# GoodFATR: A Platform for Automated Threat Report Collection and IOC Extraction

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## ABSTRACT

To adapt to a constantly evolving landscape of cyber threats, organizations actively need to collect Indicators of Compromise (IOCs), i.e., forensic artifacts that signal that a host or network might have been compromised. IOCs can be collected through open-source and commercial structured IOC feeds. But, they can also be extracted from a myriad of unstructured threat reports written in natural language and distributed using a wide array of sources such as blogs and social media. This work presents GoodFATR an automated platform for collecting threat reports from a wealth of sources and extracting IOCs from them. GoodFATR supports 6 sources: RSS, Twitter, Telegram, Malpedia, APTnotes, and ChainSmith. GoodFATR continuously monitors the sources, downloads new threat reports, extracts 41 indicator types from the collected reports, and filters generic indicators to output the IOCs. We propose a novel majority-vote methodology for evaluating the accuracy of indicator extraction tools, and apply it to compare 7 popular tools with GoodFATR's indicator extraction module. We run GoodFATR over 15 months to collect 472,891 reports from the 6 sources; extract 1,043,932 indicators from the reports; and identify 655,971 IOCs. We analyze the collected data to identify the top IOC contributors and the IOC class distribution. Finally, we present a case study on how GoodFATR can assist in tracking cybercrime relations on the Bitcoin blockchain.

## KEYWORDS

Indicators of Compromise, IOC, Cyber Threat Intelligence, RSS, Twitter, Telegram

## 1 INTRODUCTION

Cyber Threat Intelligence (CTI) provides information on attacker behavior that allows to gain visibility into the fast-evolving threat landscape; to understand the techniques, tactics, and procedures (TTPs) attackers use; and to timely identify and contain attacks. CTI is a multi-billion dollar industry, expected to keep growing to more than 16 billion USD by 2026 [30]. An essential piece of CTI is extracting and sharing *indicators of compromise* (IOCs),

forensic artifacts that when observed on a device or network indicate it may have been compromised, e.g., malicious IPs, domains, and file hashes. IOCs are an actionable piece of CTI, as they can be fed to security systems (e.g., NIDS, firewall, HIDS, blacklists) to detect and block attacks.

IOCs are generally distributed through open and commercial IOC feeds [6, 27]. Such feeds provide structured IOC data, following standardized formats (e.g., STIX [36], OpenIOC [14]). However, much CTI is distributed through unstructured threat reports, written in natural language and published through a wealth of security blogs and social media platforms. For example, Twitter has become widely used for exchanging and spreading cybersecurity information, not only by cybersecurity companies, but also by experts that sometimes rush to share their discoveries [3, 47]. Natural language reports often contain IOCs and typically provide more detailed contextual descriptions about the IOCs compared to IOC feeds. In addition, while IOCs feeds usually focus on a small set of indicator types (i.e., IP addresses, domain names, file hashes), unstructured threat reports frequently provide more varied indicator types such as vulnerability identifiers, email addresses, blockchain addresses, fuzzy hashes (e.g., SSDeep [25]), MAC addresses, and target countries.

In a large and fast-evolving landscape of threats, coverage is difficult to achieve by any single entity, as shown by different sources having little IOC overlap [6, 27]. Thus, it is not sufficient to rely on a single source, or a small set of sources, to build an accurate, comprehensive, and up-to-date IOC list. To overcome this limitation, organizations and security analysts can resort to collecting and extracting IOCs from multiple sources. However, there exist a myriad of sources through which threat reports are disseminated including hundreds of blogs, Twitter accounts, and Telegram channels.

To address this challenge, we present GoodFATR, an automated platform for collecting threat reports from a wealth of *sources* and extracting their IOCs. GoodFATR has a modular design that allows treating 6 diverse sources in an unified manner: RSS, Twitter, Telegram, and three report datasets Malpedia [41], APTnotes [5], and ChainSmith [58]. For RSS, Twitter, and Telegram it takes as input a list of *origins* (RSS feeds, Twitter accounts, Telegram channels) to monitor. It periodically visits those origins to identify new *entries*

(blog posts, tweets, messages). For entries that contain a URL to a report, it downloads the report's *document*. The selected sources are complementary. RSS allows collecting reports from hundreds of blogs from cybersecurity companies and individual experts, while Twitter and Telegram cover social media distribution. In addition, crowd-sourced datasets such as Malpedia and APTnotes allow identifying previously unknown blogs and Twitter accounts that should be monitored, as well as collecting reports from blogs without an RSS feed. GoodFATR also has an indicator extraction tool called SEARCHER that takes as input a document in HTML, PDF, or plain text format; applies regular expressions to extract 41 indicator types; and filters generic (i.e., benign) indicators to produce a list of IOCs.

Prior approaches for extracting indicators from unstructured threat reports most often leverage regular expressions. Even recent works that apply natural language processing (NLP) techniques to analyze threat reports still use regular expressions for identifying indicators as part of their pipeline [20, 28, 48, 58]. Regular expressions for extracting indicators can easily become complex, making it difficult to understand what they match. Also, small differences between regular expressions for the same indicator type may significantly affect the extraction results. Furthermore, regular expressions can be affected by catastrophic backtracking introducing ReDoS vulnerabilities [11]. Despite the popularity of regular expression based indicator extraction tools [7, 21, 35, 45, 46, 51] no previous work has systematically evaluated them to understand which tool is more accurate for each indicator type and how efficient their extraction is. This work addresses this gap by applying a novel majority-vote methodology to compare the accuracy of 7 popular indicator extraction tools [7, 17, 21, 35, 45, 46, 51], as well as GoodFATR's own SEARCHER tool, on 4,420 reports. The results show SEARCHER is the most accurate tool on 11 of the 13 indicator types supported by multiple tools. We also identify ReDos vulnerabilities in two of the tools, one new and one previously reported, but still unfixed.

We have used GoodFATR to collect 472,891 reports over 15 months from 3,226 origins distributed through 6 sources; extract 1,043,932 indicators from the reports; and identify 655,971 IOCs. We analyze the collected data to identify the top IOC contributors and the IOC class distribution. Finally, we detail how we have leveraged GoodFATR on a novel approach for tracking cybercrime relations on the Bitcoin blockchain [15].

This work provides the following contributions:

- We present GoodFATR, an automated platform to collect threat reports from a variety of sources, extract the indicators in the collected reports, and filter generic indicators to output IOCs.
- We implement a modular report collection module that supports 6 sources: RSS, Twitter, Telegram, Malpedia, APTnotes, and ChainSmith.
- We develop SEARCHER, an indicator extraction tool that given an HTML, PDF, or plain text document, applies regular expressions to extract 41 indicator types.
- We present a novel majority-vote methodology for evaluating the accuracy of indicator extraction tools. We apply our methodology to compare the accuracy of 7 popular tools and our own SEARCHER over 4,420 reports. The results show SEARCHER is the most accurate tool on 11 of the 13 indicator types supported by multiple tools.
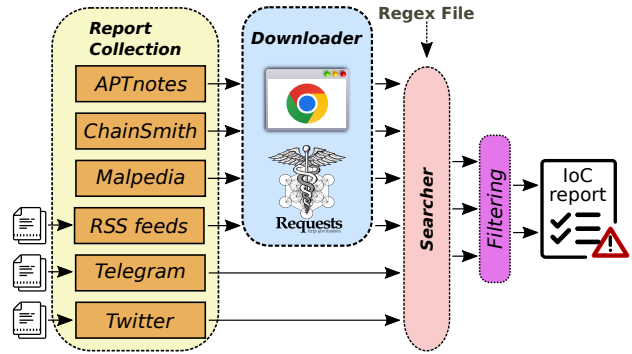


**Figure 1: The architecture of GoodFATR.**

- We use GoodFATR to collect 472,891 reports over 15 months from the 6 sources; extract 1,043,932 indicators from the reports; and identify 655,971 IOCs. We analyze the collected data to identify the top IOC contributors and IOC class distribution.
- We demonstrate GoodFATR in a case study where we apply it to extract previously unknown Bitcoin addresses from threat reports. Those addressed are tagged and used as input to a novel automated Bitcoin transaction tracing approach [15].

## 2 OVERVIEW

An *indicator* represents an artifact such as an IP address, a domain name, a URL, a file, a registry key, a blockchain address, or a company name. An indicator is typically represented as a pair of a type (e.g., *email*) and a string value (e.g., contact@test.com). An *indicator of compromise* (IOC) is a malicious indicator whose presence on a device or network indicates the device might have been compromised.

This paper presents GoodFATR, a platform for collecting threat reports from a wealth of sources and extracting IOCs from the collected reports.

Figure 1 depicts the architecture of GoodFATR. It consists of four modules: *Report Collection*, *Downloader*, *Searcher*, and *Filtering*. The Report Collection gathers documents from a wealth of sources including RSS feeds, Telegram channels, Twitter accounts, and external lists of reports like Malpedia [41], APTnotes [5], and ChainSmith [58]. The collection outputs a list of *entries* each corresponding to the observation of a report in a source. Each entry contains the URL of the report, or the content of a tweet or Telegram message. In addition, it may contain optional metadata about the report (e.g., publication date, author, language) and the source where it was observed (e.g., RSS feed, Twitter account). The Downloader leverages an instrumented Chrome browser (and Python's requests library as backup) to fetch the document pointed by an entry's URL and store it to file together with download metadata (e.g., download date, HTTP status code, redirection chain followed). For Twitter and Telegram the Downloader is not used, as their entries already contain the content of the posts. The Searcher takes as input a document in HTML, PDF, or plain text format, extracts its text (for HTML and PDF documents), and applies regular expressions to identify 41 indicators. We choose regular expressions because they are an

efficient technique for identifying, in a given string, indicators with some intrinsic structure such as email addresses or URLs. To extract indicators, the Searcher applies a match and validate approach. Matching applies each of the regular expressions to identify candidate indicators in the input string. Validation uses a function specific to each indicator type to ensure the candidate is indeed an indicator. Separating matching from validation allows the validation to perform computations that are not possible within regular expressions such as checking a checksum embedded in an indicator value (e.g., blockchain addresses, bank account numbers). It also prevents regular expressions from becoming too complex. While validation minimizes the set of incorrect indicators output, it is possible that indicators present in the text are not IOCs, but rather correspond to benign indicators (e.g., the email of the report's author). Thus, before generating the final list of IOCs, the Filtering removes generic indicators that are not IOCs.

Throughout its pipeline, GoodFATR maintains traceability. From an IOC an analyst can identify the documents that contained it, from a document the entries from where it was collected, and from an entry the sources where it was observed.

## 3 THREAT REPORT COLLECTION

Our threat report collection module has been designed to support a variety of threat report sources. We collect information from RSS, Twitter, Telegram, and publicly available report datasets such as the Malpedia malware encyclopedia [41], the APTnotes repository [5], and the ChainSmith database [58].

To handle diverse sources in a unified manner, the collection is structured around three concepts: *origin*, *entry*, and *document*.

An origin captures the distribution vector through which a report is disseminated, at a finer granularity than a source. Each source typically has many origins; for RSS, an origin corresponds to the feed from a specific blog, for Twitter to a user account, and for Telegram to a channel. For report datasets (Malpedia, APTnotes, ChainSmith) we use as origin the organization that authored the report (e.g., Norton, TrendMicro). The same threat report may be distributed through multiple origins within the same source, as well as through different sources. An example is the report about a new APT threat, authored by analysts of a security company. The report is initially published on the blog of the security company, and thus will appear in the company's RSS feed. In addition, the security company also advertises the report through its official Twitter account. After its publication, external third-party Twitter accounts and Telegram channels may advertise the report as well, and the report may end up being indexed by datasets such as APTnotes and Malpedia. In this case, the report has been disseminated through multiple origins. For each report, in addition to the source we include also the origin in its identifier in the form *source:origin*. For example, *rss:nakedsecurity* and *twitter:nakedsecurity* correspond to the RSS feed of the Naked Security blog by Sophos, and its Twitter account @NakedSecurity, respectively. The main use of origins is to produce fine-grained statistics about report distribution, e.g., to measure which Twitter accounts, Telegram channels, and RSS feeds provide more threat reports.

An entry captures a specific mention of a threat report through an origin. It corresponds to a post in a Twitter account, Telegram

**Table 1: Sources used for collecting threat reports.**

| Source | Origin | Input Origins | Cumulative | Download URL | Content | IOCs |
|---|---|---|---|---|---|---|
| aptnotes | organization | ✗ | ✓ | ✓ | ✓ | ✗ |
| chainsmith | organization | ✗ | ✓ | ✓ | ✗ | ✓ |
| malpedia | organization | ✗ | ✓ | ✓ | ✗ | ✗ |
| rss | feed | ✓ | ✗ | ✓ | ✗ | ✗ |
| telegram | channel | ✓ | ✓ | ✗ | ✓ | ✗ |
| twitter | account | ✓ | ✓ | ✗ | ✓ | ✗ |

channel, or RSS feed. For report datasets an entry is a record in the report metadata, namely a line in the report index file of APTnotes, a row in the database of ChainSmith, and a BibTex entry in the Malpedia bibliography. Each entry has an origin and it contains either a download URL pointing to the report, or in the case of social media, a string with the post's text. In addition, an entry may contain additional report metadata as provided by the source: the report author, its original publication timestamp, and the last update timestamp.

A document is identified by its SHA256 hash and it captures the HTML, PDF, or text content of a report. Multiple documents may correspond to the same report. For example, due to webpage non-determinism a report distributed as HTML might produce a new content (i.e., different SHA256) every time the webpage is downloaded. Similarly, an APT report originally distributed as a webpage in the company's blog, may be stored by APTnotes as a PDF document in a third-party storage service. When collecting the same report from the company's RSS feed and APTnotes, each source produces a different document. Every time GoodFATR downloads an entry, it links the entry information to the download information, e.g., the hash of the document downloaded from the entry's URL and the download timestamp. This information allows us to trace each document to the entries, origins, and sources from where it has been disseminated.

### 3.1 Threat Report Sources

Table 1 summarizes the six report sources currently supported by GoodFATR. Each source has a dedicated collection submodule. The RSS, Twitter, and Telegram submodules take as input a file that specifies the origins (i.e., feeds, accounts, channels) that should be monitored. The report datasets do not require an input origin list as the whole dataset is downloaded. We manually created our initial origin lists for RSS, Twitter, and Telegram by including resources from prominent companies, cybersecurity news websites, and well-known security experts. We continuously add new origins as we identify interesting RSS feeds, Twitter accounts, and Telegram channels. Adding new origins is currently the only manual step in GoodFATR. Table 4 captures the total number of origins in each source at the time of writing: 300 RSS feeds, 383 Twitter accounts, 9 Telegram channels, 2,368 organizations in Malpedia, 155 organizations in APTnotes, and 11 blogs in ChainSmith.

For each source, Table 1 shows how the origin is defined and five properties: whether it requires an input list of origins; whether the reports are cumulative (i.e., old entries are always available) or entries expire after some time; whether it provides a URL for each entry from where the report needs to be downloaded; whether it includes the actual report or only the URL to the report content; and whether it includes IOCs extracted from the content.

**RSS.** We use RSS feeds to collect reports from 300 security blogs. Each RSS feed is uniquely identified by a URL pointing to the feed's XML file. At a given moment, an RSS feed provides only a configurable number of entries, *e.g.,* the 10 most recent ones. To minimize the risk of missing entries, the RSS module queries each feed on a daily basis. Between two consecutive visits, we collect data using an incremental approach to avoid storing the same entry multiple times, in case a feed was not updated. After fetching a feed, the module extracts the unique URLs from the new entries and passes them to the Downloader. URLs that were previously crawled are ignored.

Previous work that collected threat reports from security blogs built dedicated crawlers for each blog of interest (e.g., [28, 58]). The advantage of dedicated crawlers is that they can be designed to collect the historical archive of reports available in a blog's website. One disadvantage is that a different crawler needs to be developed for each blog, which limits the number of monitored blogs. For example, Liao et al. [28] collected reports from 45 blogs and Zhu and Dumitras from 10 blogs [58]. In contrast, we collect reports from 300 blogs. Moreover, as websites evolve, the crawlers may break and need to be updated. For example, ChainSmith originally supported 10 blogs in 2018, but collection from different blogs gradually decreased over time, possibly due to crawlers breaking due to website updates. In mid-2020 only two blogs were still being crawled, and since mid-2021 ChainSmith does not collect any new blog posts. In contrast, our RSS feed collection still collects entries from the same set of blog supported by ChainSmith, showing that those origins are still active. It is worth highlighting that our RSS feed collection may also require updates (e.g., if the feed's XML URL changes), but updating a feed's URL is significantly easier than building a new dedicated crawler.

**Telegram & Twitter.** The Telegram and Twitter modules leverage the official APIs to query each service. Using these APIs they can fetch not just the most recent messages, but any message that was ever posted on an account or channel. Each module takes as input a list of origins that should be monitored, and connects to each origin on a daily basis to fetch all new posts. Using the API, our modules collect each post from an account, or channel, only once. However, it is possible to obtain posts with the same content from multiple origins, e.g., if different users re-tweet the same original message.

**Malpedia.** Malpedia offers a manually-curated BibTex file with reports related to malware. BibTex entries for new reports are added on a nearly daily basis [41]. The BibTex file is generated dynamically upon request and includes all reports in the database in a cumulative manner. Each bibliography entry contains the following report fields: author, title, publication date, organization (which we use as origin), URL, language, and the date when the report was added to Malpedia. The reports' document are not provided, so the URLs are passed to the Downloader to collect them.

**APTnotes.** APTnotes is a GitHub repository with manually-curated APT reports [5]. It provides an index file with report metadata containing the report's title, source (i.e., author organization which we use as origin), publication date, the filename and file hash of the report document, and the URL where the document can be obtained. Reports in webpages are converted from HTML to PDF. All reports are stored in the box.com service as PDF files.

**ChainSmith.** The ChainSmith project [58] makes available an SQLite3 database with the reports it has downloaded, their metadata, and the IOCs it has extracted from the reports. The database has been updated on a weekly basis since 2018. It contains one table where each row corresponds to an IOC extracted from a report including the report URL, the source (i.e., blog identifier we use as origin), the report title, and the publication date. The reports' documents are not provided, so we extract the document URLs and pass them to Downloader.

## 3.2 Downloader

The Downloader takes as input an entry and tries to download the content pointed to by the entry's URL. It uses Selenium, a popular framework used for testing Web applications [53]. We instrument Selenium to render URLs using a fully fledged instance of Google Chrome. The Downloader is able to follow redirects, it supports dynamic content executed with JavaScript, and, in addition to HTML pages, it can also download plain text documents as well as other MIME types such as PDFs. In case our instrumented browser did not succeed in retrieving the content, the Downloader makes an additional attempt with Python's *requests* library [43]. For each successfully downloaded URL, the Downloader stores the document to a file and it updates the entry with the download information including the download timestamp, the document hash, the HTTP status code, and the redirection chain followed. In the final step, the downloaded documents are filtered to remove resources with HTTP status code errors and HTML content where the title states the webpage was not found.

## 4 INDICATOR EXTRACTION: A COMPARATIVE STUDY

In this section, we perform a survey and functionality comparison of indicator extraction tools including our own. We further quantitatively evaluate the tools in Section 6.

To identify the tools, we search for open-source projects for extracting indicators. For this, we query GitHub for projects related to the *ioc* keyword. Then, we manually examine each matching project to select those that correspond to tools that extract indicators. We keep only popular tools with at least 30 stars, which helps avoid forks of more popular projects. If an identified tool references any other indicator extraction tools, we also include those in our search. This process identifies 7 popular open-source tools for extracting indicators. We also include our own SEARCHER tool, for a total of 8 tools in Table 2.

The 8 tools follow the same model comprising of three steps, two of which are optional. The first optional step is *text extraction*, which given an HTML or PDF document, extracts its text. The second step, present in all tools, is *indicator extraction*, which extracts the indicators present in an input string by applying a number of

**Table 2: Comparison of indicator extraction tools.**

| Tool | Language | Stars | Inputs | | | Indicator Extraction | | | | Filtering |
|------|----------|-------|--------|------|-----|-------|----------|--------|------|-----------|
| | | | Text | HTML | PDF | Rearm | Validate | Dedup. | IOCs | |
| JAGER [45] | Python | 69 | ● | ● | ● | ○ | ○ | ● | 11 | ○ |
| IOC_PARSER [7] | Python | 378 | ● | ● | ● | ◐ | ○ | ◐ | 11 | ● |
| CACADOR [46] | Go | 119 | ● | ○ | ○ | ◐ | ○ | ● | 12 | ◐ |
| CYOBSTRACT [51] | Python | 66 | ● | ○ | ○ | ● | ◐ | ○ | 25 | ○ |
| IOC-FINDER [17] | Python | 96 | ● | ○ | ○ | ● | ○ | ◐ | 25 | ○ |
| IOCEXTRACT [21] | Python | 356 | ● | ○ | ○ | ● | ○ | ○ | 8 | ○ |
| IOC-EXTRACTOR [35] | JavaScript | 35 | ● | ○ | ○ | ● | ○ | ● | 18 | ○ |
| SEARCHER | Python | - | ● | ● | ● | ● | ● | ● | 41 | ● |

regular expressions, grammars, and rules. Finally, some tools apply an optional *filtering* step whose goal is to remove indicators that are benign (e.g., domains of security vendors), and thus cannot be considered IOCs. The dominant language for implementing the tools is Python used by 6 tools including the two most popular tools (IOC_PARSER and IOCEXTRACT) and our own SEARCHER tool. CACADOR is written in Go and IOC-EXTRACTOR in JavaScript.

In Table 2, a solid circle (●) indicates full support, a half-filled circle (◐) partial or optional support, and an empty circle (○) no support. Next, we detail each of the three steps.

### 4.1 Text Extraction

Since most security reports are distributed as HTML and PDF documents, text extraction is an important step in the complete indicator extraction process. However, it can be performed as a separate pre-processing step that takes as input an HTML or PDF document and outputs its content as text. Content extraction is a an independent process from identifying indicators, and this is likely the reason why 5 of the tools do not support it and they assume that the input is a string, e.g., containing the full text of a report. In summary, all 8 tools can take an input string, or read text from standard input or from file, and extract indicators in the string. In addition, three tools including our own, accept directly input HTML and PDF files, including the text extracting from the input document, before extracting indicators. This is convenient for the user since it does not need to write its own text extraction code and allows the tool developer to customize the text extraction.

Text extraction is a common step in many Natural Language Processing (NLP) pipelines such as those used to analyze privacy policies (e.g., [4, 16, 52, 59, 60]). Text extraction can have a significant impact on the extracted indicators. For example, the text extraction process may pre-pend or append text to the indicator value, making the extraction to miss the indicator or to output an incorrect indicator with extraneous characters. It is also possible for the extracted text to split indicators across multiple lines, causing them to be missed. For example, PDF text extraction libraries oftentimes split long URLs appearing in footnotes across multiple lines in the output text (e.g., URLs that do not fit the length of a column).

All three tools that support HTML and PDF files are written in Python. They all use the pdfminer.six [50] library for PDF text extraction. JAGER and IOC_PARSER use the BeautifulSoup [44] library for HTML text extraction, while our SEARCHER tool supports both BeautifulSoup and Readability.js [33]. Recently, Hosseini et al. [18] analyzed 7 HTML text extraction approaches used in privacy policy

analysis showing wide variability among the produced text. They concluded that the best performing HTML text extraction libraries for privacy policies were Boilerpipe [24] and Readability.js [33], while the worst-performing one was BeatifulSoup [44]. BoilerPipe is written in Java and Readability.js in JavaScript, but both have Python wrappers available.

### 4.2 Indicator Extraction

Given an input string, indicator extraction identifies indicators present in the string. Seven of the tools use regular expressions for the extraction, while IOC-FINDER uses grammars instead. The tools using regular expressions process the text in a loop, each time applying one regular expression at a time to the whole text. Each regular expression is associated to one indicator type that is assigned to each of the regular expression matches. Most tools have one regular expression for each supported indicator type, although some tools (e.g., IOCEXTRACT, SEARCHER) support multiple regular expressions for the same indicator.

The middle part of Table 2 captures four properties of the indicator extraction step: whether defanged indicators are supported and rearmed, whether tools split the extraction process into matching and validation, whether the indicators are deduplicated, and the supported indicator types. We describe each property next.

**Defanged and rearmed indicators.** It is common for security reports to *defang* malicious indicators, (i.e., IOCs) in case a user inadvertently clicks on them in a navigation tool like a browser. For example, IP address 9.9.9.9 may appear in a security report as 9[.]9[.]9[.]9, while URL http://malicious.com/badfile may appear as hxxp://malicious(.)com/badfile. Such indicators are often called *defanged* to indicate that they have been converted in less harmful, and they are not dangerous anymore. These transformations are similar to the ones applied to email addresses to limit automated collection by spammers, e.g., "contact_at_somewhere[.]com". Of the 8 tools, only JAGER does not identify defanged indicators. The other tools support a subset of the following defang transformations: (I) replacing the dot in IPv4 addresses, domain names, URLs, emails, and filenames, (II) replacing the @ sign in emails, (III) replacing the scheme in URLs (e.g., using hxxp:// instead of http://), and (IV) replacing the backslash in URLs. Two tools are marked as having partial support: IOC_PARSER only supports the dot in URLs and domain names, while CACADOR only supports the dot in IPv4 addresses. The other tools are marked as full support, however they may not exactly support the same transformations, e.g., only IOC-EXTRACTOR supports

the replacement of the backslash in URLs. The space of defang transformations that users can apply is very large and the extraction tools only support the limited set presented above, which is clearly incomplete. Intuitively, the defang transformations most important to support are those most often used by security report authors (or by users when analyzing other sources like webpages). However, it is hard to know the most popular transformations a priori, so it is typical to add support for new defang transformations as they are observed in the wild.

The tools use two approaches to handle defanged indicators. The most popular approach, used by six tools, is broadening the regular expressions used to identify the indicators to cover common defang operations. For example, the regular expression should support that an IP address optionally contains brackets or parenthesis around the dots. Once the defanged indicators have been matched by the regular expression, they can be *rearmed* (or *refanged*) to output the original indicator values. Four tools rearm the defanged indicators by default, while another two (IOC_PARSER, IOCEXTRACT) allow the user to if defanged or rearmed values should be returned. The alternative approach used by IOC-FINDER and IOC-EXTRACTOR is to first apply a rearm transformation to the raw text before applying the regular expressions. This approach does not require broadening the regular expressions to handle different defang transformations. On the other hand, blindly rearming the text before applying the regular expressions could incorrectly modify the text (e.g., rearming some text that is not part of an indicator). It also prevents returning the defanged value as it appears in the text since it has been rewritten.

**Match and validate.** One goal of indicator extraction is to minimize false positives (FPs), i.e., avoid to output indicators that are not real indicators, such as a two tokens concatenated with a period, that is not a fully qualified domain name. This requires making the regular expressions as narrow as possible, without introducing false negatives. For example, it is typical that a regular expression for domain names will check that the top-level domain (TLD) is one of the IANA-approved TLDs. For this, it is common for tools to include a long list of valid TLDs inside the regular expression. Unfortunately, the IANA list already contains over 1,500 TLDs and may continue to grow over time making the regular expression cumbersome. An alternative approach is to split the indicator extraction process into two steps: regular expression matching and validation. In this model, the regular expression can be a bit wider (i.e., produce more matches) because the validation, which is specific to each indicator type, which will discard incorrect matches. This match and validate process was first used by CYOBSTRACT, with basic checks such as validating that ASN numbers are in hard-coded ranges or that the length of a domain name is below 160 characters (which is not entirely correct as the maximum length is 255 octets).

Our SEARCHER tool implements a more complete match and validate process where each indicator type has an optional validation function that checks the returned regular expression matches. For example, in SEARCHER the *fqdn* regular expression does not need to include the list of valid TLDs because there is a *fqdn* validation function that ensures the matched valued indeed contains a valid TLD. The advantage is that the list of IANA-approved TLDs can be kept in a separate file, which can be updated without modifying the regular

expression. More importantly, the match and validate approach allows to perform Turing-complete processing on the matches such as validating an embedded checksum in a bank account or a Bitcoin address. Such validation is not possible using only a regular expression, and it can significantly reduce FPs. For example, it is common for MD5 hashes to match a Bitcoin regular expression, but it is highly unlikely those spurious matches will pass the checksum validation. It is worth mentioning, that the implementation in our SEARCHER tool performs validation after the indicator has been rearmed, so that the validation does not need to handle defang transformations.

**Deduplication.** It is possible for the same indicator to appear multiple times in the same string at different locations. We say that a tool *deduplicates* if it removes duplicated indicators from its output. For example, if the same URL appears twice in the input string, the output only contains the *url* indicator once. Tools can be classified into those that always deduplicate (●), those that do not deduplicate (○), and those where deduplication is optional (◑). None of the open-source tools return the position (i.e., start offset) at which the indicator is matched. Thus, the main value of not deduplicating is to know how many times an indicator appeared in the input string. The most flexible approach is to make deduplication optional, as done by IOC_PARSER and IOC-FINDER.

Our SEARCHER tool offers two different APIs. The raw API does not deduplicate. It returns all indicators identified, with its indicator type, starting offset, raw value, and rearmed value. In contrast, the deduplicated API first invokes the raw API, and then it deduplicates the received values by removing the starting offset and the raw values, i.e., returns only deduplicated rearmed indicators. Providing all matches with their starting offset allows the raw API to be used in additional scenarios. For example, Gao et al. [13] propose IOC protection to handle IOCs that contain dots (e.g., URLs, domains, IPs) in NLP pipelines. Such indicators negatively impact sentence tokenization in NLP libraries that leverage dots to identify the end of sentences. IOC protection first identifies the indicators (e.g., using regular expressions), replaces their value in the text with a keyword that does not contain dots, tokenizes the text into sentences, and finally replaces back the keyword with the original indicator value. IOC protection requires the starting offset and the raw value of the indicator in the input string, precisely what our raw API provides.

**Indicators.** One key difference between indicator extraction tools is the set of indicator types they support, i.e., the set of indicators for which they have regular expressions, grammars, or extraction rules. Overall, we have identified 63 indicators that the tools extract, as summarized in Table 3. We group indicator types into 16 classes: network (13 indicators), social (12), blockchain (9), cryptographic hashes (6), analytics (3), attack (3), contact (2), file (2), intellectual property (2), organization (2), payment (2), vulnerability (2), fuzzy hash (1), information sharing (1), location (1), registry (1), and yara (1).

The largest class corresponds to network-related artifacts such as domain names (*fqdn*), URLs (*url*), IP addresses (*ip4*, *ip6*), IP subnets in CIDR form (*ip4cidr*, *ip6cidr*), IP address ranges (*ipv4range*, *ipv6range*), AS numbers (*asn*), MAC addresses (*macaddress*), Tor onion addresses used to access hidden services (*onionAddress*), Internet Content Provider numbers that uniquely identify the owner

**Table 3: Indicators extracted by different tools.**

| Indicator | JAGER | IOC_PARSER | CACADOR | CYOBSTRACT | IOC-FINDER | IOCEXTRACT | IOC-EXTRACTOR | SEARCHER | NumTools |
|---|---|---|---|---|---|---|---|---|---|
| asn | | | | ✓ | ✓ | | ✓ | | 3 |
| asnOwner | | | | ✓ | | | | | 1 |
| attackType | | | | ✓ | | | | | 1 |
| attCk | | | | | ✓ | | | | 1 |
| authentihash | | | | | ✓ | | | | 1 |
| avLabel | | | | ✓ | | | | | 1 |
| bitcoin | | | | | ✓ | | ✓ | ✓ | 3 |
| bitcoincash | | | | | | | | ✓ | 1 |
| copyright | | | | | | | | ✓ | 1 |
| country | | | | ✓ | | | | | 1 |
| cve | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | 7 |
| dashcoin | | | | | | | | ✓ | 1 |
| dogecoin | | | | | | | | ✓ | 1 |
| email | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| ethereum | | | | | | | ✓ | ✓ | 2 |
| facebookHandle | | | | | | | | ✓ | 1 |
| filename | ✓ | ✓ | ✓ | ✓ | | | | | 4 |
| filepath | | ✓ | | ✓ | ✓ | | | | 3 |
| fqdn | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | 7 |
| githubHandle | | | | | | | | ✓ | 1 |
| googleAdsense | | | | | ✓ | | ✓ | ✓ | 3 |
| googleAnalytics | | | | | ✓ | | ✓ | ✓ | 3 |
| googleTagManager | | | | | | | | ✓ | 1 |
| iban | | | | | | | | ✓ | 1 |
| icp | | | | | | | | ✓ | 1 |
| importHash | | | | | ✓ | | | | 1 |
| incident | | | | ✓ | | | | | 1 |
| instagramHandle | | | | | | | | ✓ | 1 |
| ip4 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| ip4cidr | | | | ✓ | ✓ | | | ✓ | 3 |
| ip4range | | | | ✓ | | | | | 1 |
| ip6 | | | ✓ | ✓ | ✓ | ✓ | ✓ | | 5 |
| ip6cidr | | | | ✓ | | | | | 1 |
| ip6range | | | | ✓ | | | | | 1 |
| isp | | | | ✓ | | | | | 1 |
| linkedinHandle | | | | | | | | ✓ | 1 |
| litecoin | | | | | | | | ✓ | 1 |
| macAddress | | | | | ✓ | | ✓ | | 2 |
| md5 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| monero | | | | | ✓ | | ✓ | ✓ | 3 |
| onionAddress | | | | | | | | ✓ | 1 |
| phoneNumber | | | | | ✓ | | | ✓ | 2 |
| pinterestHandle | | | | | | | | ✓ | 1 |
| regKey | | ✓ | | ✓ | ✓ | | | ✓ | 4 |
| sha1 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| sha256 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| sha512 | ✓ | | ✓ | | | | ✓ | ✓ | 4 |
| ssdeep | ✓ | | ✓ | ✓ | ✓ | | ✓ | | 5 |
| telegramHandle | | | | | | | | ✓ | 1 |
| tezos | | | | | | | | ✓ | 1 |
| tlpLabel | | | | | ✓ | | | | 1 |
| trademark | | | | | | | | ✓ | 1 |
| twitterHandle | | | | | | | | ✓ | 1 |
| url | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| userAgent | | | | ✓ | ✓ | | | | 2 |
| webmoney | | | | | | | | ✓ | 1 |
| whatsappHandle | | | | | | | | ✓ | 1 |
| xmppHandle | | | | | ✓ | | | | 1 |
| yara | | | | | | ✓ | | | 1 |
| youTubeChannel | | | | | | | | ✓ | 1 |
| youtubeHandle | | | | | | | | ✓ | 1 |
| zcash | | | | | | | | ✓ | 1 |

includes three Google identifiers: Google Adsense, Google Analytics, and Google Tag Manager. The attack category contains MITRE ATT&CK techniques, tactics, and procedures, a list of attack-related keywords (e.g., DoS, spam), and antivirus labels (*avLabel*). The payment category includes IBAN bank account numbers and WebMoney addresses [56]. The vulnerability category includes CVE identifiers and also a variety of identifiers for other vulnerability sources (e.g., BugTrack, Microsoft Bulletins) grouped into a generic *incident* indicator by CYOBSTRACT. The information sharing category comprises of a single indicator for the traffic light protocol (*tlpLabel*) that controls dissemination of information [12]. Indicators in the remaining categories are straightforward and capture: contact (*email*, *phoneNumber*), files (*filename*, *filepath*), intellectual property (*copyright*, *trademark*), organization names (*asnOwner*, *isp*), locations (*country*), Windows registry keys (*registryKey*), and Yara rules (*yara*).

There are only 6 indicators that are extracted by all 8 tools: Emails, IPv4 addresses (*ip4*), hashes (*md5*, *sha1*, *sha256*), and URLs. Another two indicators are extracted by 7 tools: CVE vulnerability identifiers (*cve*) and domain names (*fqdn*). Next come two indicators extracted by 5 tools: IPv6 addresses (*ip6*) and SSDeep fuzzy hashes. However, the majority corresponds to 38 (61%) indicators extracted by a single tool.

Among the indicators in Table 3 there are some that deserve discussion. There are three indicators (*country*, *tlpLabel*, *attackType*) that are identified using regular expressions that are a disjunction of keywords. For example TLP labels can have only four values: *TLP:white*, *TLP:green*, *TLP:amber*, *TLP:red*. Since the set of possible TLP values is finite, the regular expression can identify all possible indicator values. Similarly, there is only a finite number of recognized countries. However, *attackType* includes a number of attack-related keywords that CYOBSTRACT identifies. Such list only includes attack topics of interest for the tool authors and may not include attack topics other users are interested in. The approach of building a regular expression from a set of keywords can be applied to any taxonomy of terms (e.g., family names, exploit kit names). CYOBSTRACT provides support for building such regular expressions, how, the main limitation of this technique is that it cannot identify new terms (e.g., new family names or exploit kits). CYOBSTRACT extracts two indicators that aim to capture organization names (*asnOwner*, *isp*). However, organization names do not have a clear structure save when using company-related suffixes (e.g., Ltd., Inc.) and thus are typically extracted using Named Entity Recognition (NER) techniques based on machine learning classifiers. Furthermore, trying to separate whether an organization name corresponds to an ISP or ASN owner is a challenging problem that is better suited for NLP techniques. There are also some indicators that one could argue should be split into multiple indicators. For example, the regular expression for the *incident* indicator extracted by CYOBSTRACT captures a disjunction of regular expressions, each for a different vulnerability report identifier (e.g., BugTrack, Microsoft Bulletins). Such disjunction is more efficient than having a separate regular expression for each identifier, but does not allow users to extract only those identifiers they are interested in. Another interesting case are cryptographic hashes like *authentihash* and *importHash* that are really *subtypes* of other cryptographic hashes. For example, *importHash* is the MD5 of the import table of a PE executable [29],

of a Chinese website (*icp*), and HTTP User-Agent strings (*userAgent*). The social category comprises of user handles for social networks (Facebook, Instagram, LinkedIn, Pinterest, Twitter), open source repositories (GitHub), Instant messaging tools (Jabber, Telegram, WhatsApp), as well as YouTube usernames and channel identifiers. The blockchain category comprises of addresses for 9 popular blockchains (Bitcoin, BitcoinCash, DashCoin, DogeCoin, Ethereum, LiteCoin, Monero, Tezos, ZCash). Cryptographic hashes include MD5, SHA1, SHA256, and SHA512, as well as their application on specific parts of a Windows executable such as the import table (*importHash*) and the whole executable without Authenticode codesigning fields (*authentihash*). There is also a fuzzy hash (*ssdeep*) used to identify files with similar content [25]. The analytics category

while *authentihash* is the SHA256 of a PE executable excluding Authenticode code signing fields. Thus, it is not possible for a regular expression to differentiate an *importHash* from a *md5* or an *authentihash* from a *sha256* except if the subtype indicators appear with some specific keywords before or after. Such regular expressions are very specific, they rarely produce FPs but they will introduce FNs when the expected keywords do not appear before or following the hashes. On the other hand, regular expressions for the parent types will also identify indicators subtypes (e.g., the *md5* regular expression will also identify *importHash* indicators), but classifying an MD5 into what the MD5 captures (e.g., a file hash, a certificate hash, an import table hash) is a challenging problem that is may be easier to tackle through NLP. There are also two indicators that correspond to ranges of IP addresses (*ip4range*, *ip6range*). Similar range indicators could be defined for any integer indicators, e.g., ASN numbers. The last interesting case are Yara rules extracted by IOCEXTRACT. Yara rules can be long and have internal structure with mandatory and optional fields. Thus, for some readers they may not fit the concept of indicator.

## 4.3 Filtering.

The extracted indicators may contain benign indicators that are not IOCS. The goal of filtering is to remove such generic indicators leaving only the IOCs. There are three tools that support filtering: IOC_PARSER, CACADOR, and our SEARCHER. IOC_PARSER and CACADOR both make use of hand-crafted filter lists to avoid including some indicator values in the results. IOC_PARSER uses 11 filter lists, one per indicator type it supports. However, only 4 of those filter lists (*email*, *fqdn*, *ip4*, *url*) have entries. The *email* filter list contains 6 contact addresses for large cybersecurity companies. The *ip4* filter list contains 6 reserved IP address ranges. The *fqdn* filter list contains 143 manually-curated domains. Finally, the *url* filter list contain 79 entries for popular cybersecurity blogs. CACADOR uses a hard-coded filter list of 15 domains that belong to popular Web services and cybersecurity companies.

All indicators SEARCHER extracts are passed to the filtering module, which applies different rules depending on the indicator type. First, the filtering treats as generic any indicator that embeds a domain name that appears in the list of URLs provided as input to the Report Collector and the Downloader. An analogous filtering rule is applied to the domains in the Tranco top-100K list [42]. Next, the module excludes IP addresses and network ranges of private or local networks (*e.g.,* "192.168.1.0/24"). To avoid including contact emails that often appear in security reports, the filtering module does not consider as IOCs email addresses of known providers[1] that appeared more than 10 times in the same origin. Finally, for handles from the social category, the filtering module excludes identifiers whose name usually refers to web resources on social networks (e.g., "profile.php", "media", "photo", etc).

## 5 EVALUATION

We have applied GoodFATR to collect reports from the six sources over the last 15 months. We started our collection with RSS on April 1st, 2021. We then added Telegram in September 9th, 2021 and

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[1]Our manually curated list includes: Gmail, Protonmail, Yahoo, AOL, Tutanota, Hotmail, QQ, Mail.ru, Outlook, Yandex

**Table 4: Data collection summary.**

| Source | Orig. | Start Date | Entries | Indicators | |
| | | | | Extracted | IOCs |
|---|---|---|---|---|---|
| aptnotes | 155 | 2022/07/18 | 629 | 44,619 | 41,530 |
| chainsmith | 11 | 2022/07/18 | 3,792 | 49,769 | 42,820 |
| malpedia | 2,368 | 2022/07/18 | 11,363 | 282,450 | 253,337 |
| rss | 300 | 2021/04/01 | 97,882 | 368,211 | 231,937 |
| telegram | 9 | 2021/09/09 | 61,892 | 44,534 | 33,200 |
| twitter | 383 | 2021/10/28 | 397,333 | 337,663 | 125,733 |
| *ALL* | *3,226* | *2021/04/01* | *472,891* | *1,043,932* | *655,971* |

Twitter on October 10th, 2021. On July 18th, 2022, we added the three report datasets (APTnotes, ChainSmith, Malpedia), but these datasets are cumulative so GoodFATR can also process their past entries.

Table 4 summarizes the data collection and IOC extraction results for each source. It captures the number of origins in the source at the end of the collection, the collection start date, the number of collected entries, as well as the number of extracted indicators (before filtering) and IOCs (after filtering). The most diverse source by number of origins is Malpedia with reports from 2,368 organizations, followed by Twitter with 383 accounts, RSS with 300 feeds, and APTnotes with reports from 155 organizations. In contrast, ChainSmith has reports from only 11 blogs and GoodFATR tracks only 9 Telegram channels.

Twitter is the source with the largest number of collected entries despite being introduced later than RSS and Telegram, but its entries are tweets and thus short compared to full reports collected from RSS and the three datasets. RSS is the most stable contributor with an average of 6.1K new report URLs per month. Among the three report datasets, Malpedia provides the most reports (11,363), with ChainSmith providing one third (3,792), and APTnotes only 629 reports. The relative small size of APTnotes is due to its more focused goal of only collecting reports for APTs.

**IOC extraction.** The lasts two columns in Table 4 show the indicators extracted by SEARCHER (before filtering) and the final IOCs (after filtering). Overall, GoodFATR extracted over 1M indicators of which 656K (63%) are IOCs. Thus, filtering is extremely important for discarding over one third of indicators that are generic and thus are not IOCs. Filtering affects each source differently. In the extreme case of Twitter, two thirds of the indicators are filtered. Across all sources, domain names and IPv4 addresses account for 99% of the generic indicators. Filtered domains names are those matching the domain from where the report was collected and those included in the Tranco top-100K list. Filtered IPv4 addresses are those of private and local networks,

The average number of IOCs per report is highest for the report datasets: APTnotes (66), Malpedia (22), and ChainSmith (11). Of those, APTnotes and Malpedia are manually-curated, which prevents the collection of non-technical reports. The collection in ChainSmith is automated, but it leverages a small number of blogs from large security companies known for their high quality technical content. In contrast, reports from RSS have a lower ratio of IOCs (2.2), likely due to the variety of feeds and reports they disseminate. For example, some feeds may focus on technology news for the wider public (and thus provide less IOCs), while blogs from security companies may mix technical reports with less technical reports that focus on the virtues of their products. Still, the large number of RSS feeds
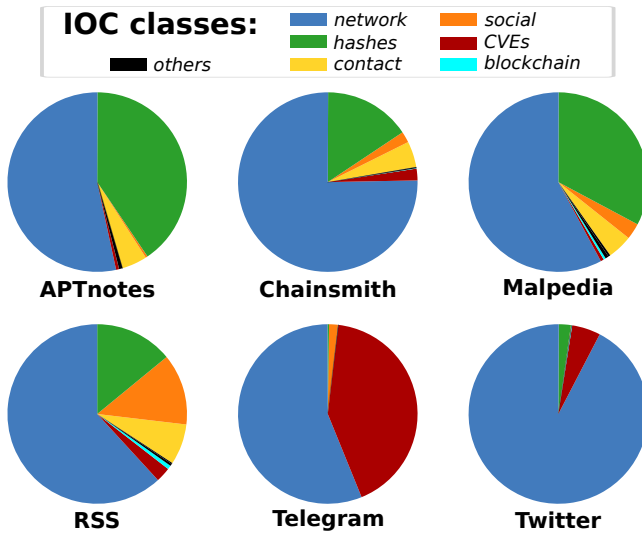
**IOC classes:**
- network
- social
- hashes
- CVEs
- others
- contact
- blockchain

**Figure 2: Distribution of IOC classes grouped per source.**

GoodFATR monitors compensates for the lower ratio, making RSS a consistent IOC contributor. Finally, Telegram (0.5) and Twitter (0.3) have the lowest ratios, which is expected due to the limited content in each entry.

**IOC class distribution.** To understand what type of indicators each source distributes, we group indicators using the categories introduced in Section 4.2. Figure 2 reports the filtered IOCs split by class and source. The plots include only the six most popular classes, the rest are aggregated in the *other* category. Across all sources, *network* indicators dominate. Malpedia, Telegram and Twitter are the biggest contributors to the *network* category, with more than 110K IOCs of this category per source. The *hash* category ranks second with most indicators in this category coming from Malpedia (82K file hash IOCs). In third place we find *contact* and *social* indicators, both having similar distributions with the vast majority coming from RSS and Malpedia. These two sources are also the highest contributors of IOCs that survive the filtering and exhibit the highest variety in terms of indicator types. For example, RSS and Malpedia provide 94% of the *blockchain* IOCs and over 61K email addresses, phone numbers and social network handles. Telegram and Twitter show significantly smaller variety of IOC types. For example, the union of the *contact* and *social* classes represent only 1.6% of the IOCs in Telegram, and they only account for 92 of the IOCs extracted from Twitter. One possible reason is that Twitter accounts are more specialized with some accounts focusing only on certain indicator types such as malicious file hashes or vulnerability identifiers.

**Top origins.** Table 5 shows the top-10 origins for each source, ranked by the percentage of IOCs the origin contributes to the source. Overall, we notice a long tail distribution, with the top-10 origins generating 50% of all IOCs. This pattern is consistent across all sources and IOC classes. All three report datasets are dominated by large security companies, with the exception of the Citizen Lab at University of Toronto (rank 8 in APTnotes) and three personal blogs (ranks 8–10 in ChainSmith). A surprising contributor is Price Waterhouse

Coopers (rank 10 in APTnotes), one of the largest financial accounting companies, but less known for their security services. In general, personal blogs exhibit less activity compared to company blogs with 7% of all IOCs coming from personal blogs. RSS has more variety in the origins. Surprisingly, the top contributor is the personal blog from Dancho Danchev, followed by two Medium blogs that aggregate blockchain and cybersecurity news. The RSS top-10 is rounded by the research labs of three large companies (Cisco, F5, Malwarebytes), two other personal blogs (Bruce Schneier, contagiodump), and two magazines (Cointelegraph.com and BleepingComputer). Interestingly, two of the RSS top 10 origins focus on blockchain. We added blockchain-specific sources motivated by the case study in Section 7. Telegram is largely dominated by the cybsecurity channel, which provides 76% of all Telegram IOCs. Similarly, Twitter also has one dominant account @ecarlesi with more than 140K tweets and responsible for 76% of the Twitter IOCs. Second, but far behind with 4.7% of IOCs, comes @threatmeter, an automated bot that publicizes vulnerabilities and accounts for 90% of *vulnerability* IOCs.

## 6 EVALUATION OF IOC EXTRACTION TOOLS

To evaluate the indicator extraction tools, we design a majority-vote methodology that runs the 8 tools in Table 2 on the text of the same set of threat reports. Then, we compare the indicators extracted by the different tools on the same report, assuming that the correct indicators are those extracted by a *majority* of tools. The advantage of such evaluation is that it can be run on a large set of reports bypassing the challenge of building a ground truth that is representative of the wealth of indicators the tools extract. The disadvantage is that this approach works only when indicators are extracted by multiple tools, and that in some occasions it is possible that the *minority* of tools is actually correct. We detail our methodology and the obtained results next.

We first build a document dataset by extracting the text using GoodFATR from all reports in APTnotes and ChainSmith. We choose these two sources because they cover different report file types (APTnotes has PDF reports and ChainSmith mostly HTML reports) and because both sources have a high average of IOCs per report, as shown in Section 5. In four PDF reports the text extraction failed: two were Excel spreadsheets that our text extraction does not support and the other two were corrupted. We evaluate the tools using the 4,420 successfully extracted text documents.

**Methodology.** We run all tools on each document, saving the indicators each tool extracts to a separate file. To compare all tools in a similar setting, we disable filtering for tools that support it (IOC_PARSER, CACADOR, SEARCHER) and deduplicate indicators. Since each tool may assign slightly different names to indicator types (e.g. ipv4addr, ip, and ipv4 for IPv4 addresses), we normalize them to match the names in Table 3. Additionally, some tools transform case-insensitive indicator values (e.g., domain names, email addresses) to lower case or upper case, while others output them as they appear in the text. To address such differences, we also normalize indicator values. In particular, we lower case the following indicator values: hashes (*md5*, *sha1*, *sha256*, *sha512*, *ssdeep*), *regkey*, *ip6*, *fqdn*, and *email*. Finally, we normalize AS numbers to

**Table 5: Top-10 origins that contribute with the highest number of IOCs, grouped per source. In brackets we report the percentage of IOCs associated to each origin.**

| Rank | APTnotes | ChainSmith | Malpedia | RSS | Telegram | Twitter |
|------|----------|------------|----------|-----|----------|---------|
| #1 | Kaspersky (13.11%) | Webroot (27.92%) | Palo Alto Networks ( 4.16%) | Dancho Danchev's Blog (26.21%) | cybsecurity (76.70%) | ecarlesi (76.42%) |
| #2 | Palo Alto Networks ( 7.18%) | Sucuri (22.07%) | Trend Micro ( 4.11%) | Blockchain on Medium ( 9.06%) | VulnerabilityNews ( 8.28%) | threatmeter ( 4.73%) |
| #3 | Norman ( 6.11%) | Malwarebytes (15.01%) | Kaspersky ( 2.92%) | Cybersecurity on Medium ( 8.63%) | Cyber_Security_Channel ( 7.33%) | malwrhunterteam ( 2.54%) |
| #4 | Symantec ( 5.24%) | Virus Bulletin (14.12%) | ESET ( 2.82%) | Cisco Talos ( 6.57%) | cKure ( 4.01%) | bgpstream ( 2.02%) |
| #5 | ClearSky ( 4.74%) | Sophos ( 4.88%) | Proofpoint ( 1.68%) | BleepingComputer News ( 2.44%) | malwr ( 2.18%) | YourAnonRiots ( 1.54%) |
| #6 | FireEye ( 4.24%) | Forcepoint ( 4.60%) | Cisco Talos ( 1.66%) | Cointelegraph.com News ( 2.33%) | androidMalware ( 0.84%) | cryptolaemus1 ( 1.44%) |
| #7 | ESET ( 3.72%) | ESET ( 4.34%) | FireEye ( 1.65%) | F5 Labs ( 1.28%) | ckuRED ( 0.48%) | ActorExpose ( 1.32%) |
| #8 | Trend Micro ( 2.67%) | TaoSecurity ( 4.15%) | BitDefender ( 1.44%) | Schneier on Security ( 1.26%) | canyoupwnme ( 0.16%) | MalwarePatrol ( 0.98%) |
| #9 | Citizen Lab ( 2.40%) | Hexacorn ( 1.70%) | 360netlab ( 1.39%) | Malwarebytes Labs ( 1.12%) | itsecalert ( 0.03%) | 1zrr4h ( 0.97%) |
| #10 | PwC UK Blogs ( 1.88%) | Roger McClinton ( 0.90%) | Microsoft ( 1.34%) | contagiodump ( 1.08%) | - | dubstard ( 0.74%) |

**Table 6: Precision (P), recall (R), and F1 score achieved by each indicator extraction tool on the comparative evaluation over 4,420 documents. Only indicator types extracted by at least two tools are included.**

| | | JAGER | | | IOC_PARSER | | | CACADOR | | | CYOBSTRACT | | | IOC-FINDER | | | IOCEXTRACT | | | IOC-EXTRACTOR | | | SEARCHER | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Indicator | Count | P | R | F1 | P | R | F1 | P | R | F1 | P | R | F1 | P | R | F1 | P | R | F1 | P | R | F1 | P | R | F1 |
| asn | 202 | - | - | - | - | - | - | - | - | - | 0.93 | 0.95 | 0.94 | **0.99** | **1.00** | **0.99** | - | - | - | 0.69 | 0.97 | 0.81 | - | - | - |
| bitcoin | 2,698 | - | - | - | - | - | - | - | - | - | - | - | - | 0.77 | 1.00 | 0.87 | - | - | - | **1.00** | **1.00** | **1.00** | 1.00 | 0.01 | 0.03 |
| cve | 2,135 | 0.96 | 0.99 | 0.98 | **1.00** | **1.00** | **1.00** | - | - | - | 0.98 | 0.97 | 0.97 | 0.98 | 1.00 | 0.99 | - | - | - | 0.96 | 1.00 | 0.98 | 1.00 | 1.00 | 1.00 |
| email | 1,947 | 0.60 | 0.85 | 0.70 | 0.89 | 0.75 | 0.81 | 0.60 | 0.73 | 0.66 | 0.99 | 0.98 | 0.98 | 0.93 | 1.00 | 0.96 | 0.75 | 0.97 | 0.85 | 0.97 | 0.99 | 0.98 | **0.99** | **1.00** | **1.00** |
| filename | 17,082 | **0.98** | **0.97** | **0.98** | 0.97 | 0.71 | 0.82 | 0.87 | 0.97 | 0.92 | 0.78 | 0.87 | 0.82 | - | - | - | - | - | - | - | - | - | - | - | - |
| filepath | 1,551 | - | - | - | **0.73** | **0.66** | **0.69** | - | - | - | 0.29 | 0.97 | 0.45 | 0.25 | 0.76 | 0.37 | - | - | - | - | - | - | - | - | - |
| fqdn | 41,360 | 0.48 | 0.06 | 0.10 | 0.99 | 0.91 | 0.94 | 0.56 | 0.39 | 0.46 | 0.97 | 0.96 | 0.97 | 0.95 | 0.99 | 0.97 | - | - | - | 0.92 | 0.99 | 0.95 | **0.98** | **1.00** | **0.99** |
| googleAdsense | 4 | - | - | - | - | - | - | - | - | - | - | - | - | **1.00** | **1.00** | **1.00** | - | - | - | 1.00 | 1.00 | 1.00 | 1.00 | 0.75 | 0.86 |
| googleAnalytics | 3 | - | - | - | - | - | - | - | - | - | - | - | - | **1.00** | **1.00** | **1.00** | - | - | - | 0.75 | 1.00 | 0.86 | 1.00 | 1.00 | 1.00 |
| ip4 | 9,479 | 0.99 | 0.87 | 0.92 | 0.98 | 0.92 | 0.95 | 0.97 | 1.00 | 0.98 | 1.00 | 0.98 | 0.99 | 0.99 | 0.99 | 0.99 | 0.98 | 0.97 | 0.98 | 0.98 | 1.00 | 0.99 | **1.00** | **1.00** | **1.00** |
| ip4cidr | 287 | - | - | - | - | - | - | - | - | - | **1.00** | **0.99** | **0.99** | 0.97 | 1.00 | 0.99 | - | - | - | - | - | - | 1.00 | 0.99 | 0.99 |
| ip6 | 967 | - | - | - | - | - | - | 0.50 | 0.91 | 0.65 | **0.87** | **0.66** | **0.75** | 0.91 | 0.12 | 0.21 | 0.15 | 0.80 | 0.25 | 0.51 | 0.97 | 0.66 | - | - | - |
| macAddress | 64 | - | - | - | - | - | - | - | - | - | - | - | - | **1.00** | **1.00** | **1.00** | - | - | - | 1.00 | 1.00 | 1.00 | - | - | - |
| md5 | 14,635 | 1.00 | 0.98 | 0.99 | 1.00 | 1.00 | 1.00 | 0.45 | 1.00 | 0.62 | 1.00 | 0.97 | 0.98 | **1.00** | **1.00** | **1.00** | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| monero | 2 | - | - | - | - | - | - | - | - | - | - | - | - | **1.00** | **1.00** | **1.00** | - | - | - | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| regkey | 608 | - | - | - | 0.96 | 0.72 | 0.82 | - | - | - | **0.80** | **0.90** | **0.85** | 0.69 | 0.73 | 0.71 | - | - | - | - | - | - | - | - | - |
| sha1 | 4,150 | **1.00** | **1.00** | **1.00** | 1.00 | 0.99 | 0.99 | 0.41 | 1.00 | 0.58 | 1.00 | 0.99 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| sha256 | 5,336 | **1.00** | **1.00** | **1.00** | 1.00 | 1.00 | 1.00 | 0.97 | 1.00 | 0.99 | 1.00 | 0.94 | 0.97 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| sha512 | 1 | **1.00** | **1.00** | **1.00** | - | - | - | 0.07 | 1.00 | 0.12 | - | - | - | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | - | - | - |
| ssdeep | 74 | 1.00 | 0.28 | 0.44 | - | - | - | 0.16 | 0.30 | 0.21 | **0.81** | **0.88** | **0.84** | 0.55 | 0.91 | 0.69 | - | - | - | 0.47 | 1.00 | 0.64 | - | - | - |
| url | 14,818 | 0.61 | 0.56 | 0.59 | 0.53 | 0.56 | 0.54 | 0.51 | 0.52 | 0.52 | 0.76 | 0.96 | 0.85 | 0.62 | 0.83 | 0.71 | 0.60 | 0.99 | 0.75 | 0.70 | 0.80 | 0.74 | **0.77** | **1.00** | **0.87** |
| All | 117,403 | 0.87 | 0.57 | 0.69 | 0.91 | 0.85 | 0.88 | 0.61 | 0.70 | 0.65 | 0.92 | 0.96 | 0.94 | 0.87 | 0.96 | 0.91 | 0.77 | 0.99 | 0.87 | 0.90 | 0.96 | 0.93 | **0.95** | **0.97** | **0.96** |

the format *AS1234* (e.g. from asn1234 to AS1234) and URLs by prepending "http://" when no scheme is present.

The evaluation keeps for each tool counters for true positives (TPs), false positives (FPs), false negatives (FNs), and true negatives (TNs). The evaluation processes one document at a time, updating the counters with the document results. For each document, it examines all indicators extracted from the document by at least one tool. For each indicator, it generates three sets: the *found* set captures the tools that identified the indicator in the document, the *missed* set captures the tools that support the indicator type but did not identify it, and the *unsupported* set captures the tools that do not support the indicator type. If the size of the found set is larger than the size of the missed set, then the evaluation assumes the majority is correct and therefore the indicator was indeed present in the document. Thus, it adds a TP for each tool in the found set and a FN for each tool in the missed set. If the size of the missed set is larger than the size of the found set, then the evaluation assumes the majority is correct and therefore the indicator was not present in the document. Thus, it adds a FP for each tool in the found set and a TN for each tool in the missed set. If the size of the found and missed sets is the same, then there is no majority. In such cases we skip the indicator and do not update the counters. In future work, we plan to investigate how to break such ties. After processing all documents, we compute the precision, recall, and F1 score for each tool across all indicators, as well as separately for each indicator type.

**Handling errors.** When running all tools on the 4,420 documents we observed that IOCEXTRACT, the second most popular tool, needed hours to process some documents, compared to seconds or a few minutes for other tools. We suspected that one of their regular expression had a ReDoS vulnerability that caused a worst case triggered only in some documents [11]. We found an open issue in the IOCEXTRACT repository regarding catastrophic backtracking in the regular expression used to identify defanged URLs that modify the backslash [10]. To be able to complete the evaluation in reasonable time, we configured IOCEXTRACT to avoid using the problematic regular expression. This change does not affect the accuracy results, as IOCEXTRACT is the only tool supporting that defang transformation. Similarly, there are two documents where IOC-EXTRACTOR does not terminate. We identify the root of this issue in the regular expressions used to extract domain names. Of the four domain regular expressions used, only one avoids the problem, while the others require hours to process the document. For these two documents, we added IOC-EXTRACTOR to the missed set for all indicators in the document. These results show that ReDoS vulnerabilities are a serious problem for indicator extraction tools, but oftentimes these issues occur only when examining large volume of documents.

There are also a few documents where a tool throws an exception and thus extracts no indicators. This happens for CYOBSTRACT in 41 documents and for JAGER in 20. For CYOBSTRACT, since each indicator is processed individually, only the indicators of the type

causing the exception are missed. We included JAGER in the missed set for all indicators in those documents.

**Results.** Table 6 summarizes the results for the 21 indicator types that are extracted by more than one tool. The columns show the indicator type, the number of indicators of that type considered TPs, as well as the precision (P), recall (R) and F1 score for each tool. We do not include indicators extracted only by a single tool, as there is no concept of majority for those.

Overall, SEARCHER is the tool that achieves both best precision (0.95) and F1 score (0.96), while IOCEXTRACT achieves best recall (0.99). The highest overall F1 scores are for SEARCHER (0.96), CYOBSTRACT (0.94), IOC-EXTRACTOR (0.93), and IOC-FINDER (0.91). The lowest F1 scores are for CACADOR (0.65) and JAGER (0.69). These results seem to indicate that recent tools (SEARCHER, IOC-EXTRACTOR, IOC-FINDER) perform better than those released earlier (JAGER, CACADOR), possibly because newer tools could use older ones for comparison.

The table also presents the accuracy results for each indicator type. We observe perfect agreement for MAC address extraction (although only 64 MAC addresses are found by two tools) and nearly perfect agreement on the hashes, with the exception of CACADOR that has low F1 scores for *sha512* (0.12), *sha1* (0.58), and *md5* (0.62). SEARCHER performs best in 11 of the 13 (85%) indicator types it supports in the table, IOC-EXTRACTOR in 8 out of 17 (47%), and IOC-FINDER in 9 out of 20 (45%). CYOBSTRACT is the best tool for extracting registry keys (0.85) and SSDeep hashes (0.84); JAGER for extracting filenames (0.98), IOC_PARSER for filepaths (0.69), and SEARCHER for emails (1.0), domain names (0.99), IPv4 addresses (1.0), and URLs (0.87). These results are useful for future work in this area, to identify which prior tool may have the best regular expression for an indicator type. For example, if we were to add registry key support to SEARCHER we would start by looking at CYOBSTRACT and for filenames to JAGER.

The indicator types with lowest agreement are IPv6 addresses with F1 score ranging 0.21–0.75; filepaths (0.37–0.69); URLs (0.52–0.87); and registry keys (0.71–0.85). These are arguably the indicator types for which regular expressions are harder to build. We observe that most IPv6 addresses extracted are actually FPs caused by a regular expressions that matches serial numbers in certificates and certificate fingerprints.

One surprising result is that SEARCHER has an F1 score of 0.03 on Bitcoin addresses, while it achieves best F1 score on most other indicators it extracts. We manually checked the extracted Bitcoin addresses and observed that SEARCHER is actually always correct in identifying Bitcoin addresses. Both IOC-EXTRACTOR and IOC-FINDER return hashes that are erroneously included as Bitcoin addresses. SEARCHER avoids those FPs by examining the checksum in the regular expression matches, which do not validate. This is an example of the minority of tools being correct and the majority being wrong. In general, the more tools support an indicator, the higher confidence we have on the majority results. An alternative approach for evaluation tools is to use a ground truth (GT) dataset. However, the manual effort required to build a GT with thousands of documents would be very large, and it would be difficult to cover different indicator types. For this reason regular expression evaluations tend to be built leveraging synthetic examples (e.g., [31]).

**Table 7: Top-10 indicator types extracted by all tools.**

| Indicator | Count | Tools |
|---|---|---|
| fqdn | 41,360 | 7 |
| attackType | 26,109 | 1 |
| country | 17,654 | 1 |
| filename | 17,082 | 4 |
| url | 14,818 | 8 |
| md5 | 14,635 | 8 |
| ip4 | 9,479 | 8 |
| sha256 | 5,336 | 8 |
| avLabel | 4,660 | 1 |
| sha1 | 4,150 | 8 |

**Table 8: Indicator extraction runtime (in seconds) across all APTnotes and average by indicator type.**

| Tool | Runtime (sec) | Ind. | Avg. per Ind. (sec) |
|---|---|---|---|
| CACADOR | 489.23 | 12 | 40.76 |
| IOCEXTRACT | 1350.69 | 8 | 168.83 |
| IOC_PARSER | 1563.33 | 11 | 142.12 |
| IOC-EXTRACTOR | 1978.51 | 18 | 109.91 |
| JAGER | 2360.02 | 11 | 214.54 |
| SEARCHER | 2847.98 | 41 | 69.46 |
| CYOBSTRACT | 6945.03 | 25 | 277.80 |
| IOC-FINDER | 96596.23 | 25 | 3863.84 |

Unfortunately, synthetic examples may not represent results on real documents.

Table 7 shows the Top 10 most popular indicator types across the 4,420 documents. The count column represents the number of TPs, and the last column reports the number of tools that extract each indicator. Among those, 7 correspond to indicators supported by most tools, namely domain names, file names, URLs, IPv4 addresses, and hashes (*md5*, *sha256*, *sha1*). On the other hand, the other three indicators are extracted only by CYOBSTRACT and correspond to attack-type keywords, countries, and AV labels. A total of 16 indicator types are not found in the 4,420 reports. These include *attribution*, *groupName*, *authentihash*, *ip6range*, *useragent*, *iban*, *icp*, 7 blockchain addresses (*dashcoin*, *dogecoin*, *ethereum*, *litecoin*, *tezos*, *webmoney*, *zcash*), and two social handles (*telegramHandle*, *whatsappHandle*). These correspond to less popular indicators in APTnotes and ChainSmith reports. However, other sources may differ. For example, RSS collection includes blockchain-related blogs, which leads to SEARCHER extracting indicators for all blockchain addresses in Section 5 (e.g., 726 *ethereum* addresses).

**Runtime.** Table 8 shows the total time in seconds each tool took to extract indicators on the 4,420 text documents, the number of indicator types supported, and the average time by indicator type. In our tests the fastest tool is CACADOR, likely due to being implemented in Go and compiled to native code. The slowest tool is IOC-FINDER, which is 14 times slower than the second slowest tool (CYOBSTRACT). This is likely due to IOC-FINDER being the only tool that uses grammars for the extraction, which highlights the efficiency of using regular expressions to extract indicators. All tools perform one pass on the text for each regular expression and they typically use one regular expression for each indicator type. Thus, the runtime is highly influenced by the number of indicator types extracted. When normalizing the total runtime by the number of extracted indicator types, CACADOR is still fastest with 40.8 seconds, followed by SEARCHER (69.5), and IOC-EXTRACTOR (109.9).

**Table 9: Social indicators validation.**

| Indicator | Total | Validated |
|---|---|---|
| facebookHandle | 150 | 124 |
| gitHubHandle | 258 | 242 |
| instagramHandle | 10 | 8 |
| pinterestHandle | 1 | 1 |
| youTubeHandle | 24 | 24 |
| youTubeChannel | 6 | 6 |
| twitterHandle | 516 | 431 |
| All | 965 | 836 |

**Social handle validation.** Our majority-based evaluation cannot be applied to the 38 indicators only extracted by one tool. Among those, there are 11 social indicators only extracted by SEARCHER, of which 9 appear in APTnotes and ChainSmith reports (no Telegram and WhatsApp handles are found in these sources). For social network handles we perform an alternative validation, which checks whether there *currently* exists an account in the social network for that handle. For this, we use the Blackbird [37] open-source tool, which given a username checks if there currently exists an account with that handle on 143 different social networks. Blackbird supports 6 social networks SEARCHER extracts handles for (Facebook, GitHub, Instagram, Pinterest, Telegram and YouTube). In addition, we expanded Blackbird to also support *youtubeChannel* indicators. For Twitter handles, we leverage the official Twitter API for the same purpose [55]. LinkedIn does not allow searching for account names.

Table 9 summarizes the results. Our automated approach successfully validated 87% of the social indicators. We manually inspect the 102 indicators that we could not validate with Blackbird, using a web browser to search for a particular handle on each social network. For Twitter, 15 of of the 85 usernames that did not validate, were linked to suspended accounts (e.g., @MalwareSigs). In all of the remaining cases the social networks returned a page to inform us that the particular account does not exist. For 75 of the 87 accounts for which we could not find the user profile page, the identifier contained a meaningful sequence of characters (e.g., "sucuri_security", "avast_antivirus"), suggesting that the identifier could belong to an old account that was closed. Overall, this evaluation suggests that over 90% of the social identifiers SEARCHER extracted are likely true positives. For the rest we cannot determine if they are false positives or correspond to accounts that have been closed since they appeared in the sources.

## 7 CASE STUDY: BLOCKCHAIN ADDRESS TAGGING

Cryptocurrencies such as Bitcoin are frequently abused by cybercriminals. A key property of Bitcoin is that its transaction ledger is public, which allows to inspect and analyze all transactions. Related work has leveraged this visibility on transactions for tracking payments from victims of ransomware [19, 38] and scams [32, 39]; buying and selling of illegal items in underground marketplaces [9, 26], and identifying malware C&C channels hosted on the blockchain [40, 54]. Bitcoin addresses are pseudo-anonymous, but in some cases it is possible to identify a set of addresses owned by an entity, e.g., by transacting with a service [32] or by analyzing malware samples [23]. Related work that analyzed malicious Bitcoin transactions leveraged Bitcoin tagging databases. These databases contain Bitcoin addresses together with information on whether the address is malicious or benign and who the owner is. Tagging databases are a cornerstone of many commercial blockchain analysis companies [1, 2].

Building and updating tagging databases is currently a largely manual process, and analysts are in desperate need of tools to assist them. This case study shows how we leveraged GoodFATR to assist us in building and maintaining a Bitcoin tagging database. We used this database in a research project related to identifying relationships between cybercriminals that abuse Bitcoin [15].

To generate the tagging database we included blockchain-related blogs into the list of RSS origins input to GoodFATR. Every day, GoodFATR collects new RSS entries, downloads the documents using the entry URLs, and extracts the indicators. On a weekly basis, a cron job selects the Bitcoin addresses identified over the week, tags them with the URLs of the reports from where the addresses have been extracted, filters those already present in our tag database, and sends an email with the untagged addresses to an analyst.

It is worth noting we do not know if addresses reported in the email were used only in legitimate transactions, as our Bitcoin address validation step only discards indicators with an invalid checksum, without further filtering. We are interested in collecting both malicious and benign addresses, as cybercriminals often abuse addresses of legitimate services (e.g., cryptocurrency exchanges). After receiving the list of new Bitcoin addresses, the analyst visits the report URLs (or examines the documents downloaded by GoodFATR) and manually tags each address. To this end, the analysis searches for the address in the report text, reads the part of the report in which the address is mentioned, and tags the address accordingly.

Using this approach, GoodFATR is able to gather a continuous feed of fresh Bitcoin addresses, which can be tagged within a few days since they were first published in one of our monitored origins. The tagged addresses are added to the database used by our automated system [15]. Malicious addresses can also be used as input to the automated system, so that they their transactions are traced. In a period of 1.3 years (68 weeks), this approach automatically identified 854 new Bitcoin addresses, for an average of 12.6 Bitcoin addresses per week, a median of one address, a maximum of 497, minimum of zero, and a standard deviation of 60.4. In future work, we plan to investigate NLP techniques to automate the tagging of Bitcoin address with context information obtained from the threat report, thus avoiding any manual steps by the analyst.

## 8 RELATED WORK

Over time, several threat intelligence tools and platforms have been developed [7, 8, 20–22, 28, 57, 58]. These platforms focus on the automatic extraction of IOCs from different sources including technical articles [20, 28, 57, 58], social networks [34, 49], and public/private IOC feeds [27] . Regular expressions are a common choice for IOC extraction, as most IOCs follow a well defined structure that can be matched, *e.g.,* IP addresses are formatted as a set of four base-10 written hexadecimal bytes separated by dots. Commonly, such platforms focus on a limited set of IOCs (URLs, IP addresses, and file hashes). Our approach also relies on regular expressions to detect IOCs, but we cover a significantly larger number of IOC classes (*i.e.,* network and social handles, contact information, CVEs), and support a variety of document formats (HTML, PDF, plain text).

Moreover, GoodFATR uses a real web browser to download documents, allowing us to follow complex redirection chains and render dynamic content. A common challenge is to select the best sources to track. Niakanlahiji et al. [34] combine graph theory, machine learning (ML), and text mining to build reputation models to identify valuable Twitter users to follow, based on their posts. Li et al. [27] define a special set of metrics that can be used to measure the quality of an IOC feed. We start with a manually generated list of origins, and then perform the analysis in Section 5 to identify the best and worst contributors. This is possible because GoodFATR can backtrack each IOC to its origin, and can aggregate them to identify the most active sources, as well as sources that specialize on particular indicator types. We can easily include new sources to our platform, and remove those that are less active, or that do not generate IOCs. In addition, the validation of the IOCs found is considered an open problem. For example, in [8] authors propose to identify web-IOCs by searching for external resources added to a web application once it gets compromised. Still, it is extremely challenging to figure out that an external resource (*e.g.,* a URL or a JavaScript snippet) is indeed an indicator of the attack, and not just a generic indicator that appears also in non-compromised web sites. Our platform leverages the insight that some IOCs can be validated, significantly lowering generic indicators, *e.g.,* Bitcoin addresses can be easily validated using their embedded checksum. In addition, GoodFATR also includes filtering to remove generic IOCs, *e.g.,* a URL whose domain is the same as an origin we track.

## 9 CONCLUSIONS

We have presented GoodFATR, an automated platform for collecting threat reports from 6 sources and extracting IOCs from the collected reports. GoodFATR continuously monitor the sources, downloads new threat reports, extracts indicators from the reports, and filters generic indicators to produce a list of IOCs. GoodFATR includes the SEARCHER tool for extracting 41 indicator types from HTML, PDF, and text files using regular expressions. We have compared 7 popular indicator extraction tools with SEARCHER and compared their accuracy using a novel majority-vote methodology. We have run our platform for over 15 months to collect 472,891 reports from the 6 sources; extract 1,043,932 indicators from the reports; and identify 655,971 IOCs. We have analyzed the collected data to identify the top IOC contributors and the IOC class distribution. Finally, we have presented a case study on how GoodFATR can assist in tracking cybercrime relations on the Bitcoin blockchain.

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