If You’ve Seen One, You’ve Seen Them All: Leveraging AST Clustering Using MCL to Mimic Expertise to Detect Software Supply Chain Attacks

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Abstract—Trojanized software packages used in software supply chain attacks constitute an emerging threat. Unfortunately, there is still a lack of scalable approaches that allow automated and timely detection of malicious software packages. However, it has been observed that most attack campaigns comprise multiple packages that share the same or similar malicious code. We leverage that fact to automatically reproduce manually identified clusters of known malicious packages that have been used in real world attacks, thus, reducing the need for expert knowledge and manual inspection. Our approach, AST Clustering using MCL to mimic Expertise (ACME), yields promising results with an $F_1$ score of 0.99. Signatures are automatically generated based on representative code fragments from clusters and are subsequently used to scan the whole npm registry for unreported malicious packages. We are able to identify and reproduce six malicious packages that have been removed from npm consequentially. Therefore, our approach is able to reproduce clustering based on expert knowledge and hence may be employed by maintainers of package repositories like npm to timely detect possible maliciousness of newly uploaded or updated packages.

Index Terms—Software Supply Chain, Malware, Abstract Syntax Tree, Markov Cluster Algorithm

1. Introduction

Over the past few years, software supply chain attacks that leverage trojanized software packages kept emerging [1]. A central role in the ecosystem that comprises software, developers, maintainers, and end users is held by maintainers of package repositories like npm or Python Package Index (PyPI). These platforms are repeatedly abused for the distribution of trojanized software packages that are part of a software supply chain attack.

A very prominent example is the event-stream incident from 2018. A supposedly benign contributer was able to convince the maintainer of the project to transfer publishing rights to him. As soon as the attacker got hold of the rights, he published a new version of event-stream that included a malicious dependency called flatmap-stream. This newly added dependency aimed at overwriting critical functions of the Copay Bitcoin wallet – that depended on event-stream – in order to steal private keys and passwords of the wallet’s owner. With over 1.5 million downloads per week this surely highlights the possible scope and impact of software supply chain attacks that leverage trojanized software packages. Furthermore, this particular attack went undetected for nearly two months. [2]

While event-stream was a highly targeted and sophisticated attack, most other attacks comprised multiple packages that share similar malicious code. This technique is easy to implement for an attacker and thus often employed to increase the probability of installation of a malicious package. Moreover, this also increases the defenders’ efforts to detect all related packages as the identification and clustering of related packages requires expert knowledge and intense manual analysis. As a consequence, malicious packages tend to be available from package repositories for roughly 200 days. [1]

Clearly, an improvement of automated capabilities for timely detection of such attacks is mandatory. The earliest point in the lifecycle of a software package, at which a third party gets access to the source code, is when a maintainer uploads it to a package repository. As said, package repositories play a central and critical role in the software supply chain ecosystem. Thus, maintainers of package repositories should ensure the quality and integrity of uploaded packages. This has been acknowledged and implemented to some extent. For instance PyPI performs Malware Checks¹. However, they are implemented rather rudimentary.

Based on a manual annotated dataset, we evaluate various approaches that mimic the manual clustering of malicious packages by an expert. Following the saying “if you’ve seen one, you’ve seen them all” we keep the upper hand. Consequently, we propose a timely detection of malicious packages based on signatures derived from identified clusters. To this end, we leverage Abstract Syntax Trees (AST) that are generated from known malicious packages that have previously been used in real world attacks. Eventually, clusters of packages that share source code are identified through Markov Cluster Algorithm (MCL). Our results indicate excellent performance ($F_1 = 0.99$) and good scalability. This way, malicious packages

¹. 1. https://warehouse.pypi.io/development/malware-checks.html
are detected as soon as they are published to a package repository.

Thus, the contribution of this paper is the automated detection of related malicious packages. Furthermore, signatures are generated automatically which further reduces manual work. Thus, the approach is suited for an early detection of trojanized software packages. It may be employed by maintainers of package repositories in order to stop software supply chain attacks by removing malicious packages before they are distributed. Eventually, we were able to detect and report six incidents of malicious packages on npm that share code with previously distributed malicious packages.

The remainder of this paper is organized as follows. Section 2 provides related work to frame the academic context of our approach. The underlying methodology for our approach is depicted in Section 3. Our results are presented in Section 4 and subsequently discussed in Section 5. In Section 6 necessary backgrounds for this work are presented. Section 7 concludes the paper and provides an outlook for future work.

2. Related Work

This work touches several fields of research. Most fundamental, the detection of similar code fragments is of interest. Moreover, it’s application in cyber security to detect vulnerable packages should be considered. Last, approaches concerning the presence and detection of malicious packages on popular package repositories are taken into account.

The detection of similar code fragments is the main challenge for detection of software plagiarism [3]–[7]. To this end, a vast majority of approaches leverage ASTs. In fact, we also leverage ASTs in order to identify currently unreported clones of known malicious packages.

The detection of software vulnerabilities constitutes another aspect where code similarity is evaluated. Vulnerable source code is used to generate signatures which are used to scan other source codes for these known patterns [8]–[11]. These approaches are related to cyber security but with respect to software flaws that have been implemented through negligence. However, we focus on malicious software packages that are created deliberately to harm users. Nonetheless, similar techniques may be used.

There also exist approaches for the detection of suspicious or even malicious packages that are published on package repositories like npm or PyPI. Martin Čarnogurský [12] analyzed PyPI packages for anomalies. For each package, an AST is derived and compared to the set of all ASTs of the remaining packages. Hence, packages with abnormal behavior may be identified. This approach is related to our approach as ASTs are leveraged in order to detect malicious packages. We, however, do not try to find anomalies but detect code that has previously been used in attacks.

Brian Pfretzschner and Lotfi ben Othmane [13] implemented a heuristic-based static code analysis for JavaScript. Due to missing real life data they evaluated on artificial data without great success. The lack of missing real life data is now solved and thus our approach can be evaluated on real data.

Duan et al. [14] employed static analysis as part of their vetting pipeline. It is used to determine whether a package is benign or malicious based on its api calls. They also leveraged ASTs for that purpose. We do not focus on API calls but rather leverage ASTs to focus on the structure of malicious code.

Aurore Fass, Michael Backes and Ben Stock [15] developed HIDE NOSEEK, which is able to hide malicious semantic in benign syntax. Eventually, it is able to mislead detection based on ASTs. Hence, it might have the possibility to deceive our approach.

In this work, we focus on static code analysis in order to detect malicious packages based on known signatures. However, dynamic analysis of suspicious packages might be considered in order to detect malicious behavior. [14], [16]

3. Methodology

While highly targeted and sophisticated attacks on well-known incidents, most attackers comprise multiple packages that share similar malicious code. This technique is easy to implement for an attacker and thus often employed to increase the probability of installation of a malicious package. Moreover, this also increases the defenders’ efforts to detect all related packages as the identification and clustering of related packages requires expert knowledge and intense manual analysis. In order to gain the upper hand over said malware authors, we study the following question.

Q What is an efficient, automated strategy to detect and cluster packages that share similar malicious code?

We provide an answer to this question by solving the two problems described in this section.

3.1. Mimicking the Expert’s Clustering

First of all, various strategies that cluster packages with malicious code are evaluated. Hereby, we aim for a strategy that mimics the manual clustering by an expert. To this end, we leverage the “Backstabber’s Knife Collection” dataset [1]. For sake of brevity and with respect to the amount of npm packages in the dataset, we focus on packages written for Node.js in JavaScript. However, our approach is transferable to all kind of programming languages.

In order to mimic the experts task of manually clustering packages containing similar malicious code, the similarity of each pair of packages is computed using various metrics that compare strings [7], Program Dependence Graphs (PDGs) [17] or Abstract Syntax Trees (ASTs) [18], see also Section 4.1 and Section 6. Then, a diverse set of clustering algorithms is leveraged to determine clusters of packages based on their similarity, see Section 4.1.

In order to compare the manual clustering in [1] with a fixed automated clustering approach, the conceiving
metrics Precision, Recall and \( F_1 \)-score are employed as follows. First of all, we assume that the manual clustering in [1] is complete and accurate, i.e., every malicious code similarity is found and packages are clustered correctly. Then, a pair of packages is said to be a

- **true positive** if the two packages are in the same cluster in both approaches.
- **true negative** if the two packages are in different clusters in both approaches.
- **false positive** if the two packages are in different manually generated clusters but in the same automatically generated cluster.
- **false negative** if the two packages are in the same manually generated clusters but in the different automatically generated clusters.

With this definition, the metrics Precision, Recall and \( F_1 \)-score are interpreted as follows. By definition, Precision is the ratio of true positives in all positives. Therefore, the Precision is high if the number of false negatives is relatively low. Observe that this is the case if the automated approach generates clusters that are overall finer or as fine as the manual approach. Observe analogously that the Recall is high if the automated approach generates clusters that are overall coarser or as coarse as the manual approach. Consequently, the \( F_1 \)-score (which is the harmonic mean of Precision and Recall) measures how well the automated clustering mimics the manual approach.

In this article, we solve the following problem.

**P1** Determine an automated clustering approach that mimics the experts task of manually identifying and clustering similar malicious code blocks in packages, i.e., find a clustering approach with a high \( F_1 \)-score.

In Section 4.1, various approaches are evaluated. The superior strategy that mimics the experts clustering almost perfectly with an \( F_1 \)-score of 0.99 is the combination of AST and MCL. We denote this approach by AST Clustering using MCL to mimic Expertise (ACME).

### 3.2. Deriving Signatures

Having at hand an automated approach that mimics the manual clustering of an expert nearly perfectly, the next problem is solved.

**P2** Determine a strategy to derive high quality signatures from the ACME.

To this end, from each cluster a signature is derived as follows. By construction, each cluster is a set of packages and each package contains one or more source files. For each source file its corresponding AST is constructed. From each AST, a set of so called fingerprints is derived following the approach of Chilowicz et al. [3]. Roughly speaking, each function represented in the AST yields a single fingerprint by hashing the subgraph corresponding to this function (ignoring nested function definitions). For more details, we refer the reader to Section 6. Now, the signature \( S_c \) of a given cluster \( c \) is the set of all "relevant fingerprints" derived from this cluster. More precisely, a fingerprint \( h \) is "relevant" if the following conditions are met.

1. The fingerprint \( h \) is unique to its cluster, i.e., \( h \) is not derived from any package in any other cluster.
2. The fingerprint \( h \) is derived from at least two packages in its cluster.
3. The fingerprint \( h \) cannot be derived from one of the 108 most depended upon packages\(^3\) from npm.

Observe that 1) ensures that the signatures of the clusters are pairwise disjoint. Observe further that conditions 2) and 3) ensure that the signatures focus on recurring code blocks that are written by malware authors (assuming that the 108 most depended upon packages do not contain malicious code fragments).

Now, a package \( p \) matches the signature \( S_c \) of cluster \( c \) if at least one of \( p \)'s fingerprints \( h_{p}^{1}, \ldots, h_{p}^{N_p} \) matches a fingerprint \( h \in S_c \).

\[
\text{Match}_{p,S_c} = \begin{cases} 
\text{True} & \text{if } h_{p}^{i} \in S_c \text{ for some } i \\
\text{False} & \text{else }
\end{cases}
\]

(1)

In Section 4.2 and Section 4.3, we demonstrate that these automatically generated signatures are quite good and yield high quality signatures with just a few minutes of manual refinement. In particular, we are able to identify and report six malicious packages that have been removed from npm consequentially. Overall, this solves P2.

### 3.3. Efficiency

Note that the solutions to problems P1 and P2 almost answer our initial question. In order to show that our approach is efficient and feasible on the large scale, it is evaluated on the latest version of the full npm repository in Section 4.3. As a result, we identified and report six malicious packages that have been removed from npm consequentially.

### 4. Results

This section summarizes our results from experiments as introduced in the previous sections. First, we evaluate which combination of similarity detection and corresponding clustering is suited best to reproduce the results of the manual clustering in Section 4.1. The best approach is leveraged in Section 4.2 to automatically generate signatures based on identified clusters and corresponding signature optimization. These signatures are subsequently used in Section 4.3 to scan the whole npm registry for unreported malicious packages that have code fragments common to known malicious packages.

#### 4.1. Reproduction of Clustering

Recall from Section 3 that we aim to automate the tedious and time consuming task of manually finding (variations of) recognized malicious code blocks in a given package repository. Hereby, packages with similar malicious code blocks are clustered. In this subsection, we evaluate the quality of various approaches that attempt to

3. https://www.npmjs.com/browse/depended, we are limited to the 108 most depended upon packages due to technical issues of the website.
reproduce the result of the manual clustering of Ohm et al. [1]. More precisely, we compute the similarity via string similarity [7], Program Dependence Graph (PDG) [17], and Abstract Syntax Tree (AST) [18]. After computing the similarities of all pairs of packages, we evaluate the quality of the clustering approaches connected component (ccomp), maximal cliques (clique), Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [19], Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) [20] and Markov Cluster Algorithm (MCL) [18]. At the time of evaluation, the dataset used as ground truth contained 114 packages from npm from which 104 packages belong to a cluster [1].

For text-based similarity the Python package FuzzyWuzzy [21] is employed. It offers multiple modi but with respect to the work of Ragkhitwetsagul et al. [7] solely simple_ratio, partial_ratio, token_sort_ratio, and token_set_ratio are evaluated. All of these modi leverage the Levenshtein distance [22] to calculate the difference between two inputs. In our case, the whole content of two files that are to be compared is used as input.

Similarity based on ASTs is implemented by leveraging AcornJs [23], a lightweight parser for JavaScript, that is used to transform source code into AST representation. From each AST a set of fingerprints is derived based on the approach presented by Chliowicz et al. [3]. Roughly speaking, each function represented in the AST yields a single fingerprint by hashing the subgraph corresponding to this function (ignoring nested function definitions). More details about the fingerprinting are found in Section 6.

We implemented Program Dependence Graph (PDG) according to the description of Liu et al. [17]. However, in the generation of PDG for the malicious packages, we observed disproportionate runtime in combination with performance below average. Thus, we discarded PDG for further experiments.

The clustering of similar packages is performed through several clustering algorithms. We evaluate connected component (ccomp) and maximal cliques (clique) by leveraging the Python package NetworkX [24]. DBSCAN is implemented by using the Python package scikit-Learn [25] and HDBSCAN by hdbscan [26]. Lastly, we examine Markov Cluster Algorithm (MCL) [18] for which we leverage the Python package Markov-Clustering [27].

In Section 3.1, the interpretation of Precision, Recall and $F_1$-score is given: We achieve a high Precision if the automated approach generates clusters that are overall finer or as fine as the manual approach. The Recall is high if the automated approach generates clusters that are overall coarser or as coarse as the manual approach. Therefore, the $F_1$-score measures how well the automated clustering mimics the manual approach.

Table 1 displays the $F_1$ score of each similarity detection methods when used in conjunction with one of the clustering algorithms. While most combinations yield solid results, ASTs in conjunction with MCL outperforms all of them. Maximal cliques seem to work well in combination with most text-based similarity approaches. Whereas, MCL performs poorly for these it yields very good results ($F_1 = 0.99$) in conjunction with ASTs. Hence, we focus on that combination and give it a name: AST Clustering using MCL to mimic Expertise (ACME). For a complete list of more detailed results from all combinations including Precision, Recall, and optimal parameters we refer the interested reader to the appendix in Table 5.

Looking into detail at ASTs in conjunction with all clustering algorithms (Table 2), it is noticeable that most clustering algorithms yield either high Precision or high Recall. Solely, MCL is capable of reaching both high Precision and high Recall thus recreating the manual cluster as similar as possible. With a Precision of 0.97 and a Recall of 1.00 the $F_1$ score is at 0.99. Through the use of ACME we are able to recreate the manual clustering performed by expert almost perfectly. This solves problem P1 introduced in Section 3.1.

### 4.2. Quality of Signatures

The previous subsection showed that the experts task of manually clustering malicious code is automated almost perfectly by combining ASTs with MCL. We denote this approach by AST Clustering using MCL to mimic Expertise (ACME). Using the ACME approach described in Section 3.1, a signature $S_c$ is derived for each cluster $c$. Recall from Section 3.2 that a signature is a set of relevant fingerprints. Recall further that a fingerprint is relevant if it is unique to its cluster 1), if it occurs at least twice in its cluster 2) and if it is not derived from a fixed family of very popular benign packages 3). In this subsection, we discuss the sizes of the clusters, and we demonstrate that the first two conditions yield signatures with a promising Recall. However, the signatures are to coarse, i.e., they produce a huge number of false positives. The third condition is mandatory to reduce the number of false positives. The quality of the signatures is further improved in the next section.

In Table 3, the resulting clusters, their sizes, and corresponding number of signatures are shown. Our approach automatically identified seven clusters that cover 97 packages which is also visualized in Fig. 1. As stated initially, 104 packages belong to a manual created cluster in the dataset. However, the manual clustering by Ohm et

| Algorithm      | Precision | Recall | $F_1$ |
|----------------|-----------|--------|-------|
| ccomp          | 0.6761    | 0.9958 | 0.6091|
| clique         | 0.9878    | 0.6074 | 0.7522|
| DBSCAN         | 0.6761    | 0.9958 | 0.8054|
| HDBSCAN        | 0.6580    | 0.9967 | 0.7927|
| MCL            | 0.9747    | 0.9958 | 0.9851|

| Algorithm      | Precision | Recall | $F_1$ |
|----------------|-----------|--------|-------|
| simple_ratio   | 0.6927    | 0.7404 | 0.6935|
| partial_ratio  | 0.6993    | 0.7086 | 0.6869|
| token_sort_ratio | 0.6658    | 0.6942 | 0.6748|
| token_set_ratio | 0.6999    | 0.7230 | 0.7153|
| AST            | 0.6091    | 0.7522 | 0.7927|

**TABLE 1.** The $F_1$ score for each combination of similarity detection and clustering. Bold faced scores represent the maximum for each similarity algorithm.

**TABLE 2.** Precision, Recall and $F_1$ for all evaluated clustering algorithms on ASTs.
al. also took dependency into account for clustering. Our approach solely relies on code syntax similarity and hence may not cluster all packages as in the dataset.

It is noticeable that the sizes of clusters varies heavily ($\sigma^2 = 230.4082$). The smallest ones comprise two packages while the biggest clusters are of size 38 and 36 respectively. This fact is also visible in Fig. 1.

The size of a signature weakly correlates with the size of the corresponding cluster (Pearson $r = 0.65$, $p = 0.12$). However, there are outliers. For instance cluster 1 and 5 yield very large signature compared to their size and in contrast to that cluster 2 yields a very small signature.

In order to demonstrate that condition 3) is mandatory, we test the quality of the signatures associated to all fingerprints satisfying only conditions 1) and 2) as follows. In a tenfold cross validation, we cluster the 114 packages containing malicious code with ACME and derive the signatures associated to all fingerprints satisfying conditions 1) and 2). These signatures are evaluated against the 10% of the split in the cross validation and against 108 benign packages. In this context, a package is positive if the automatically generated signature matches the package. On average, the Recall is 0.88 but the number of false positives is 46%. This is because the signatures contain too many fingerprints of benign functions, i.e., condition 3) is mandatory to reduce the number of false positives.

In total 3,875 fingerprints satisfying only conditions 1) and 2) are derived from the malicious packages of the seven clusters. Considering relevant fingerprints, i.e., after the removal of fingerprints that match on the 108 most depended upon packages from npm, the seven clusters yield 3,396 (-12.36%) fingerprints in total. These signatures are used to determine the number of matches our signatures produced per cluster. After the automated removal of false positive fingerprints, the amount of matches went down from 283,887 to 136,157 (-52.04%). For manual optimization we inspected the 50 most matching fingerprints for each cluster. This took roughly 10 minutes per cluster and resulted in 133 signatures (3.92%) being removed. This further reduced the amount of matches from 136,157 to 70,432 (-48.27%).

In addition to automatically generated signatures, we manually created signatures for packages that did not belong to a cluster. To this end, we extracted the fingerprint of malicious functions by hand. This resulted in eight new pseudo-cluster with corresponding signatures. However, this yielded only one additional match.

### 4.3. Large Scale Evaluation

For large scale evaluation of our signatures, we harvested the npm repository on 25th of September 2020. At this time 1,396,447 packages were listed and respectively 1,396,413 versions could be obtained. In total 20,017,543 files and 749,558,178 function were inspected.

On average, a npm package contains 15.6 files (min = 1, max = 82,530, $\sigma = 158.14$) and an average package’s size is 15.744 kB (min = 0 B, max = 145.7 MB, $\sigma = 208.82$ kB). The average time needed for the transformation of a npm package into an AST is 354.17 ms (min = 0 ms, max $\approx 58$ min, $\sigma = 5.61$ ms). A corresponding AST comprises 40.68 nodes on average (min = 1, max = 4,814,862, $\sigma = 1720.88$). Overall, the experiment took around 48 hours and 154 GB of data was persisted in the database.

Table 3 also lists the number of matches our signatures produced per cluster. After the automated removal of false positive fingerprints, the amount of matches went down from 283,887 to 136,157 (-52.04%). For manual optimization we inspected the 50 most matching fingerprints for each cluster. This took roughly 10 minutes per cluster and resulted in 133 signatures (3.92%) being removed. This further reduced the amount of matches from 136,157 to 70,432 (-48.27%).

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#### 4.3.1. Detected Packages

By the construction of the signatures, see Section 3.2, every match is treated as suspicious and hence needs manual inspection to verify actual maliciousness. Eventually, we were able to identify seven unreported but malicious packages that have code in common with known malicious packages. As listed in Table 4, we identified the packages nodetest199, nodetest1010, and plutov-slack-client based

![Figure 1. Visualization of identified clusters based on ASTs and MCL.](image)
.../a/nodetest199.js
++ b/tnsorplow.js
@@ -2,7 +2,7 @@
  var require = global.require || global.process,
      mainModule.constructor._load;
  if (!(require)) return;
  var cmd = (global.process.platform.match(/\^win/i))
    ? "+/bin/sh;"
    - var net = require("net"),
    + var net = require("tsi"),
      cp = require("child_process"),
      util = require("util"),
    + sh = cp.spawn(cmd, []);
@@ -10,7 +10,9 @@
  client.socket.pipe(sh.stdin);
  + rejectUnauthorized: false
  cp = require("child_process"),
  util = require("util"),
  sh = cp.spawn(cmd, []);
+ var counter = 0;
+ function StageRepeat() {
+   - client.socket = net.connect(1111, "50.242.118.99",
+     function() {
+       + client.socket = net.connect(443, "45.63.54.27",
+         {rejectUnauthorized: false}
+       + }, function() {
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+         {rejectUnauthorized: false}
+       + }, function() {
+         - client.socket.pipe(sh.stdin);
+         + rejectUnauthorized: false
+         cp = require("child_process"),
+         util = require("util"),
+         sh = cp.spawn(cmd, []);
+@@ -2,7 +2,7 @@
+ function StageRepeat() {
+   - client.socket = net.connect(1111, "50.242.118.99",
+     function() {
+       + client.socket = net.connect(443, "45.63.54.27",
+         {rejectUnauthorized: false}
+       + }, function() {
+         - client.socket.pipe(sh.stdin);
+         + rejectUnauthorized: false
+         cp = require("child_process"),
+         util = require("util"),
+         sh = cp.spawn(cmd, []);
+@@ -2,7 +2,7 @@
+ function StageRepeat() {
+   - client.socket = net.connect(1111, "50.242.118.99",
+     function() {
+       + client.socket = net.connect(443, "45.63.54.27",
+         {rejectUnauthorized: false}
+       + }, function() {
+         - client.socket.pipe(sh.stdin);
+         + rejectUnauthorized: false
+         cp = require("child_process"),
+         util = require("util"),
+         sh = cp.spawn(cmd, []);
+@@ -2,7 +2,7 @@
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+   - client.socket = net.connect(1111, "50.242.118.99",
+     function() {
+       + client.socket = net.connect(443, "45.63.54.27",
+         {rejectUnauthorized: false}
+       + }, function() {
+         - client.socket.pipe(sh.stdin);
+         + rejectUnauthorized: false
+         cp = require("child_process"),
+         util = require("util"),
+         sh = cp.spawn(cmd, []);
uses B-Trees and hence a lookup in \( l \) elements takes \( O(\log l) \) in time.

Considering space complexity, our approach needs to persist all ASTs, corresponding fingerprints and results of the clustering. Each AST contains at most all tokens in the source file and is hence linear in the amount of tokens. Each fingerprint is represented as a bytes-string of fixed length and thus constant in size. The database requires linear space to safe all fingerprints. Results of the clustering again depend on the number of nodes \( n \) and the parameter \( k \) which yields \( O(n + k) \).

Overall, both time and space complexity indicate good scalability and thus qualifying the approach for large scale deployment.

5.2. Limitations

The use of ASTs and the leveraged abstraction level (c.f. Section 6) are able to detect Type-1 and Type-2 clones by definition. By discarding identifier names, the approach becomes resilient against obfuscation through unreadable names and renaming in general.

However, to detect Type-3 clones, the comparison of two ASTs needs to be relaxed. One might leverage fuzzy hashes to allow similar but not exactly the same structure of code fragments. Another approach is to use tree edit distances \([30], [31]\) with an appropriate threshold. The detection of Type-4 clones – semantic similarity – is out of scope for an approach based on syntactically similarities.

Overall, we reduced the manual workload to identify malicious packages that are already published to npm from roughly 1.4 million to round about 70 thousand suspicious packages. This number mainly results from the suboptimal signature generated for cluster 1 (c.f. Table 3). Solely 204 suspicious packages need manual inspection when leaving out matches from that cluster.

However, fingerprints causing false positives may need to be sorted out by hand. By removing the 50 most matching false positive fingerprints from each cluster we reduced the amount of matches by roughly 50\%. The manual process of eradicating false positive fingerprints is cumbersome but with about 10 minutes per 50 fingerprints still feasible. Nonetheless, there is still need for manual inspection that might be canceled out through a more sophisticated signature generation.

6. Background

In this work, we identify syntactic clones of malicious packages. This requires a technique that is able to represent code fragments with a certain amount of abstractness and a clustering approach to pair similar code fragments on the chosen abstract representation.

6.1. Syntactic Clones

Walker et al. \([32]\) define four clone types which are related in varying degrees. Clones of Type-1 share two identical code fragments without respect to whitespace, blanks, or comments. If the structure of the code is the same but some functions, classes, or variables are renamed, we speak of Type-2 clones. Type-3 clones differ in naming but also show differences in structure, i.e., some code fragments may be modified. If no syntactical similarity can be observed but the function is the same, we speak of Type-4 clones.

6.2. Abstract Syntax Tree (AST)

In order to identify code clones we need to compare code fragments. As mentioned in Section 3, we evaluate several approaches. But for brevity we solely focus on ASTs here as they are used throughout the paper.

A method to generate an abstract representation of source code is through an Abstract Syntax Tree (AST). Comparison of multiple ASTs allows focusing on the identification of structural similarities. Through abstraction of source code into a structural representation naming of identifiers is of no matter.

As visualized in Fig. 3, the AST of a code fragment is a tree that represents every structural element of the code as node. Because of syntactic differences in programming languages, ASTs are language-dependent.

There exist multiple approaches to compare two ASTs. Our approach is able to identify clones of Type-1 and Type-2 as it adopts fingerprinting as proposed by Chilowicz et al. \([3]\). From each function \( f \) represented in an AST \( G \), we derive a so called fingerprint \( H_f \). To this end, we focus our attention to the subgraph \( G_f \subset G \) associated to \( f \) after all (nested) functions that are defined inside \( f \) are discarded. For each node \( v \in G_f \), we concentrate on its type \( t(v) \). For the example, in Fig. 3, each Identifier and the value of each Literal is discarded. After fixing SHA-256 as hash function \( C \), the fingerprint of \( f \) is defined recursively as follows. Given an arbitrary node \( v \in G_f \) with children \( w_1, w_2, \ldots \), we define \( H(v) \):

\[
H(v) = C \left( t(v) \| H(w_1) \| H(w_2) \| \ldots \right) \quad (2)
\]

Denoting the root of \( G_f \) by \( r_f \), the fingerprint of \( f \) is

\[
H_f = H(r_f) \quad (3)
\]

We remark that we leverage a different function \( t \) than Chilowicz et al. Our \( t(v) \) solely takes the type of node into account. Thus, our subgraph \( G_f \) is very focused on the structure of the code fragment by discarding nonstructural information like operators. For instance the code fragments \( a + b \) and \( a \ast b \) result in the same fingerprint. However, \( a + (a + a) \) and \( (a + a) + a \) yield different fingerprints.

```plaintext
function fib(n) {
    if (n < 1) return 0;
    else if (n <= 2) return 1;
    return fib(n-1) + fib(n-2);
}
```

Figure 3. Example of an AST.
Let us remark further that we grouped code into a dummy global function if it resides outside of functions, i.e., in global scope. Furthermore, we treated functions inside classes as independent functions.

### 6.3. Markov Cluster Algorithm (MCL)

In order to detect clusters of similar packages, we leverage Markov Cluster Algorithm (MCL) [18]. MCL is a clustering algorithm for graphs based on Markov chains. Let \( B \) be a random walk of length \( k \) starting at node \( v \). Roughly speaking, for a sparse graph, the random walk reaches some node \( w \) in a denser region with a high probability. However, MCL does not walk randomly on the nose but calculates the probability to reach node \( w \) from node \( v \) slightly differently.

The calculation is performed over multiple iterations simultaneous for all nodes and comprises two steps. At first, an expansion is performed in which all reachable nodes from a starting node \( v \) are added to \( v \)’s matrix of probable neighbors. In the inflation step, neighboring nodes with a high probability to reach are boosted. The algorithm terminates when convergence is detected. For more details, we refer the reader to [18].

### 7. Conclusion

In this paper, we analyzed source code similarity of known malicious packages in order to reproduce clustering based on expert knowledge and manual inspection. On a dataset of 114 malicious npm packages that have been used in real-world attacks, we evaluated several approaches to find syntactical similarities in source codes. Based on that, clusters of packages with similar structure were identified automatically.

Compared to the manual clustering of these packages at hand, our best approach yields promising results (\( F_1 = 0.99 \)). It leverages Abstract Syntax Trees (AST) to compare source code of multiple packages and Markov Cluster Algorithm (MCL) to identify clusters among these. In conclusion, we are able to systematize and automatize the detection of related malicious packages. This reduces the need for expert knowledge and manual inspection drastically.

The automatized approach identified seven clusters in the leveraged dataset. Subsequently, signatures that characterize malicious packages from a particular cluster were derived. In order to minimize false positives, we removed parts of the signatures that matched on the 108 most depended upon packages from npm.

A scan of the whole npm registry based on all generated signatures revealed seven previously unreported packages in total. A manual inspection showed that four of them are indeed malicious packages and were therefore reported by us and subsequently removed from npm. Two of the remaining three were proof of concept packages. The last package itself is not malicious but it contained a full copy of the malicious package `flatmap-stream` as dependency.

In conclusion this means that our approach is feasible to automatically generate signatures for known malicious packages which then may be used to scan packages for known malicious code. Through the use of ASTs the approach is transferable to any other programming language. However, automatically generated signatures may not yet be perfect as they still may cause false positives which may be removed manually. Nonetheless, our naive approach already yields promising results and good scalability.

For future work we plan to optimize our signature generation and support for Type-3 clones. Eventually, we would like to expand our approach to other software ecosystems like Python Package Index (PyPI) and RubyGems.

### Appendix A. Experimental data

This section contains supplemental data for completeness. Table 5 lists all combinations of similarity and clustering approaches. Moreover, the optimal parameters are provided when optimizing the respective combination for a high \( F_1 \) score. It is noticeable that AST outperforms string-based similarity approaches in all cases, especially when using MCL. However, MCL performs below average when applied to string-based similarity approaches.

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TABLE 5. RESULTS OF ALL SIMILARITY AND CLUSTERING APPROACHES WITH EMPLOYED PARAMETERS, SORTED BY $F_1$ SCORE.

| Similarity       | Clustering        | Parameter                  | Precision | Recall    | $F_1$  |
|------------------|-------------------|----------------------------|-----------|-----------|--------|
| AST              | MCL               | exp = 2, inf = 2           | 0.9747    | 0.9958    | 0.9851 |
| AST              | MCL               | ccomp                      | 0.6761    | 0.9958    | 0.8054 |
| AST              | DBSCAN            | $\varepsilon = 1$, minPts = 2 | 0.6761    | 0.9958    | 0.8054 |
| AST              | HDDBSCAN          | minClst = 2                | 0.6580    | 0.9967    | 0.7927 |
| AST              | clique            |                             | 0.9878    | 0.6074    | 0.7522 |
| simple_ratio     | DBSCAN            | $\varepsilon = 18$, minPts = 2 | 0.9446    | 0.6124    | 0.7430 |
| token_sort_ratio | ccomp             | $\tau = 70$                | 0.8950    | 0.6341    | 0.7423 |
| token_sort_ratio | DBSCAN            | $\varepsilon = 30$, minPts = 2 | 0.8950    | 0.6341    | 0.7423 |
| simple_ratio     | clique            | $\tau = 80$                | 0.9944    | 0.5898    | 0.7404 |
| simple_ratio     | ccomp             | $\tau = 80$                | 0.9281    | 0.6149    | 0.7397 |
| partial_ratio    | DBSCAN            | $\varepsilon = 7$, minPts = 2 | 0.8457    | 0.6341    | 0.7281 |
| partial_ratio    | clique            | $\tau = 60$                | 0.9492    | 0.5681    | 0.7126 |
| token_sort_ratio | HDDBSCAN          | minClst = 2                | 0.9632    | 0.5689    | 0.7153 |
| partial_ratio    | clique            | $\tau = 70$                | 0.9735    | 0.5530    | 0.7054 |
| partial_ratio    | HDDBSCAN          | minClst = 2                | 0.9588    | 0.5447    | 0.6947 |
| partial_ratio    | HDDBSCAN          | minClst = 2                | 0.8323    | 0.5848    | 0.6689 |
| partial_ratio    | HDDBSCAN          | minClst = 2                | 0.5163    | 0.9373    | 0.6659 |
| partial_ratio    | ccomp             | $\tau = 100$               | 0.5163    | 0.9373    | 0.6659 |
| token_sort_ratio | DBSCAN            | $\varepsilon = 1$, minPts = 2 | 0.5163    | 0.9373    | 0.6659 |
| token_sort_ratio | MCL               | exp = 2, inf = 4           | 0.4387    | 0.9206    | 0.5942 |
| simple_ratio     | MCL               | exp = 2, inf = 4           | 0.2586    | 0.7594    | 0.3858 |
| partial_ratio    | MCL               | exp = 3, inf = 2, $\tau = 60$ | 0.2322    | 0.9992    | 0.3768 |
| partial_ratio    | MCL               | exp = 2, inf = 2, $\tau = 95$ | 0.2361    | 0.8814    | 0.3725 |

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