed out false positives. Finally, we also employ a simple textual clone-detection technique to identify copies of malicious packages that may have been missed by the classifiers, reducing the number of false negatives. AMALFI improves on the state of the art in that it is lightweight, requiring only a few seconds per package to extract features and run the classifiers, and gives good results in practice: running it on 96287 package versions published over the course of one week, we were able to identify 95 previously unknown malware samples, with a manageable number of false positives.

CCS CONCEPTS

• Security and privacy → Malware and its mitigation.

KEYWORDS

supply chain security, malware detection

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1 INTRODUCTION

npm¹ is a system for publishing and consuming software packages for JavaScript and TypeScript. While initially closely associated with the Node.js platform² and back-end JavaScript applications, it is not architecturally tied to Node.js, and has also found widespread use with web applications and on other platforms.

The core concept of npm is the *package registry*, which is a database of JavaScript packages with associated metadata. While some organizations and enterprises host their own registries, by far the best-known registry is the public npm registry, accessible via the npm website, which also provides facilities for browsing and searching for packages, as well as viewing their metadata. In this paper, we exclusively concern ourselves with the public registry.

As of early September 2021, npm's package registry hosts over 1.7 million packages. Some of these are private packages that are only accessible to specific users or organizations, but most of them are public, and it is these public packages that are our focus. Over the course of a single week, developers publish around 100,000 public package versions, including both new packages and updated versions of existing packages. Historic versions of a package remain available on the registry unless they are explicitly removed either by the package maintainer or by npm staff, allowing dependent packages to rely on specific older versions of a package, for example to make use of an API that has been removed in the latest version.

Most developers interact with the registry through a command-line interface such as the npm CLI³ or yarn,⁴ which can be used to download a particular version of an existing package and install it locally, or to publish a new package or a new version of an existing package to the registry. When installing a package version, the package manager will first recursively install the dependencies of that package (unless they are already installed); download the tarball containing the package from the registry; unpack the tarball in the installation directory; and finally run any installation scripts specified by the package. These scripts are free-form shell scripts that typically perform setup tasks such as downloading additional artifacts not bundled with the package itself. Due to the transitive nature of package installation, popular packages are downloaded very frequently; for example, the chalk package⁵ (which offers



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¹<https://npmjs.com>

²<https://nodejs.org>

³<https://www.npmjs.com/package/npm>

⁴<https://www.npmjs.com/package/yarn>

⁵<https://www.npmjs.com/package/chalk>

support for coloring terminal output) was downloaded almost 89 million times a week at the time of writing.

Publishing a new package or package version is the dual to this process: anyone authenticated through the npm website can create a new package, thereby becoming its maintainer, and maintainers can publish new versions at any time by simply uploading a tarball to the registry. While packages can indicate a repository hosting their source code, this information is optional. It is the maintainer's responsibility to run any necessary build steps (such as compiling TypeScript to JavaScript, bundling and minifying, etc.) before publishing; the registry simply hosts the tarball and is largely agnostic to its content.

The overwhelming popularity of npm and the central role it plays in the software supply chain for JavaScript and TypeScript (which, in turn, are among the most widely-used programming languages at present) has long made it a favorite target for attackers attempting to publish malicious package versions that tamper with or exfiltrate data from the machines they are installed on, perform parasitical computations such as Bitcoin mining, or other malicious activities.

Recent examples include high-profile incidents such as the `eslint-scope` compromise,⁶ where attackers managed to steal the credentials of a maintainer of a popular package, allowing them to publish a new malicious version of the package that uploaded user credentials to a server upon installation; the `event-stream` backdoor,⁷ where social-engineering techniques were used to gain maintainer status and then launch a similar attack; and a steady stream of smaller incidents since then.

The malicious package versions were quickly removed by npm staff from the registry upon detection, but, in the case of `eslint-scope` and `event-stream`, not before being installed several million times. While the number of affected users is much smaller in most cases, the frequency with which such incidents occur still poses a significant danger to the software supply chain, both in terms of concrete damage to its users, and in terms of reputational damage that could potentially impede the flourishing not just of npm but also the wider open-source ecosystem.

Addressing this problem at a fundamental level would arguably require significant changes to npm, perhaps including a more secure package-publishing model to prevent malicious packages from reaching the registry in the first place, and/or the Node.js platform, perhaps with access-control enforcement to limit the damage a malicious package can do when it is installed.

Our aim in this paper is more modest: without making any changes to the fundamentals of npm, we want to detect potentially malicious package versions as quickly as possible, and report them to a human auditor for take-down.

To be practically useful, then, our approach has to satisfy at least three requirements: it has to be *automated*, since the sheer number of packages renders manual audits infeasible; *efficient* to keep up with the speed at which new versions are published; and *accurate* to avoid flagging benign packages or missing malicious ones.

We achieve this by combining three complementary techniques into one system, which we call AMALFI.⁸

- (1) machine-learning *classifiers* trained on labelled examples of malicious and benign packages, utilizing features that record changes in the APIs the package uses as well as package metadata extracted using a lightweight syntactic scan;
- (2) a *reproducer* that rebuilds a package from source and compares the result with the version published in the registry;
- (3) a *clone detector* that finds (near-)verbatim copies of known malicious packages.

Our feature selection, discussed in more detail below, is motivated by the observation (borrowed from Garrett et al. [10]) that malicious packages tend to make use of distinctive capabilities of the JavaScript language (such as runtime code generation), the underlying platform (such as access to the file system or the network), and the npm package manager (such as install scripts). While none of these features are dead giveaways by themselves, in combination they are worthy of closer inspection, especially if a package suddenly starts using capabilities it has never used before. For example, the above-mentioned `eslint-scope` package uses runtime code generation and an install script in its (malicious) version 3.7.2, capabilities it had never used before.

By training on a corpus of malicious and benign packages provided to us by npm, our classifiers learn to distinguish typical (and therefore most likely harmless) feature changes from atypical (and therefore suspicious) ones. The choice of classifiers is constrained by the small size of the corpus, which contains fewer than 2000 samples; we experimented with three different techniques: decision trees, Naive Bayesian classifiers, and one-class SVMs.

To eliminate false positives, we borrow another insight from the literature [13, 28, 30]: malicious package versions tend not to have their source code publicly available, in order to avoid detection.⁹ Consequently, being able to reproduce a package version from its source code is a good indicator that it is benign. As has been noted previously [13], even perfectly benign packages may fail to reproduce for a variety of reasons, but this is acceptable in our case since we are only using this criterion to filter out benign packages erroneously flagged as malicious, not to detect new ones.

Finally, we note that attackers often publish multiple textually identical copies of one and the same malicious package under different names. However, since package metadata may be different, our classifiers sometimes fail to spot these copies. We use a simple clone detector that hashes the contents of a package (minus the package name and version, which are always unique) to eliminate this source of false negatives.

An overview of how these different components work together can be seen in Figure 1.

To motivate our approach more carefully, we show two typical examples of malicious packages in Section 2 and discuss how we detect them. Section 3 provides details on feature selection and extraction for the classifier, as well as an overview of the reproducer and clone detector. We evaluate AMALFI in Section 4 in a large-scale experiment on newly published npm packages to demonstrate its ability to find previously unknown malicious packages, and in a cross-validation experiment to evaluate precision and recall. We discuss the results in Section 5, survey related work in Section 6, and outline conclusions and future directions in Section 7.

⁶<https://eslint.org/blog/2018/07/postmortem-for-malicious-package-publishes>

⁷<https://snyk.io/blog/a-post-mortem-of-the-malicious-event-stream-backdoor>

⁸Short for "Automated malicious package finder".

⁹In fact, we are not aware of a single counterexample to this rule.

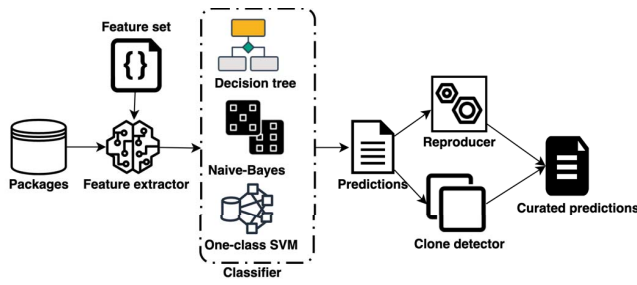


Figure 1: Overview of AMALFI

In summary, the significance of our contributions is as follows:

- We present AMALFI, an automated approach for detecting malicious npm packages that uses a novel combination of techniques and shows solid results in practice, identifying 95 previously unknown malicious packages. Among the three different classifiers we consider, the decision tree performs best, though the others also contribute findings.
- AMALFI is efficient, usually taking only a few seconds per package to extract features and run the classifier. We also show that retraining the classifiers is cheap, thus allowing continuous improvements to be made as more and more results are triaged.
- The false-positive rate, while initially quite high, drops significantly as the classifiers are retrained on more data, with fewer than one in a thousand packages being flagged spuriously. A cross-validation experiment on our training set also shows that the decision tree achieves over 40% recall, suggesting that its false-negative rate is reasonable. Supplementary materials including experimental data and results are publicly available at <https://doi.org/10.5281/zenodo.5908852> and <https://github.com/githubnext/amalfi-artifact>.

While the building blocks we use have been proposed before, the novelty of our approach lies in their combination, and a more thorough exploration and evaluation of the design space.

2 BACKGROUND

To set the scene, we discuss two representative examples of real-world malicious package versions that were (manually) detected and removed from the registry, and then explain how we could have identified them automatically.

For the purposes of this paper, we define a *malicious package version* to be a specific version of an npm package that contains code that implements malicious behavior including (but not limited to) exfiltrating sensitive or personal data, tampering with or destroying data, or performing long-running or expensive computations that are not explicitly documented. In particular, we consider a package version to be malicious even if the malicious code it contains is disabled or broken. Moreover, in line with npm’s Acceptable Content Policy¹⁰ we include in our definition malicious behavior that is ostensibly done for research purposes. For brevity, we will often use the term “malicious package”, the “version” part being understood.

¹⁰<https://docs.npmjs.com/policies/open-source-terms#acceptable-content>

From an attacker’s perspective, there are three steps to delivering malware through npm: (1) publish a malicious package version; (2) get users to install it; and (3) get them to run the malicious code.

The easiest way to go about (1) is to publish a completely new package. A classic way of achieving (2) in this scenario is *typosquatting* [27] whereby the name chosen for the new package is very similar to the name of a popular existing package; a user who accidentally misspells the name of the popular package will then end up inadvertently installing the malicious package instead. A more sophisticated approach is *dependency confusion* [5]: the attacker identifies dependencies on a package hosted in a private registry, and then publishes a malicious package with the same name and a higher version number on the public npm registry; clients of the private package may then end up installing the malicious package instead. Finally, there have been cases of attackers publishing an initially benign and useful package, getting it added as a dependency to a popular target package, and then publishing a malicious version [4].

An alternative, more laborious strategy to achieve (1) is for the attacker to compromise an existing popular package by gaining maintainer access (for example by stealing maintainer credentials or by social engineering as described in Section 1), and then publishing a new, malicious version of that package. In this case, (2) is easy since the package already has many users who will (either explicitly or implicitly) upgrade to the malicious version.

Finally, a common tactic to achieve (3) in either scenario is to use installation scripts which (as explained above) are run during installation and can execute arbitrary code. However, the commands run by installation scripts are by default logged to the console, increasing the risk of detection. Hence a more careful attacker may instead choose to hide their malicious code in some frequently executed bit of functionality in the main body of the package.

A typical example of a package employing typosquatting is *mogodb*, a putative typo for the highly popular *mongodb* package, which is currently seeing around two million installations per week. Two versions of *mogodb*, numbered 3.1.8 and 3.1.9, were published within less than a millisecond of each other on 1 August 2019, and identified as malicious and taken down a few minutes later.

As shown in Figure 2 (a), the package.json manifest file of the package registers a *postinstall* script to be run after package installation, which executes the *test.js* script included in the package. That script, shown in Figure 2 (b), harvests the hostname of the machine on which the package was installed, and sends it off to a remote host controlled by the attacker. While the information being stolen in this case is not highly sensitive, this is clearly malicious behavior.

Even before studying the package implementation in detail, a human auditor might notice features of the package that make it seem worthy of closer scrutiny, such as the presence of a *postinstall* script, the usage of the packages *os* and *request*, and most of all the extremely short time span between the publication of the two versions. While the former two features are not by themselves suspicious, their combination with each other and with the third feature strongly suggests a malicious package.

A typical example of a compromised package is *jasmin*, a web framework that was moderately popular at one point but has not seen active development in a number of years. Versions 0.0.1 and

```

1  {
2    "name": "mogodb",
3    "version": "3.1.9",
4    "scripts": {
5      "postinstall": "node_test.js",
6      ...
7    },
8    ...
9  }

```

(a) package.json

```

1  var remote = "https://attacker.controlled.host/";
2  var host = require("os").hostname();
3  require("request")(remote + "?h=" + host, function() {});

```

(b) test.js

Figure 2: Malicious code in mogodb@3.1.9 (simplified)

```

1  var remote = "https://another.attacker.controlled.host/";
2  for (var form of document.forms) {
3    for (var element of form.elements) {
4      if (element.type == "password") {
5        form.addEventListener('submit', function() {
6          var data = [...this.elements].map(function(elt) {
7            return elt.name + ":" + elt.value;
8          }).join() + "|" + document.cookie;
9          var enc = encodeURIComponent(btoa(data));
10         this.action = remote + "?data=" + enc;
11       });
12       break;
13     }
14   }
15 }

```

Figure 3: Malicious code inserted into file component.js of jasmine@0.0.3 (simplified)

0.0.2 of `jasmin` are benign, but version 0.0.3, presumably published by a malicious actor, contains the code shown in Figure 3, which traverses all forms contained in an HTML document looking for password fields and overrides their submit handler to harvest the content of these fields and send them to an attacker-controlled host.

In this case, there are no particularly suspicious features of the package that might draw the attention of a human auditor: dealing with password fields, encoding data using `encodeURIComponent` for transmission, and accessing HTTP cookies are all relatively innocent capabilities, and are often used together. What is immediately suspicious, however, is that none of these three capabilities were used in the previous version of `jasmin`. Moreover, the upgrade from 0.0.2 to 0.0.3 is a minor version upgrade, where one would not expect major new features that might require such new capabilities to be introduced.

These examples and others like them suggest that a machine-learning based approach might be able to detect malicious packages based on high-level features like usage of particular APIs, platform capabilities and package metadata, and in particular how these features change between versions, without the need for deep source-code analysis.

3 OUR APPROACH

Having motivated what kind of features are interesting for automated classification, we now describe our feature set in more detail, and then explain how to extract *single-version features* describing one package version as well as *change features* capturing the difference in features between two versions. Next, we discuss our choice of classifiers and their training regimen. Finally, we give some more details about the other two components of our approach, the reproducer and the clone detector.

3.1 Feature set

Based on manual inspection of known examples of malicious packages, we determined eleven features of interest. Nine of them are single-version features that can be extracted from the contents of a single package version, while the other two intrinsically involve two versions of a package.

The single-version features are as follows, where we group related features into categories and provide examples of each:

- (1) Access to personally-identifying information (PII): credit-card numbers, passwords, and cookies
- (2) Access to specific system resources
 - (a) File-system access: reading and writing files
 - (b) Process creation: spawning new processes
 - (c) Network access: sending or receiving data
- (3) Use of specific APIs
 - (a) Cryptographic functionality
 - (b) Data encoding using `encodeURIComponent` etc.
 - (c) Dynamic code generation using `eval`, `Function`, etc.
- (4) Use of package installation scripts
- (5) Presence of minified code (to avoid detection) or binary files (such as binary executables)

The remaining two features concern two versions of a package, and are the time between publication of the two versions, and the type of update in semantic-versioning terms (major, minor, patch, build, or pre-release).

The motivation for considering time between updates is that malicious package versions often exhibit unusual update patterns, such as multiple versions published in very rapid succession (as seen in the `mogodb` example in Section 2), or a new version being published after years of inactivity (which might suggest an account takeover). The update type, on the other hand, can determine whether a change in some other feature is suspicious or not, as explained above.

These two features, along with the changes in the values of the nine single-valued features between one package version and the previous version, constitute our feature set.

In order to accommodate the first version of a package as well, we introduce a pseudo-update type representing first versions, consider their time between updates to be zero, and take the values of the single-version features to be the remaining change features. This enables us to not only detect malicious updates, where a previously benign package becomes malicious, but also packages that were malicious from the start.

3.2 Feature extraction

To compute the first four categories of single-version features, we parse each JavaScript and TypeScript file in the package using Tree-sitter.¹¹ We then use Tree-sitter AST queries to look for syntactic constructs corresponding to the features, such as string literals containing the keyword password for PII access; imports of the fs module for file-system access; and calls to eval and Function for dynamic code generation.

Similarly, to check for the presence of installation scripts we parse the package.json file and look for definitions of preinstall, install, and postinstall properties.

Minified or binary files tend to have higher entropy than plain source code, so we compute the Shannon entropy of all files contained in the package and use the average and standard deviation of the entropy across all files as features.

To compute change features, we use the publication timestamps provided by the npm view time command to obtain the time between updates in seconds. We rely on an off-the-shelf semantic-versioning library to determine the update type and, for each given version, determine the previous version in chronological order. Finally, we simply subtract the values of the single-version features across the two consecutive versions.

3.3 Classifier training

Our choice of classifiers is dictated by the corpus of labelled training data we have available. Since malicious packages are taken down by npm immediately upon discovery, most known examples of malicious packages are no longer available for inspection. However, npm kindly agreed to make their archive of 643 malicious package versions detected up to 29 July 2021 available to us for the purposes of this study. Out of these packages, 63 are malicious versions of otherwise non-malicious packages, i.e., compromised packages. We added to the original dataset the 1147 benign versions of the same packages published by the same date, yielding a basic corpus of 1790 labelled samples of malicious and benign package versions. Since the goal of AMALFI is to detect malicious packages, the basic corpus oversamples malicious packages, i.e., it contains more malicious packages than we would expect from a similarly-sized random sample of npm packages. This is a common strategy in learning-based approaches [18].

It is worth emphasizing that while compromised packages have a much bigger potential impact on the npm ecosystem, they occur so rarely that there simply is not enough data to make them the sole focus of our study. Anecdotally, however, compromised and malicious packages use similar techniques to carry out attacks, meaning that they share features, which enables AMALFI to detect both types of malicious packages.

Since the number of malicious samples is smaller compared to the total number of package versions in our dataset and on npm, we had to use learning algorithms that handle imbalanced data well. Further, due to the novelty of the features in our approach, we sought a learning algorithm that allowed us to analyze the importance of the features we selected. In the end, the learning algorithms that satisfied the constraints were decision trees, Naive Bayesian classifiers, and One-class Support Vector Machines (SVMs). We

picked the first one due to its ability to explain which features impact the final decision, and the two latter ones because of their versatility when dealing with imbalanced datasets as seen in anomaly detection work.

To train the classifiers, we use the sklearn library for Python. For the decision tree, we use information gain as the split criterion. For the Naive Bayesian classifiers, we use the Bernoulli variant which can only deal with Boolean features, so we omit the discrete features (entropy average and standard deviation as well as update time), and collapse the others to a value of 1 if the feature is present, and 0 otherwise. For the SVM, we choose a linear kernel and train only on benign examples, since the task of this classifier is to detect outlier versions that are noticeably different from the benign ones. We determined the ν parameter of the SVM, which approximates the number of expected outliers, by conducting a leave-one-out experiment on our basic corpus. The experiment showed that optimal precision and recall are attained for a ν value of 0.001, meaning that the classifier expects about one in a thousand package versions to be malicious.¹²

3.4 Reproducer and clone detector

As explained in Section 1, the reproducer takes a given package version and then attempts to rebuild the package tarball from source. This is a heuristic process that may fail for a variety of reasons: while packages can specify the URL of their source repository in their package.json file, this information is optional and many packages do not provide it, or the repository is not publicly accessible. Package versions can also specify the git SHA of the commit they were built from, but again this information is optional. While there are popular conventions for creating branches or tags with names reflecting the package version they correspond to, many packages do not follow these conventions, making it impossible to determine the correct commit. The build commands to run to produce the package from its source are likewise not prescribed. Finally, many packages neglect to specify the precise version of the build tools (such as the TypeScript compiler) they rely on, leading to seemingly random differences between the reproduced package and the original. For all of these reasons, the success rate of the reproducer is low in practice as we shall see, but it still serves a useful purpose as an automated false-positive filter.

The third component of AMALFI is a simple clone detector that computes an MD5 hash of the contents of a package tarball and compares it to a list of hashes of known malicious packages. When computing the hash, we ignore the package name and version specified in the package.json file, since these are always unique and would cause spurious misses. No other attempt at fuzzy matching is made, so only verbatim clones are detected.

4 EVALUATION

While motivating and presenting the details of our approach above, we have informally argued that its design makes it practically useable and useful. We will now back up these claims with an experimental study, which aims to answer the following three research questions:

¹¹<https://tree-sitter.github.io/tree-sitter/>

¹²The source code of our classifier-training scripts and the list of packages in the basic corpus are included in the supplementary materials.

Date	# Versions	Decision Tree		Naive Bayes		SVM		Clones
		# TP	# FP	# TP	# FP	# TP	# FP	# TP
July 29	23,452	34+1	932-74	13+22	1453-107	20+5	102-11	0
July 30	13,849	2+0	22-1	0+0	6-0	0+0	14-3	0
July 31	7,042	17+0	16-1	0+0	1-0	18+9	4-0	0
August 1	6,050	1+0	6-2	1+0	3-2	0+0	13-0	0
August 2	13,562	2+1	17-0	4+1	12-1	0+0	10-0	1
August 3	15,269	6+0	15-2	1+0	9-1	0+0	41-3	0
August 4	17,063	16+2	9-1	1+0	9-1	1+0	10-1	17

Table 1: Results from Experiment 1; $+n$ denotes TPs contributed by the clone detector, $-n$ FPs eliminated by the reproducer.

RQ1 Does AMALFI find malicious packages in practice?

RQ2 Is it accurate enough to be useful?

RQ3 Is training and classification fast enough to be useable?

To answer these questions, we conducted two experiments: one experiment on a large set of newly published package versions to assess performance, and one smaller experiment on labelled datasets to assess accuracy. We will describe the experiments below.

4.1 Experiment 1: Classifying newly published packages

This was a large-scale experiment designed to simulate a realistic scenario for automated malware detection in which we applied AMALFI to all new public package versions published on the public npm registry over the course of a single, randomly chosen week from 29 July 2021 to 4 August 2021.

On the first day, we trained our three classifiers on the basic corpus and then used them to classify the set N_1 of all new package versions published that day. Additionally, we ran our clone detector on the same set to find copies of malicious packages in the basic corpus, acting as a fourth classifier. This yielded a set $P_1 \subseteq N_1$ of package versions flagged by at least one classifier. We ran the reproducer on this set to automatically weed out some false positives, and manually inspected the rest. The manual inspection was initially conducted by both authors, with each author examining roughly one half of the flagged versions. The package versions that were found to be malicious by one author were afterwards verified by the other author. Finally, we reported the verified malicious packages to the npm security team. All of them were subsequently taken down, meaning that the npm security experts agreed with our assessment. As such, we are confident that our manual labeling of malicious packages is highly accurate.

The manual inspection resulted in a partitioning of P_1 into two sets TP_1 and FP_1 of true positives (i.e., genuine malicious packages found by the classifiers) and false positives (i.e., benign packages falsely flagged as malicious). As a last step, we ran the clone detector again to find additional copies of packages in TP_1 that were missed by the classifiers, and added them to TP_1 .

On the second day, we retrained the classifiers on the basic corpus as well as the set N_1 triaged the previous day, adding TP_1 to our set of labelled malicious packages, and everything else (that is, $N_1 \setminus TP_1$) to the set of benign packages. In other words, for the purposes of this experiment we assumed that any package *not* flagged by any of the classifiers was benign. This is not true

in general, but the enormous number of new package versions published each day made it infeasible to inspect them all, and since we expect the number of malicious packages on any given day to be low it is not an unreasonable approximation to the unknown ground truth.

As on the first day, we then applied the classifiers to the set N_2 of packages published that day, ran the reproducer on the resulting set P_2 , manually inspected the rest, and ran the clone detector to mop up anything that was missed, yielding a set TP_2 of newly identified malicious packages. On the third day, we retrained the classifiers using the basic corpus as well as both N_1 and N_2 , and so forth for each subsequent day.¹³

The intuition here is that we want to mimic a usage pattern where results from the classifiers are inspected by a human auditor, and the classifiers are then retrained with the additional ground truth obtained in this way.

4.2 Experiment 2: Classifying labelled data

While the first experiment can provide insight into the performance of our approach under real-world conditions and in particular its false-positive rate, it cannot tell us much about false negatives.

Hence we ran a second experiment, measuring the precision and recall of AMALFI on the basic corpus. Its small size prevented us from separating it in a train-and-test fashion, so instead we performed a 10-fold cross validation experiment, repeatedly training the classifiers on 90% of the corpus and measuring precision and recall on the remaining 10%. Given the imbalance in our dataset, we used stratified sampling to maintain the distribution of malicious and benign versions for each fold.

Furthermore, we also measured precision and recall on a labelled dataset from recent work by Duan et al. describing their MalOSS system [8]. This dataset had some overlap with our basic corpus which we removed, leaving only the unique data points for this experiment. Also, the dataset initially only contained malicious packages; to balance it, we followed the same strategy as for the basic corpus and added all benign versions of the contained packages. In the end, this yielded a dataset with 372 package versions, out of which 40 were malicious.¹⁴

Based on the results from these two experiments, we will now answer the research questions posed above.

¹³The list of packages considered in this experiment and the results of the classification are included in the supplementary materials.

¹⁴Detailed results for this experiment are included in the supplementary materials.

4.3 RQ1: Practical performance on newly published packages

The results of the first experiment are presented in Table 1. The table contains the date for which we collected the package versions (**Date**) as well as the total number of versions published on that date (**# Versions**). Then, for each classifier, the table contains the number of true positives (**#TP**) and false positives (**#FP**) flagged by the classifier, annotated with the number of additional true positives found by the clone detector ($+n$) and the number of false positives eliminated by the reproducer ($-n$). As explained above, all true positives were confirmed by the npm security team.

Thus, for example, the entry $16 + 2$ in the **#TP** column for the decision tree on August 4 means that the classifier flagged 16 true positive among the 17,063 package versions published that day of which the clone detector found two additional copies. The entry $9 - 1$ in the **#FP** column means that among the nine false positives it flagged, one was successfully reproduced and hence eliminated automatically.

As explained above, the clone detector is also treated like a fourth classifier. It has no false positives and never misses identical copies, hence this column only contains a single number per day. Note again that in this column we show the number of clones found on that same day, as opposed to the entries after the $+$ sign which depict the number of clones from the previous days.

The first takeaway from this table is that the number of new packages published every day is high, but quite variable, with almost four times as many packages being published on July 29 (a Thursday) than on August 1 (a Sunday).

Secondly, we can see that all our classifiers are able to correctly classify malicious package versions, with varying degrees of success. The decision tree performs better than the rest, especially in terms of true positives. Removing the overlap between classifiers, we were able to identify 95 previously unknown malicious packages over the course of these seven days, which is a significant number, especially considering that the entire set of malicious packages detected prior to our work only contained 643 samples.

Third, we notice that on the first day all three classifiers produce an unmanageable number of results. We therefore had to modify our approach and only examined a subset of all flagged packages in detail, assuming all the rest to be false positives. This means that the false-positive counts for this day are likely to be overstated. However, once this set of packages is added to the training set on the second day, the number of results drops dramatically, and by the end of the week all three classifiers yield a relatively low number of false positives.

Fourth, our results show that the reproducer has a low success rate in practice, only being able to reproduce one or two packages on any given day. However, given the overall low number of alerts towards the end of the week this is still a valuable improvement. Similarly, clone detection only contributes a few additional true positives each day (the 17 packages detected on August 4 being an outlier, and mostly overlapping with the results from the decision tree), but it still improves the overall results. Both mechanisms are computationally inexpensive, and thus the help they provide comes at a low cost, making them worth keeping in spite of their limited contributions. Conversely, this shows that our classifiers add value

beyond a purely textual scan looking for verbatim copies of known malware.

In summary, we can answer RQ1 in the affirmative: AMALFI does indeed detect malicious packages in practice. Further, since all the packages found by AMALFI and reported to npm had not been identified before, we can confidently claim that our approach complements existing solutions for malicious package detection in npm.

Dataset	Decision Tree		Naive Bayes		SVM	
	Prec.	Recall	Prec.	Recall	Prec.	Recall
Basic	0.98	0.43	0.90	0.19	(0.98)	(0.27)
MalOSS	0.35	0.64	0.62	0.64	0.73	0.61

Table 2: Results from Experiment 2

4.4 RQ2: Accuracy

The results from Experiment 2 are presented in Table 2.

The first row shows precision and recall measurements from the 10-fold cross-validation experiment on our basic corpus, averaged over all ten runs. The numbers for the SVM classifier have to be interpreted with care, since its ν parameter was fitted on this very dataset, hence we have put them in brackets. All our models achieve very high precision, but the recall of Naive Bayes and SVM is somewhat poor. This is expected due to the low prior of malicious packages.

The second row shows precision and recall from running AMALFI on the MalOSS dataset derived from the literature [8] as explained above. We see that the recall is higher than with the previous row, at the expense of precision. These results point to the trade-off between these two metrics, but it is also worth pointing out that the MalOSS dataset contains a number of packages labeled as malicious where npm disagreed with the authors' assessment and did not take them down.

A more detailed comparison of AMALFI to MalOSS is unfortunately not possible since they do not present statistics on false positives or performance. The heavy-weight nature of their approach and its complicated setup involving a sophisticated pipeline combining static and dynamic components made it infeasible to run on our dataset.

Based on these results and the false-positive numbers discussed above, we can give a cautiously positive answer to RQ2: AMALFI is reasonably precise and does not produce an overwhelming number of results, making manual triaging of results by a human auditor feasible. The second experiment suggests that there may be a good number of false negatives, but at least the numbers for the decision tree look promising.

4.5 RQ3: Performance

To characterize the performance of our approach, we measured three metrics: (i) the time it takes to train the classifier, (ii) the time it takes to extract features for a package version, and (iii) the time it takes to classify a package version. All three measurements were obtained as a byproduct of Experiment 1.

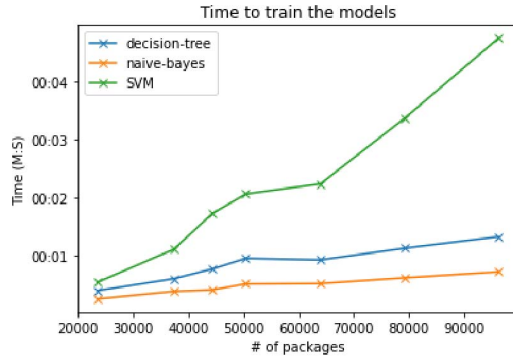


Figure 4: Classifier training time

Figure 4 shows how long it took to train the classifiers for each day of our experiment as a function of the size of the training set. As can be seen, training is quite fast, taking no more than a few seconds despite the steady increase in training data. The SVM-based classifier takes the longest time, though it still seems to scale more or less linearly in the training-set size. The other two classifiers are very quick to train, and it is clear that the training set size could be increased substantially before training time becomes a bottleneck.

To benchmark feature extraction, we post-processed logs from our run of Experiment 1 to measure the time it takes to extract features for a randomly chosen set of around 500 package versions. By and large, feature extraction takes less than ten seconds, and for over half the packages considered it takes less than one second. However, a single outlier package containing more than 11,000 files takes more than ten minutes to extract, somewhat skewing the distribution for an average extraction time of six seconds.

Lastly, we measured the time it took to predict whether a given package was malicious. For all the classifiers, the time for prediction was less than a second.

Based on these results, we can give a positive answer to RQ3: AMALFI is fast enough for practical use.

4.6 Threats to validity

While the results of our evaluation are overall very promising, there are some threats to the validity of our conclusions.

First, while the set of packages we considered in Experiment 1 was taken from the wild, it may have been biased in ways that we did not anticipate, and so our results may not generalize. Also, the basic corpus is to some degree biased in that it contains clusters of similar malware samples resulting from copy-cat campaigns.

Second, while we examined all packages flagged by AMALFI and reported the true positives to npm, we limited ourselves to at most five minutes' inspection time per package, which prevented detailed investigation of some of the larger ones and may have caused us to miss true positives. Conversely, we may have been mistaken in labelling some packages malicious, leading to missed false positives, but this seems unlikely considering that npm have taken all reported packages down, meaning that they agree with our assessment.

Finally, as noted above in our retraining step in Experiment 1 we assumed packages that were not flagged by any classifier to be benign. This is not a sound assumption in general, and might end up increasing the number of false negatives over time. For this reason, and also to escape the slow but inexorable rise in training time suggested by Figure 4, in practice one would not want to continue retraining in this fashion indefinitely. Table 1 suggests diminishing returns from retraining after a few days, but the data is clearly too sparse to draw a definite conclusion.

5 DISCUSSION

In this section we review the types of malicious packages our models found, take a closer look at the models themselves, and finally touch upon tweaks to our approach we investigated but were shown to be unsuccessful or unnecessary.

Table 3 details the types of discrete features exhibited by the 95 malicious packages we found, while Figure 5 shows the distribution of the entropy and time features of malicious and benign packages using boxplots.

All packages used installation scripts or code in their main module to connect to a remote host, with almost all of them sending PII to that host except for a small handful of packages that only pinged the host without sending any information, perhaps as a proof-of-concept or in preparation for an actual attack. Our feature extractor did not detect the PII accesses themselves (pointing to a need to improve our detection of this feature), but the packages were detected anyway, usually because of the usage of the installation scripts or network access. This suggests that our approach is robust enough to find various types of malicious package versions. The fact that some features do not appear in these specific packages does not necessarily indicate they are useless or unnecessary; those features attempt to paint a general picture of maliciousness in packages and they may prove to be useful in other batches.

A surprising observation in the data was the distribution of update types: the majority of the malicious package versions we found were major updates, contradicting our assumption that malicious package updates tend to “hide” behind a minor update. This could also mean that we missed malicious package versions representing a minor update.

The distribution of average entropy values shows that the median, highlighted by the thick red bar, is significantly higher for

Feature	# of packages
File-system access	11
Process creation	1
Network access	10
Data encoding	1
Use of package installation scripts	33
Update type: major	52
Update type: minor	1
Update type: patch	3
Update type: prerelease	9
Update type: first	30

Table 3: Features found in the 95 malicious packages

malicious packages (4.69) than for benign packages (0.001), suggesting they are more likely to contain minified code or binary files, in line with our expectation. The time between updates also follows a rather expected distribution, with malicious packages exhibiting a shorter median time between updates (7.02 s) than the benign ones (2217.18 s).

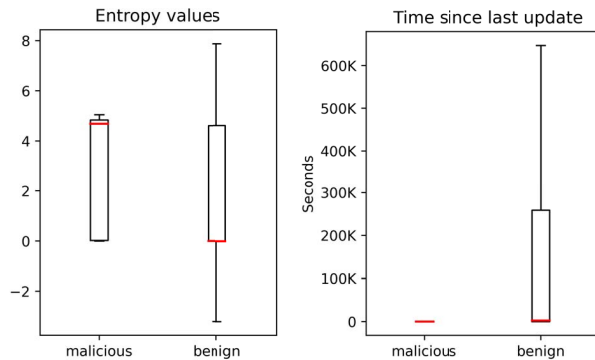


Figure 5: Entropy (left) and time (right) value distributions

Next, we took a look at the generated classifiers and how their predictions overlap. Figure 6 shows a summary of the results on the 90 packages flagged by the classifiers (the remaining five having been flagged only by the clone detector). While the decision tree takes the lion's share, each individual algorithm makes its own contribution, suggesting that a combination of all three might be a good choice in practice.

Since the decision tree classifiers are the ones that facilitate interpretation we took a look at the features they use to make decisions. We noticed that the classifiers for July 29 to July 31 examine all features except the one representing uses of cryptographic functionality, and the remaining four classifiers from August 1 onwards employ all eleven features, suggesting that there is not much redundancy in our feature set.

Overlap between classifiers' predictions of packages

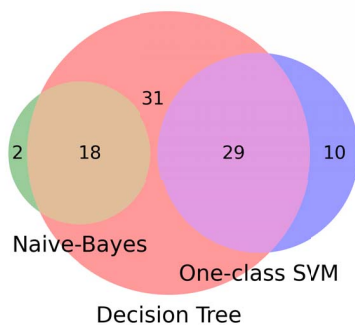


Figure 6: Overlap among the three different classifiers on the 90 malicious packages they flag

Lastly, we tried out several tweaks that ultimately did not prove successful. The literature often recommends using Random Forest classifiers instead of plain decision trees, but we did not find them to provide any advantage in our setting. We also investigated booleanizing features for the decision tree and one-class SVM, but in both cases this led to worse performance, in the latter case increasing the rate of false positives by more than 100%.

6 RELATED WORK

Our work has connections with four different research areas, which we survey briefly: malicious package detection proper; malware and anomaly detection more generally; package-registry security; and security implications of code reuse.

Malicious-package detection. Previous work in this area can be broadly divided into four categories: general-purpose malicious-package detection approaches using machine learning [10] or program analysis [8, 21, 23]; techniques for rebuilding packages from source [13, 28, 30]; and finally work that specifically targets typosquatting [26, 31].

Garret et al.'s work on detecting malicious npm packages using machine-learning techniques [10] is very closely related to our work. They use a k-means clustering algorithm to identify anomalies, and hence suspicious, package updates.

Like us, they collect features for package updates, not just single package versions, and the set of features they consider overlaps to some extent with ours, as shown in Table 4. In particular, they also consider access to system resources, dynamic code generation, and use of installation scripts. We additionally consider access to PII and several specific APIs as features, which they do not, though to some extent this is covered by their feature recording added dependencies. Their feature set also does not directly model the presence of minified code or binary files, though again they do have a more general feature for added code that is similar in spirit. They do not consider update type a feature, instead accounting for their different characteristics by training separate models for each type of update. Finally, they do not have any feature corresponding to our time between updates.

Our work is larger in scope than theirs, considering three different kinds of classifiers instead of just one, and complementing the classifiers with package reproduction and clone detection. Their evaluation on a set of 2288 package updates suggests that their approach leads to many more alerts than ours, flagging 539 updates as potentially suspicious; they did not triage the results in detail, so it is unknown whether they succeeded in finding malicious packages. Our experiments cover a much larger set of packages, and we have shown that we can detect a significant number of previously unknown malicious packages.

Duan et al. [8] study recent examples of supply-chain attacks, pinpointing root causes and classifying attack vectors and malicious behaviors. Based on their results, they built an analysis pipeline leveraging a combination of static and dynamic program-analysis techniques to detect malicious packages across three different package registries (npm, PyPI,¹⁵ and RubyGems¹⁶). In a large-scale experiment covering more than one million packages, their approach

¹⁵<https://pypi.org/>

¹⁶<https://rubygems.org/>

Category	Feature	AMALFI	Garrett et al.
Access to PII		✓	
Access to system resources	File system access	✓	✓
	Process creation	✓	✓
	Network access	✓	✓
Use of specific APIs	Cryptographic functionality	✓	
	Data encoding	✓	
	Dynamic code generation	✓	✓
Use of installation scripts		✓	✓
Presence of minified code and binary files		✓	
Time between updates		✓	
Update type		✓	
Added dependencies			✓
Added code			✓

Table 4: Comparison of features considered in our models and those of Garrett et al. [10]

identified 339 previously unknown malicious packages, 41 of them on npm. They do not provide precise statistics on false positives or on the performance of their approach.

On the whole, our goals differ from theirs: where they aim to provide a comparative framework for the security of registries, we specifically focus on finding malicious npm packages. They update their detection rules manually as results are assessed, while our classifiers can be retrained without further manual effort beyond the assessment of results itself. Our approach seems simpler and more lightweight than theirs, not requiring (potentially expensive) deep static analysis or (potentially dangerous) code execution for dynamic analysis.¹⁷ Nevertheless, we manage to find more malicious packages on a smaller set than they do.

Pfretzschner et al. [23] propose the use of static analysis to detect uses of JavaScript language features that can make a package vulnerable to interference from a malicious downstream dependency. They present four different attack scenarios involving global variables, monkey patching, and caching of modules, though they did not find real-world examples of such attacks.

Ohm et al. [21] propose a dynamic analysis for observing and measuring the creation of artifacts during package installation as a way of detecting malicious packages. While this is a promising research direction and potentially practically very useful, approaches relying on code execution inherently tend to be more heavyweight and harder to scale than our lightweight feature extraction.

At the shallower end of the analysis spectrum, tools like Microsoft Application Inspector¹⁸ and OSSGadget¹⁹ offer regular-expression based scanning as a way of quickly detecting various types of potential malware, including malicious packages. However, these tools tend to be very noisy in practice and produce many false positives, precluding large-scale usage.

Several researchers have proposed checking for differences between packages hosted on registries and their purported source code as a way of detecting malware. Goswami et al. [13] report that

this is difficult for npm packages due to many irrelevant but non-malicious differences, an experience that tallies with ours. Vu et al. [28, 30] study the same problem for PyPI, and similarly conclude that non-reproducibility by itself is a weak indicator of maliciousness and needs to be combined with other techniques to become effective, which is what we have done in this work.

For the specific problem of detecting typosquatting, Vu et al. [31] propose using edit distance as a metric for finding packages whose name is very similar to another, while Taylor et al. [26] employ a combination of lexical similarity and package popularity. Our work does not specifically focus on typosquatting, but may still be able to identify such packages from other criteria.

Anomaly detection. Malicious-package detection is a particular instance of the more general problem of malware detection, which in turn is often phrased in terms of anomaly detection [22], where malware is characterized as anomalous outliers in a larger set of benign samples. This framework has been brought to bear in a wide variety of contexts, including detecting anomalous commits on GitHub [12, 14], as well as malicious websites [15], binaries [29], and mobile apps [2, 6, 7].

Applying machine-learning techniques in these domains often faces the problem of imbalanced datasets just like in our case. This line of research pointed us to the advantages of using decision trees [22], Naive-Bayes [15], and One-class SVMs [22] as the base algorithms for our models. More complicated models based on neural networks [29] were not suitable for our problem given the relatively small dataset in our possession. However, with more and better data, this could be an avenue for future research.

Package-registry security. The security mechanisms of the package registries and the impact of malicious packages on these registries have also been studied extensively. Ohm et al.'s study [20] explores the forms attacks can have on different registries. Others have focused on specific registries such as PyPI [1, 3, 25], or npm [34]. On one hand, mechanisms to understand the impact of malicious packages have been proposed [19, 33]. On the other hand, studies have also focused on ways registries can mitigate the impact of malicious packages [9]. Compared to these longer-term solutions

¹⁷While the reproducer does execute code, it only runs build scripts, which are less likely to be malicious.

¹⁸<https://github.com/microsoft/ApplicationInspector>

¹⁹<https://github.com/microsoft/OSSGadget>

(which are, of course, well worth investigating), our focus is on short-term mitigation measures that do not require any changes to the registries themselves, as explained in Section 1.

Code reuse and security. Our work touches upon the risks of code reuse, which has recently seen a fair amount of interest in the research literature.

Wang et al. [32] investigate third-party library usage in Java, with particular focus on the problem of outdated libraries that may be lacking recent bug fixes. They find that maintainers of client projects are often unwilling to update to more recent library versions even when alerted to severe bugs in the version they depend on. Prana et al. [24] report similar results from a study covering vulnerable dependencies in Java, Python, and Ruby. Interestingly, they conclude that different levels of development activity, project popularity, and developer experience do not affect the handling of vulnerable-dependency reports.

Mirhoseini et al. [17] find that automated upgrade pull requests improve the situation to some extent, although they can also have the adverse side effect of overwhelming maintainers with upgrade notifications. For the case of malicious npm packages, this is less of a problem since they are taken down upon discovery and hence can no longer be depended on.

Gkortzis et al. [11] specifically examine the relationship between software reuse and security vulnerabilities. As one might expect, they find that the larger a project the more likely it is to be affected by security vulnerabilities, and similarly that projects with many dependencies are more exposed to security risks. While their work focusses on vulnerable code as opposed to malware, it stands to reason that similar correlations exist in the latter case.

To mitigate this problem, Koishybayev et al. [16] propose a static analyzer called Mininode that eliminates unused code and dependencies from Node.js applications, thereby reducing their attack surface.

7 CONCLUSION

We have presented AMALFI, an approach to detecting malicious npm packages based on a combination of a classifier trained on known samples of malicious and benign npm packages, a reproducer for identifying packages that can be rebuilt from source, and a clone detector for finding copies of known malicious packages. The classifier works on a set of features extracted using a light-weight syntactic analysis, including information about the capabilities the package makes use of and how these change between versions.

We have presented an evaluation of our approach employing three different kinds of classifiers: decision trees, Naive Bayesian classifiers, and SVMs. In our experiments, all three techniques succeeded in detecting previously unknown malicious packages, with the decision tree outperforming the other two, though each classifier contributed unique results. While all three classifiers produce false positives, their precision can be improved dramatically through continuous retraining as past predictions are triaged. We have also shown that training, feature extraction, and classification are very fast, suggesting that AMALFI is practically useful.

For future work, we are planning on investigating deeper feature extraction that goes beyond the purely syntactic approach we have used so far, perhaps employing light-weight static analysis. We

would also like to experiment with more advanced clone-detection approaches to identify similar but not textually identical copies of malicious packages. Another area worth exploring would be how to combine results from multiple classifiers, perhaps in the form of a ranking of results that could aid in manual triaging. Finally, it would be very interesting to apply our techniques to other ecosystems such as PyPI or RubyGems, which also suffer from malicious packages in much the same way as npm.

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