End-to-End Analysis of In-Browser Cryptojacking

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Abstract—In-browser cryptojacking involves hijacking the CPU power of a website’s visitor to perform CPU-intensive cryptocurrency mining, and has been on the rise, with 8500% growth during 2017. While some websites advocate cryptojacking as a replacement for online advertisement, web attackers exploit it to generate revenue by embedding malicious cryptojacking code in highly ranked websites. Motivated by the rise of cryptojacking and the lack of any prior systematic work, we set out to analyze malicious cryptojacking statically and dynamically, and examine the economical basis of cryptojacking as an alternative to advertisement. For our static analysis, we perform content-, currency-, and code-based analyses. Through the content-based analysis, we unveil that cryptojacking is a wide-spread threat targeting a variety of website types. Through a currency-based analysis we highlight affinities between mining platforms and currencies; the majority of cryptojacking websites use Coinhive to mine Monero. Through code-based analysis, we highlight unique code complexity features of cryptojacking scripts, and use them to detect cryptojacking code among benign and other malicious JavaScript code, with an accuracy of ≥96.4%. Through dynamic analysis, we highlight the impact of cryptojacking on system resources, such as CPU and battery consumption (in battery-powered devices); we use the latter to build an analytical model that examines the feasibility of cryptojacking as an alternative to online advertisement, and show a huge negative profit/loss gap, suggesting that the model is impractical. By surveying existing countermeasures and their limitations, we conclude with long-term countermeasures using insights from our analysis.

I. INTRODUCTION

Recently, blockchain-based cryptocurrencies have emerged as an innovation in distributed systems, enabling a transparent and distributed storage of transactions. To prevent abuse and improve trustworthiness in cryptocurrencies, various proof mechanisms, such as the Proof-of-Work (PoW) and Proof of Stake (PoS), are used. In Bitcoin, one of the most prominent blockchain-based cryptocurrencies, for example, PoW is used to embed trustworthiness in the system. In Bitcoin, new coins are mined by individual miners through extensive hash operations, which are then verified by distributed nodes in a peer-to-peer (P2P) network. However, the use of PoW in Bitcoin has led to abuse: an adversary may employ various techniques to abuse public resources for mining purposes and to perform extensive hash calculations at no or low cost.

One such technique that has emerged recently is called cryptojacking, which involves outsourcing hash calculations in PoW-based cryptocurrencies. Cryptojacking is the use of system resources of a target device to compute hashes and make profit out of mining without the consent of the target device’s owner. Conventional cryptojacking involved installation of a software binary on a target machine that secretly solved PoW and communicated the results to a remote server [1]. Such conventional cryptojacking required user permission to download the software and a persistent Internet connection to communicate the PoW result to the adversary or a dropzone server controlled by him. However, conventional cryptojacking proved infeasible for several reasons. First, not all devices have a persistent Internet connection when needed to send PoW results; PoWs are time sensitive, and if not sent immediately after being solved they become easily outdated. Secondly, antivirus companies can easily identify binaries used for cryptojacking and detect them [2]. Finally, this form of attack requires an infection vector, whereby users enable the attack by mistakenly installing the cryptojacking binaries on their machines.

A recent form of in-browser cryptojacking that does not suffer from those issues has emerged. In-browser cryptojacking does not require installing binaries, or authorization from users to operate the system. In-browser cryptojacking instances use JavaScript code to compute PoW in web browser and transmit the PoW to a remote dropzone server [3], [4]. As such, and since they are shielded in the browser’s process, they are undetected by the antivirus scanners. Moreover, mining during web browsing ensures uninterrupted transmission of PoW over a persistent in-place Internet connection.

Initially intended for good use as an alternative revenue source to online advertisement [5], in-browser cryptojacking was made easy by online services such as Coinhive [6], which provided JavaScript templates for cryptojacking. Coinhive provides scripts to mine Monero, a cryptocurrency that is hard to trace, and to reward miners based on the aggregated hashes they contribute. Google terms search reports for “Cryptojacking”, “Monero”, and “Coinhive” from May 2017 to March 2018 demonstrate the increasing interests in cryptojacking as a global phenomenon, as shown in Figure 1 (and detailed in Figure 2). This rise has coincided with the rise in malicious use of in-browser cryptojacking: more than 32,000 websites running Coinhive scripts, many of which are the result of compromise and Coinhive scripts injection, are reported [5].

In-browser cryptojacking serves as an attack avenue for hackers who inject malicious JavaScript code into popular websites without the knowledge of website owners and mine cryptocurrency for themselves. This is known as a cryptojacking attack, and become a major problem recently. According to Symantec’s latest Internet Security Threat Report (ISTR), cryptojacking attacks on websites rose by 8500% during 2017 [7], [8]. In February 2018, a major cryptojacking attack hit more than 4000 websites across the world including the websites of US Federal Judiciary and the UK National Health Service (NHS) [9]. Also in February 2018, Tesla became the victim of a cryptojacking attack in which attackers hijacked Tesla cloud and deployed their own cryptojacking code [10]. After
such unusual incidents, UK’s National Cyber Security Centre (NCSC) indicated cryptojacking as a “significant threat” in its latest cyber security report [11], [12].

The use of cryptojacking as a replacement to advertisement also has witnessed a great debate. For example, some popular websites such as “The Pirate Bay”, among others, started using cryptojacking as a revenue substitute to online advertisement [13], [14], [15]. The Pirate Bay website later disclosed to its users that it will be using CPU cycles of the visitors in exchange for ads-free web browsing, garnering users approval. As some other websites started using cryptojacking as a revenue generation-mechanism, further debate was sparked surrounding the ethics of using cryptojacking [16], and the absence of user consent. Furthermore, it was later observed that the continuous CPU-intensive mining, especially on battery-powered devices, has resulted in the quick drainage of those devices, adding a new variable to the debate of whether cryptojacking is a good alternative to online advertising.

Motivated by these fast-paced and recent events, we carry out the first in-depth study on in-browser cryptojacking and its effects on the website visitors and their devices. We start by analyzing and characterizing more than 5,700 websites that have cryptojacking scripts in them. We then explore both static and dynamic analysis tools to understand the behavioral traits of in-browser cryptojacking scripts towards their detection. Using various features extracted through this analysis, we build a clustering scheme that is used to for detecting cryptojacking scripts among benign scripts, as well as other malicious types of JavaScript codes. We also measure the impact of in-browser cryptojacking on user devices in terms of CPU usage and battery drainage. Finally, in examining the feasibility of cryptojacking as an alternative to online advertisement, we conduct an in-depth end-to-end analysis that considers the implications of such an alternative on both users and websites.

**Contributions and Roadmap.** We make the following major contributions: 1) Using more than 5,700 websites with cryptojacking scripts, we conduct the first in-depth analysis and characterization of cryptojacking in the wild, highlighting categories and affinities, including sectors, top-level domains, etc. (§III). 2) Using the same dataset, we conduct static analysis of the cryptojacking scripts, to highlight distributions of cryptocurrency used in cryptojacking and code (script) complexity analysis (§IV). As an application of our static analysis, using code complexity features we built an unsupervised clustering system that automatically identifies cryptojacking, malicious, and benign scripts (§IV-D). A reference-based (using ground truth) evaluation of our clustering algorithm yielded an accuracy of $\approx 96\%$. 3) Using the same dataset, we performed dynamic analysis to highlight the unique characteristics of process usage, battery usage, and dynamically generated data analysis through WebSocket inspection of cryptojacking scripts (§V). 4) As an application of our dynamic analysis, we explore the economic arguments made for cryptojacking as an alternative to online advertisement, and build an analytical model to estimate the cost of cryptojacking to the users as well as the gain to websites conducting cryptojacking (§VI). We supplement this analysis by contrasting it with the existing online advertisement model. We show the economical model of cryptojacking is impractical for benign use, and unprofitable for malicious use. 5) We explore the limitations of existing countermeasures and suggest more robust defense techniques to address in-browser cryptojacking using our static and dynamic analysis insights (§VII).

Additionally, the rest of this paper includes a background in §II, the related work in §VIII, discussion in §VII-C, and concluding remarks in §IX, respectively.

**II. Background**

In this section, we review the preliminaries of this work, including an introduction to cryptocurrency, the mining process, and cryptojacking. We then outline the problem statement and motivation and data collection.

**A. Blockchain-based Cryptocurrencies**

In 2009, the first blockchain-based digital currency “Bitcoin” was introduced by Satoshi Nakamoto [17] that involved exchange of transactions without the use of a central authority. In Bitcoin, the role of the trusted central authority was replaced by a transparent and tamper-proof public blockchain that acted as a public ledger to maintain the records of transactions. The consensus in the decentralized peer-to-peer Bitcoin network was augmented by cryptographically secure algorithm known as the proof-of-work (PoW). Bitcoin remained the only cryptocurrency for two years after which several more digital currencies joined the market. As of today, there are more than 5000 cryptocurrencies have been introduced in the market [18] with more than 5.8 million active users [19]. Bitcoin is leading the cryptocurrency market with a 58% market share, or $\approx 4.9$ Billion USD trade volume and more than 12,000 transactions per hour [20]. Towards the end of 2016, the price of 1 bitcoin was a little under $1000 USD and during 2017 it witnessed exponential growth rising to a market price of $19,000 USD [21]. Some other notable cryptocurrencies that make use of public blockchain are Ethereum, Litecoin, Ripple, Monero, and Dash.

**B. Mining in Cryptocurrencies**

The key operations in every cryptocurrency involve exchange of transactions among peers, the mining of transactions in blocks, and publishing those blocks. Computing a valid block results in the generation of new coins in the system...
However, computing a valid block is a non-trivial process in which miners have to solve mathematical challenges and provide a PoW for their solutions. In Bitcoin, PoW involves finding a `nonce` that, when hashed with the data in the block, produces a hash value less than the target threshold set by the system. The target is a function of network difficulty and is denoted by a 256-bit unsigned integer that is encoded in a 32-bit “compact” form and stored in the block header. In the process of solving the challenge, miners spend effort and in return get rewarded with 12.5 bitcoins for each valid PoW. As more miners join, the hash power of the network and the probability of computing a block increase. To keep the average block computation time within the fixed range, the network’s difficulty is adjusted every two weeks (2016 blocks).

In Equation 1, we show how the block computation time, \( T(B) \), is affected by the hashing rate, \( H_r \), the target, \( Target \), the probability of finding a block, \( P_r(B) \), and the average number of hashes required to solve the target, \( H \). To keep \( T(B) \) in a fixed range (10 minutes), as the \( H_r \) increases, the target value is adjusted to keep \( P_r(B) \) constant.

\[
P_r(B) = \frac{Target}{2^{256}}, \quad H = \frac{1}{P_r(B)}, \quad T(B) = \frac{1}{P_r(B) \times H_r}
\]  

(1)

To maximize mining reward, multi-homed mining pools—all participants collaboratively compute hashes based on the hash power of their machines—have emerged. When a block is computed, the rewards are distributed among the participants based on their contribution towards the produced hashes. Mining pools enable even ordinary users with limited mining hardware to effectively participate in the mining process. As a result of this paradigm, there has been an exponential growth in the aggregate hash rate of the cryptocurrencies as more people have shown interest in mining.

C. Cryptojacking

Generally, attackers utilize two main strategies for unauthorized use of a victim’s machine to mine digital currencies through cryptojacking: by installing a binary on the machine, or by using an in-browser script. The first one loads the mining code on the victim’s machine as a stand-alone binary (or an infection of a binary). As such, it requires information about the target machine including its operating system and hardware constructs. For example a malicious cryptojacking binary developed for Windows cannot be executed on Linux. However, the second strategy is platform agnostic, the cryptojacking JavaScript is executed upon loading the website in victim’s browser. In both cases, the mining code works in the background while the unaware victim is using his machine. The focus of this paper is the latter type, which we highlight at length below. In this rest of this paper, we will refer to the abuse case of cryptojacking, whereby an adversary injects cryptojacking scripts to mine cryptocurrencies.

1) In-Browser Cryptojacking: In-browser cryptojacking is done by injecting a JavaScript code in a website, allowing it to hijack the processing power of a visitor’s device to mine a specific cryptocurrency. Generally, JavaScript is automatically executed when a website is loaded. Upon visiting a website with cryptojacking code, the visiting host starts a mining activity, by becoming part of a cryptojacking mining pool. A key feature of in-browser cryptojacking is being platform-independent: it can be run on any host, PC, mobile phone, tablet, etc., as long as the web browser running on this host has JavaScript enabled in it. JavaScript, however, is one of the most popular web languages and, by default, is enabled in most major browsers. Furthermore, in-browser cryptojacking allows for mining at-scale without requiring any custom hardware: as more visitors visit the website with cryptojacking scripts, more processing power is available for mining.

2) Cryptojacking as a Replacement to Advertisement: An ongoing debate sparked in the community for whether cryptojacking can serve as a replacement to online advertisement. Those advocating the approach have pointed out that users providing their CPU power to a website for mining can use the website without viewing online advertisements. Towards that, some websites, including the aforementioned ‘The Pirate Bay’, started using cryptojacking as a revenue substitute for online advertisements [13], [14], [15] and become “ads-free operation”. However, a counter argument to this model is the claimed to be the excessive abuse of the cryptojacking website to the visitor’s CPU resources. In-browser cryptojacking scripts will not only run in the background without a user consent, but would also drain batteries in battery-powered platforms, would indirectly affect the user experience, and by locking the CPU power and not allowing him to use other applications.

III. Dataset and Preliminary Analysis

With the objective of this work, as stated earlier, being the characterization, analysis, and detection of in-browser cryptojacking, as well as testing the economical argument for the cryptojacking as an alternative to online advertisement, we proceed by outlining the data collection procedure we followed and basic characteristics. In the subsequent two sections, we outline the static analysis and dynamic analysis we conducted to uncover cryptojacking scripts.

Figure 2: Heatmap of the global distribution of Google searches for each term. Notice that US is the most prevalent country in all three search results. Moreover there is more similarity in the search for Coinhive and Monero.
### Table I: Distribution of cryptojacking websites with respect to top-level domains in our dataset

| Rank | TLD   | Type | Sites | Sites% |
|------|-------|------|-------|--------|
| 1    | .com  | generic | 1945  | 34.1%  |
| 2    | .net  | generic | 1392  | 24.2%  |
| 3    | .si   | country | 358   | 6.2%   |
| 4    | .online | generic | 349   | 6.1%   |
| 5    | .ru   | country | 242   | 4.2%   |
| 6    | .org  | generic | 191   | 3.3%   |
| 7    | .sk   | country | 169   | 2.9%   |
| 8    | .info | generic | 169   | 2.9%   |
| 9    | .br   | country | 157   | 2.7%   |
| 10   | .site | new    | 116   | 2.0%   |
| 11   | others | —      | 1648  | 28.8%  |
| Total| —     | —     | 5703  | 100%   |

### A. Data Collection

We assembled a data set of cryptojacking websites published by Pixalate [22] and Netlab 360 [23]. Pixalate is a network analytics company that provides data solutions for digital advertising and research. In Nov. 2017, they collected a list of 5,000 cryptojacking websites that were actively stealing visitors processing power to mine cryptocurrency. We obtained that list of cryptojacking websites from Pixalate. Netlab 360 (Network Security Research Lab at 360) is a data research platform that provides a wide range of datasets spanning Domain Name Servers (DNS) and Distributed Denial-of-Service (DDoS) attacks. From Netlab 360, we obtained 700 cryptojacking websites, released on Feb 24, 2018.

The top-level domain (TLD) distribution of the combined dataset, including the TLD type (generic, new, or country-level) and the corresponding percentage, is shown in Table I. While, unsurprisingly, .com and .net occupy the first and second spot of the top-10 TLDs represented in the dataset, with a combined total of 40.3% of the websites belong to them, country-level domains have a significant presence, with countries such as Slovenia, Russia, and Brazil well represented in the dataset. New-gTLDs were also present in the top-10 gTLDs, with .site having ≈2.0% of the sites.

In the Pixalate’s dataset, 6 websites were found in the Alexa top-5000 websites and 13 were among the Alexa top-10000 websites. Among the cryptojacking site, 68.3% did not have a privacy policy, while 56.8% websites had no “terms and conditions” statement, and 49.3% did not have both the privacy policy and the terms and conditions. This indicates that the majority of those websites could not formally, through those statements, inform their visitors regarding the usage of their processing resources for mining cryptocurrencies, where cryptojacking is used instead of online advertisement.

During our analysis we also observed that 11% of the websites in our dataset had stopped cryptojacking, due to key revocation by the server, removal of the code from the website, or the closure of websites. We exclude them from our analysis.

### B. Methodology

After gathering the dataset, we perform static and dynamic analysis of the cryptojacking JavaScript code. In the static analysis, we categorize the websites based on content and the currency they mine during cryptojacking. We extract the cryptojacking code and develop code-based features to examine their properties. We compare them, using those static properties, with malicious and benign JavaScript code. We use standard code analyzers to extract program specific features.

In our dynamic analysis, we explore the CPU power consumed by cryptojacking websites and its effects on the user devices. We run test websites to mimic cryptojacking websites and carry out a series of experiments to validate our hypothesis. For our experiments, we use Selenium-based scripts to automate browsers and various end host devices, including Windows and Linux operated laptops and an Android phone, to monitor the effect of cryptojacking under various operating systems and hardware architectures. For website information, we use services provided by Alexa and SimilarWeb to extract information regarding websites ranking, volume of traffic, and the average time spent by visitors on those websites [24].

### IV. Static Analysis

For static analysis, we pursue three directions: content-, currency-, and code-based analysis. Content-based categorization provides insights into the nature of websites used for cryptojacking activities, while the currency-based categorization shows the distribution of service providers and platforms providing cryptojacking templates for those websites. Finally, the code-based analysis provides insight into the complexity of the cryptojacking scripts, using various code complexity measures from the literature.

#### A. Content-based Categorization

For a deeper insight into their usage, it is important to understand what kind of websites have cryptojacking scripts in them. To this end, and as a first step, we categorized the websites based on their contents into various categories using the WebShrinker URL categorization API. WebShrinker assigns categories to websites based on the main usage of those websites using their contents. The results are shown in Figure 3. As it can be seen in Figure 3, miners have utilized a wide range of categories for in-browser cryptocurrency mining, including education, business, entertainment, etc. Notice in Figure 3, some websites are categorized as “Illegal Content.” These websites are mostly torrent websites that serve illegal copies of movies and software. Moreover, 19% websites were categorized as “Education” which can be attributed to the exploitation of trust by adversaries behind cryptojacking, since educational sites are highly trusted by their visitors [25].

#### B. Currency-based Categorization

To understand the cryptojacking ecosystem, it is critical to find out what cryptocurrencies are typically being mined through in-browser cryptojacking. Therefore, we inspected the websites’ scripts to extract information about the platforms and cryptocurrencies. From our dataset we found that there were eight platforms providing templates to mine two types of cryptocurrencies namely, Monero and JSEcoin. In Table II, we provide details about the eight platforms and their respective mining cryptocurrency. As a result, we found that a very large proportion of the websites (≈81.57%) use Coinhive [6]
platform to mine Monero cryptocurrency [26], which is one of the few cryptocurrencies that supports in-browser mining. We found that \( \approx 86.37\% \) of the websites in our dataset are mining Monero cryptocurrency through seven platforms. In addition, \( \approx 2.61\% \) of the websites are using the JSEcoin platform [27], which is responsible for mining the JSEcoin cryptocurrency.

Although PoW-based cryptocurrencies have many traits in common, they may vary in terms of their market cap, user base, application protocols, and mining rewards. In our dataset, we found two cryptocurrencies, namely Monero and JSEcoin, which are used for in-browser cryptojacking. In Table III, we report the differences among the two cryptocurrencies. While both of them are used for cryptojacking, at the time of writing of this paper, JSEcoin was not launched in the market and did not have any “Initial Coin Offering” (ICO), which explains its low prevalence in our dataset. Furthermore, unlike Monero, which is resource-intensive, JSEcoin uses minimal CPU power and does not add a significant processing overhead to the target device. One of the key objectives in this paper is to characterize resources abuse in cryptocurrency mining, where Monero is shown to be a better example than the “browser-friendly” JSEcoin. Therefore, due to its high prevalence in dataset, and the significant contribution towards the broader goal of this study, we mainly focus our work on Monero cryptocurrency.

C. Code-based Analysis

We perform static analysis on the cryptojacking scripts to analyze the performance and complexity of their code. Static analysis reveals standard code-specific features that provide deeper insights into the flow of information upon code execution. For static analysis, we gathered cryptojacking scripts from all the major cryptojacking service providers found in our dataset, such as Coinhive, JSEcoin, Crypto-Loot, Hashing, deepMiner, Freecontent, Miner, and Authedmine. We observed that all the service providers had unique codes, specific to their own platform. In other words, the websites using Coinhive’s services had the same JavaScript code template across all of them. Therefore, \( \approx 81.57\% \) of the websites in our dataset were using the same JavaScript template for cryptojacking. Similarly, all the websites using JSEcoin used the same standard template for their mining. However, the code template of each service provider was different from one another, which led us to believe that each script had unique static features. With all of that in mind, we performed static analysis on the cryptojacking websites and compared the results with other standard JavaScript for a baseline comparison.

1) Data Attributes: We prepared our dataset for static analysis by collecting all of the popular cryptojacking scripts from our list of websites. We found eight unique scripts among all the websites, each of which belongs to one of the service providers. As a control experiment, we collected an equal number of malicious and benign JavaScript codes to design a clustering algorithm. Our aim was to obtain a set of features that were unique only to the cryptojacking scripts, and aid in their detection. With such knowledge of those features, more accurate countermeasures can be further developed that will accurately predict if a given host machine is under cryptojacking attack. To avoid bias towards a certain class, we were limited to include equal size of malicious and benign JavaScript samples for the static analysis. Although there are many samples of malicious and benign JavaScript in the wild [28], only eight cryptojacking scripts are available in comparison. Since our work is focused on distinguishing cryptojacking scripts from both malicious and benign JavaScript, we had to balance the size of each class. While the number of scripts might seem as a limitation of our work, we believe the promise of this work is substantial: as more currencies and platforms start to use cryptojacking, more samples will be available for a broader study. Demonstrating a baseline analysis to support the argument that cryptojacking scripts are uniquely identifiable can open for further analysis of cryptojacking scripts across well-understood analysis tools, which we explore in this paper.

In lieu, we used the existing data of the cryptojacking websites (§III-A) and online resources from GitHub for malicious JavaScript sample [29], [30]. For benign JavaScript, we used the set of non-cryptojacking websites and parsed their HTML code to extract benign JavaScript code [31]. In summary, we

Table II: Detailed results of currency-based analysis. \(^1\) The variable name is abbreviated. No CJ: No cryptojacking.

| Platform | Websites \# | Cryptocurrency | Websites \# |
|----------|-------------|----------------|-------------|
| Coinhive | 4652        | Monero         | 4926        |
| Hashing  | 67          | Monero         | 86.37       |
| deepMiner | 56         | Monero         | 2.61        |
| Freecontent | 39        | Monero         | 0.68        |
| CryptoLoot | 38        | Monero         | 0.67        |
| Miner    | 38          | Monero         | 0.67        |
| Authedmine | 35        | Monero         | 0.61        |
| JSEcoin  | 149         | JSEcoin        | 149         |
| No CJ    | 628         | —              | 628         |
| Total    | 5703        | —              | 5703        |

Table III: Comparison of Monero and JSEcoin. JSEcoin has not been released in the market as yet.

| Currency | Market Cap | Consensus Algorithm | Resource Intensive | Dataset Prevalence |
|----------|------------|---------------------|--------------------|-------------------|
| Monero   | 2.3B       | CryptoNight         | ✓                  | 86.37\%           |
| JSEcoin  | — SHA-256  | —                   | ×                  | 2.61\%            |

Figure 3: Categorization of websites based on the main topic of their content. Notice that most websites belong to Entertainment, Business, and Education. A sizable chunk (12\%) belonged to the Adult category.
Table IV: Features extracted from cryptojacking, malicious, and benign samples for static analysis. The left most column shows the title of the features in each class while the remaining columns show the features extracted from *Plato*. Mean ($\mu$) and Standard deviation ($\sigma$) of the features are reported. The features obtained from these tables were used to perform correlation analysis and FCM clustering.

| Cat.          | Platforms | M | $\mu$ | $\sigma$ |
|---------------|-----------|---|-------|----------|
| Cryptojacking | JSCoin    | 128 | 25.7 | 3.72   |
|               | Deploy    | 128 | 25.7 | 3.72   |
|               | Freecontent | 128 | 25.7 | 3.72   |
|               | JSEcoin   | 128 | 25.7 | 3.72   |
|               | Crypto-loot | 128 | 25.7 | 3.72   |
|               | Malicious | 128 | 25.7 | 3.72   |
|               | Benign    | 128 | 25.7 | 3.72   |

Cyclomatic Complexity. Cyclomatic complexity [32], [33] measures the complexity of code using Control Flow Graph (CFG). It relies on a directed flow graph where each node represents a function to be executed and a directed edge between the two nodes indicates that the node representing the function will be executed after the previous one. Let $E$ be the number of edges, $N$ be the number of nodes, and $Q$ be the number of connected components in the CFG of a program, then $M$ can be used to denote the cyclomatic complexity of the program, and is calculated as $M = E + 2Q - N$.

Cyclomatic Complexity Density. Cyclomatic complexity density [34] is a measure of Cyclomatic Complexity density, defined, spread over the total code length. Usually, malware authors obfuscate their code to avoid detection. As such, among many other possibilities of obfuscation, they may alter the flow of a program and add extra functions. While adding more functions and lines of code will certainly increase the size of the code, its complexity will remain the same, which could be used as a feature of their detection. Let $c_I$ be the total number of lines of code, then the cyclomatic complexity density, denoted by $M_d$, can be computed as $M_d = \frac{E + 2Q - N}{c_I}$.

Halstead Complexity Measures. In software testing, the Halstead complexity measures are used as metrics to characterize the algorithmic implementation of a programming language [35]. Those measures include the vocabulary $n_v$, the program length $n_c$, the calculated program length $n_c$, the volume $V$, the effort $E$, the delivered bugs $B$, the time $T$, and the difficulty $D$. Let the number of distinct operators be $n_1$, the number of distinct operands be $n_2$, the total number of operators be $n_1$, the total number of operands be $n_2$, the $n_1, n_1, V, E$, and $B$ are defined as follows:

$$
\begin{align*}
\eta &= n_1 + n_2, \\
\alpha &= (n_1 \log_2 n_1) + (n_2 \log_2 n_2), \\
\beta &= V = n \times \log_2 V, \\
\gamma &= (D/2) \times (n_2/2), \\
\pi &= E \times V/18, \\
\end{align*}
$$

The maintainability score $M$ is calculated using Halstead volume $V$, cyclomatic complexity $M$, and the total lines of code in the *Java* file $c_I$. The maintainability score index $M_c$ is calculated between [100] and is defined as:

$$
M_c = 171 - 5.2\log(V) - 0.23M - 16.2\log(c_I); \\
M = \frac{Max(0, M_c)}{171};
$$

Source Lines of Code. Source lines of code (SLOC) is a measure of the lines of code in the program after excluding the white spaces. SLOC is used as a predictive parameter to evaluate the effort required to execute the program. It also provides insights about program maintainability and productivity.
(b) Correlation in malicious JavaScript

Figure 4: Heatmap of correlation coefficients among the features of three categorizes of JavaScript. These are the subset features of Table IV, obtained by using algorithm 1. It can be noted that features among benign scripts appear to be highly correlated while the features among malicious scripts remain highly uncorrelated. Correlation among the features of cryptojacking scripts remains in the middle, relative to the other two.

Results: To extract the aforementioned features in our code-based analysis, we used Plato, a JavaScript static analysis and source code complexity tool [36]. For each JavaScript code, we run Plato and record the 17 extracted features, highlighted above, as reported in Table IV. From Table IV, we observed that certain features, such as $M$, $M_d$, $V$, and $T$, are clearly discriminative among all the categories. For further analysis, in the next section we will look into the correlation of these features among each category to see whether there is a unique pattern among each category, which allow us to build a clustering system that can automatically identify different JavaScript categories based on the extracted features.

3) Correlation Analysis: Presenting individual features among those analyzed above, while meaningful, might not shed light on their distinguishing power given their large numbers. To this end, we pursue a correlation analysis to understand their patterns. In particular, we conducted a correlation analysis to observe the similarity of features among the three categorizes of scripts, the cryptojacking, malicious, and benign. The correlation analysis showed the consistency of the relationship distinctive to each category of the JavaScript codes. As such, this provided us with insights into coding patterns and features unique to the style of coding cryptojacking scripts, malware scripts, and benign scripts. We computed the correlation of the features in all the scripts belonging to each category of JavaScript. We used the Pearson correlation coefficient for this analysis, which is defined as 

$$
\rho(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)Var(Y)}},
$$

where $X$ and $Y$ are the random variables, $Var$ and $Cov$ are the variance and covariance of the random variables, respectively.

To identify distinguishing features and reason about their prevalence in cryptojacking JavaScript, we performed comparative analysis on the correlation matrix obtained for each class. In algorithm 1, we outline the procedure used to identify those features. The algorithm takes as an input the correlation matrix of cryptojacking $C$, malicious $M$, and benign $B$ JavaScript features reported in Table IV, computes the mean of the column vector with respect to one feature in the row, compares the mean feature of each class, and outputs the most distinguishing features in cryptojacking scripts that are highly correlated within their class. The distinguishing aspect of a feature in cryptojacking class is obtained by subtracting its mean from complementary mean values of features from the other two classes, and selecting the maximum difference.

Algorithm 1: Identifying Significant Features

| Inputs: C, M, B |
|-----------------|
| 1 $i = \text{len}(C)$; |
| 2 $Cmean, Mmean, Bmean, Array = []$; |
| 3 for $(k = 0; \ k < i; \ k = k + 1)$ { |
| 4 $Cmean[k] \leftarrow \frac{\sum_{j=1}^{i} c(i, j)}{i}$; |
| 5 $Mmean[k] \leftarrow \frac{\sum_{j=1}^{i} m(i, j)}{i}$; |
| 6 $Bmean[k] \leftarrow \frac{\sum_{j=1}^{i} c(i, j)}{i}$; |
| 7 if $(Cmean[k] - \sum_{j=1}^{i} c(i, j) \& \& \& Cmean[k] - Mmean[k]) > (Mmean[k] - Cmean[k])$ then |
| 8 $\text{Array} \leftarrow Cmean[k]$; |
| 9 end |
| 10 } |
| Output: Array |

The output $\text{Array}$, in algorithm 1, contains a subset of features from the total seventeen features that are unique to cryptojacking scripts. In particular, we found eight features and plotted their result in Figure 4. It can be observed that cryptojacking scripts are more correlated with respect to the cyclomatic complexity density $M_d$ and the maintainability score $Ms$, while malicious and benign scripts are not as correlated over those same parameters. From the description of
those features provided in §IV-C2, deeper insights can be developed regarding the coding patterns, code complexity, CFGs, and maintainability of cryptojacking scripts. Furthermore, high correlation also provides a valuable insight into code contents: that all cryptojacking scripts must be performing a sequence of similar actions with complementary execution patterns and information flows. We apply this understanding in our dynamic analysis and validate it using WebSocket inspection.

D. Clustering

In this section, we build a classification system that automatically recognizes cryptojacking scripts from malicious and benign scripts based on the code complexity features alone, which could be easily extracted from the cryptojacking scripts and are common among a large number of cryptojacking websites. It is desirable for our classification system to classify scripts even with minimal information regarding the labels of the scripts. Therefore, we utilized the Fuzzy C-Means (FCM) clustering algorithm [37], which has the advantage of being an unsupervised learning algorithm. In the other words, in comparison with supervised classification algorithms, such as the Support Vector Machine (SVM) and Random Forest (RF), which require labels of the dataset in the training phase, FCM has the advantage of performing well on the unlabeled dataset.

The main goal of the FCM is to group a dataset $X$ into $C$ clusters in which every data point belongs to every cluster to a certain degree. In other words, a data point that lies close to the center of a certain cluster will have a higher membership degree to that cluster, whereas the membership degree of the data point that lies far away from the center of this cluster will be lower [37]. We utilized the FCM clustering algorithm to group the scripts to cryptojacking, malicious, and benign clusters. In order to evaluate the performance of the clustering experiment, we used standard evaluation metrics; the confusion matrix, Accuracy Rate (AR), False Positive Rate (FPR), and False Negative Rate (FNR), which are reported in Table V.

As shown in Table V, the clustering algorithm is able to identify the scripts with high performance: AR of $\approx 96.4\%$, FPR of $3.3\%$, and FNR of $3.7\%$. In addition, we have visualized these clusters based on two major principal components of their features which, in Figure 5, clearly show natural separation between the clusters using the underlying features.

V. Dynamic Analysis

Despite the clear benefits of the static analysis outlined above, it is limited, and subject to circumvention through

Table V: Confusion matrix and evaluation metrics of the cryptojacking (CJ), malicious, and benign scripts’ clustering results based on FCM clustering algorithm. Evaluation metrics’ names are abbreviated. FPR= False Positive Rate, FNR= False Negative Rate, and AR= Accuracy Rate.

| Class         | Benign | Malicious | CJ | FPR | FNR | AR  |
|---------------|--------|-----------|----|-----|-----|-----|
| Benign        | 9      | 0         | 1  | 10  | 0   | 90  |
| Malicious     | 0      | 10        | 0  | 0   | 11.1| 100 |
| CJ            | 0      | 0         | 8  | 0   | 1   | 0   |
| Total         | 3.3    | 3.7       | 96.42 |     |     |     |

Figure 5: Clustering of the cryptojacking, malicious, and benign scripts using FCM clustering algorithm.

JavaScript code obfuscation. To this end, we conduct dynamic analysis that looks into profiling the usage of cryptojacking JavaScript code of various host resources: CPU, and battery. We then look into the characteristics of cryptojacking in their use of network resources.

A. Resource Consumption Profiling

We conduct an extensive analysis of CPU and battery usage of the various cryptojacking scripts.

1) Settings and Measurements Environment: We noticed that in each cryptojacking website, a JavaScript snippet encodes a key belonging to the code owner and a link to a server to which the PoW is ultimately sent. Listing 1 provides a script found in websites that use Coinhive for mining. The source (src) refers to the actual JavaScript file that is executed after a browser loads the script tag. In this script, we also noticed a throttling parameter, which is used as a means of controlling how much resources a cryptojacking script uses on the host. We use such a throttling parameter, $\alpha$ as an additional variable in our experiment. We experiment with $\alpha = \{0, 0.1, 0.5, 0.9\}$.

To understand the impact of cryptojacking on resources usage in different platforms, we use battery-powered machines running Microsoft Windows, Linux, and Android operating systems (OSes). For our experiments, we selected three laptops, each with one of those OSes. The Windows laptop used in the experiment was Asus V502U, with Intel Core i7-6500U processor operating at 3.16 GHz. The Linux laptop was Lenovo G50, with Intel Core i5-5200U processor (4 cores) running at 2.20 GHz, and the Android phone was Samsung Galaxy J5, with Android version of 6.0.1.

For our cryptojacking script construction, using the various parameters learned above, we set up an account on Coinhive to obtain a key that links our “experiment website” to the server. Next, we set up a test website and embedded the code in Listing 1 within the HTML tags of the website. Finally, to measure the usage of resources while running cryptojacking websites, we set up a Selenium-based web browser automation and run cryptojacking websites, for various evaluations. Selenium is a portable web-testing software that mimics actual web browsers [38], [39].

2) CPU Usage: First, we baseline our study to highlight CPU usage as a fingerprint across multiple websites that
employ cryptojacking using the aforementioned configurations and measurement environment. We study the usage of CPU with and without cryptojacking in place. For this experiment, we select four cryptojacking websites. To measure the impact of cryptojacking on CPU usage, we ran those websites in our Selenium environment, for 30 seconds, with JavaScript enabled (thus running the cryptojacking scripts) and disabled (baseline; not running the cryptojacking scripts). We use this test experiment as our control.

Results. We obtained two sets of results for each website, with and without cryptojacking. In Figure 6, we plot four test samples obtained from our experiment to demonstrate the behavior of websites with and without cryptojacking. From those results, we observe that when a website is loaded initially it consumes a significant CPU power (shaded region), in both cases. Once the website is loaded, the CPU consumption decays if the JavaScript is disabled, indicating no cryptojacking. When JavaScript is enabled, the CPU consumption is high, indicating cryptojacking. It can also be observed in Figure 6, that the CPU usage varied across the websites, indicating the usage of the throttling parameter highlighted above. The same behavior as with JavaScript disabled is exhibited when loading a page with JavaScript that is either benign or of other types of maliciousness than cryptojacking. Through this experiment, we found that cryptojacking consumes anywhere between 10 and 20 times the processing power compared to when not using cryptojacking on the same host. To further understand the impact of throttling on CPU usage in different platforms, we conduct another measurement where we used $\alpha = \{0.1, 0.5, 0.9\}$ with the different testing machines. We found a consistent pattern, whereby the relationship between $\alpha$ and the CPU usage is linear, as demonstrated in Figure 7.

3) Battery Usage: Clearly, high CPU usage translates to higher power consumption, and quicker battery drainage. To further investigate how cryptojacking affects battery drainage, we carried out several experiments using various $\alpha$ values for the various platforms. Here we are interested in the order of battery drainage from a baseline, rather than comparing various platforms. The batteries of the different machines are as follows: 65 watt-hour for Windows, 41 watt-hour for Linux and $\approx 9.88\%$ watt-hour for Android.

Results. For each $\alpha \in \{0.1, 0.5, 0.9\}$, and using the different devices, we ran the JavaScript script on a fully charged battery. We logged the battery level every 30 seconds, as the script ran on each device with the given $\alpha$ value, starting from a fully-charged battery. Finally, we measure the baseline by running our script without the cryptojacking code. The results are shown in Figure 8. As expected, with $\alpha = 0.1$, corresponding to the lowest throttling and highest CPU usage, the battery drained very quickly, to $\approx 10\%$ of its capacity within 80 minutes, compared to $\approx 85\%$ within the same time when not using cryptojacking. The same result is demonstrated for both the Linux laptop and Android phone. We also notice that relationship between $\alpha$ and the battery drainage is also linear.

In examining the CPU and battery usage by cryptojacking websites, as shown above, we highlight a clear and unique patterns that can be used to identify those websites. We also notice that the different operating systems do not have any architectural support to prevent activities like cryptojacking from happening on the device.

B. Network Usage and Profiling

Dynamic network-based artifacts are essential in analyzing cryptojacking scripts, especially when those scripts are obfuscated. To this end, we also explore the network-level artifacts to reconstruct the operation of cryptojacking services.

We noticed that during cryptojacking website execution, the JavaScript code establishes a WebSocket connection with a remote server and preforms a bidirectional data transfer. The WebSocket communication can be monitored using traffic analyzers such as Wireshark. However, a major issue when using traffic analyzers is that browsers encrypt the web traffic during WebSocket communication. Although significant information can still be gathered, such as source, destination, payload size, and request timings, the actual data transferred remain encrypted, preventing further analysis. To perform a deeper analysis on WebSocket traffic, we examined the actual data frames in the browser to understand the communication protocol and payload content of WebSocket connection, for possible analysis of cryptojacking websites, outlined below.

When a WebSocket request is initiated, the client sends an auth message to the server along with the user information, including sitekey, type, and user. The length of auth message is 112 bytes. The sitekey parameter is used by the server to identify the actual user who owns the key of the JavaScript and adds balance of hashes to the user’s account. The server then authenticates the request parameters and responds back with authed message. The authed message length is 50 Bytes and it includes a token and the total number of hashes received so far from the client’s machine. In the authed message, the total number of hashes is 0, since the client has not sent any hashes yet. Then, the server sends job message to the client. The job message has a length of 234 Bytes with a job_id, blob, and target. The target is a function of the current difficulty.

Listing 1: Coinhive code found in cryptojacking sites.

```html
<script src='./Welcome_files/coinhive.min.js'></script>
<script>
    var miner = new coinhive.Anonymous("owner key",
    {throttle: 0.1});
    miner.start();
</script>
```
in the cryptocurrency to be mined. The client then computes hashes on the nonce and sends a submit message back to the server, with job_id, nonce, and the resulting hash. The submit message has a payload length of 156 Bytes. In response to the submit message, the server sends hash_accept message with an acknowledgement and the total number of hashes received during the session. The hash_accept message is 48 Bytes long. This is to be noted that once a webpage is refreshed, the WebSocket connection terminated and restarted. On the other hand, if multiple tabs are opened in the same browser, the WebSocket connection remains unaffected. In Table VI, we provide details about the WebSocket connection during a cryptojacking session. In Listing 2, we provide the the actual data frames exchanged between the browser and the server during WebSocket session. The data frames are structured in “JavaScript Object Notation” (JSON).

VI. ECONOMICS OF CRYPTOJACKING

In this section, we evaluate the economic feasibility of cryptojacking by extrapolating on the results in our dynamic analysis. We look at the economic feasibility from the perspective of a cryptojacking website’s owner, intentional cryptojacking, malicious cryptojacking, and website visitors. For cryptojacking, the reward of the website owner or adversary depends on the number of hashes produced while a website visitor visits the website. We formulate the analysis as a feasibility: how much of the energy consumed by cryptojacking scripts (cost) is transferred to the cryptojacking website owner,
Table VII: Results of cryptojacking with different devices. Here $\alpha$ is the throttling parameter, $h$, $\Delta t$, $b_n$, $b_c$, $W$, $P$, and $L$ are the parameters obtained from Equation 8 and Equation 9. $T$ is the estimated time required for each device to mine 1 XMR.

| Device    | $\Delta t$ (mins) | $b_n(\%)$ | $\alpha$ | $h$ (bps) | $b_c (%)$ | $W$ (Watt) | $P$ (USD) | $L$ (USD) | $L-P$ (USD) | $T$ (years) |
|-----------|-------------------|------------|----------|-----------|-----------|------------|------------|------------|-------------|--------------|
| Windows   | 85                | 82         | 0.1      | 21        | 10        | 65         | $6.4 \times 10^{-3}$ | $4.5 \times 10^{-4}$ | $3.8 \times 10^{-4}$ | 50          |
|           | 0.5               | 14         | 19       | 65        | 3.1       | $3.7 \times 10^{-4}$ | $3.4 \times 10^{-4}$ | 104        |
|           | 0.9               | 5          | 57       | 65        | 4.4       | $1.6 \times 10^{-3}$ | $1.5 \times 10^{-3}$ | 367        |
| Linux     | 71                | 70         | 0.1      | 26        | 3         | 41         | $6.6 \times 10^{-3}$ | $5.5 \times 10^{-4}$ | $4.8 \times 10^{-4}$ | 40          |
|           | 0.5               | 16         | 22       | 41        | 4.1       | $4.2 \times 10^{-3}$ | $3.8 \times 10^{-3}$ | 66         |
|           | 0.9               | 5          | 54       | 41        | 1.3       | $2.6 \times 10^{-4}$ | $2.5 \times 10^{-4}$ | 214        |
| Android   | 163               | 76         | 0.1      | 5         | 11        | 9.9        | $2.8 \times 10^{-4}$ | $9.5 \times 10^{-4}$ | $6.7 \times 10^{-4}$ | 224         |
|           | 0.5               | 3          | 32       | 9.9       | $1.7 \times 10^{-4}$ | $7.2 \times 10^{-4}$ | $5.5 \times 10^{-4}$ | 369        |
|           | 0.9               | 2          | 49       | 9.9       | $1.1 \times 10^{-4}$ | $5.4 \times 10^{-4}$ | $4.3 \times 10^{-4}$ | 374        |

whether malicious or benign, and how that translates as an alternative to online advertisement.

A. Analytical Model

To set a stage for our analysis, in Figure 9 we present the results from one sample experiment conducted on Windows i7 machine with cryptojacking website set to minimum throttling ($\alpha$=0.1), indicating a maximum cryptojacking. In this figure, the region between $b_n$ and $b_c$ is a baseline, unrelated to cryptojacking–due to normal operation of the system. On the other hand, the region between $b_n$ and $b_c$ is the battery drainage due to cryptojacking. We refer to the energy loss due to such cryptojacking as $L$ for a given user. To formulate the cost (to users) and benefit (to cryptojacking website), let $P$ be the benefit (profit) during a cryptojacking session of $\Delta t$ minutes, and $h$ be the hash rate of the device in hashes/second. At the time of writing this paper, Coinhive pays 2.894 $\times 10^{-8}$ (XMR; currency unit) for 1 million hashes, where 1 XMR equals $200 USD. Therefore, the profit $P$ in XMR in $\Delta t = t_f - t_s$ ($t_f$ and $t_s$ refer to the finish and start time of a session, respectively) can be computed as:

$$P(\text{XMR}) = (2.894 \times 10^{-8} \times h \times \Delta t) / 10^6$$  (8)

The average hash rate of our test device was 21 hashes/second, and for the time $\Delta t = 85$ minutes from Figure 9, the profit $P$ earned during the session was $3.19 \times 10^{-6}$ XMR or $6.38 \times 10^{-4}$ USD ($1.06 \times 10^{-5}$ USD/second). This is the upper bound of profit that the device can make in one battery charge.

To calculate $L$, corresponding to battery drainage due to cryptojacking ($b_n - b_c$), we first measure the time it takes to recharge 1% of the battery and denote it by $t_r$. Therefore, the time required to recover $b_n - b_c$ can be calculated as $t_r \times (b_n - b_c)$. Let $W$ be the power consumed by the laptop to run for one hour and $C$ be the cost of electricity in USD/KWH. Therefore, the loss $L$ in USD for the use of battery during cryptojacking can be computed using:

$$L(\text{USD}) = C \times W \times t_r \times (b_n - b_c)$$  (9)

For our test device, we had the following parameters: $W = 65$ watt-hour, $C = 6.418 \times 10^{-5}$ USD/(watt-hour), $b_n = 82\%$ (in Figure 9), $b_c = 10\%$ and $t_r = 0.015$ hour. Thus, the estimated loss during cryptojacking session $L$ was $\approx 4.5 \times 10^{-3}$ USD, which is 7 times the value of $P$, highlighting a big gap cryptojacking’s operation model.

Using the same analysis, we examine if cryptojacking can be used as a source of income by users. With the same device as above, the number of hashes required to make 1 XMR

Figure 9: Battery drain sample of Windows i7. Here $b_n$ denotes the starting point of the battery, $b_c$ denotes the normal 80 minutes battery drain without cryptojacking and $b_c$ denotes the battery drain with maximum cryptojacking.

($200 USD) is $3.45 \times 10^{10}$ hashes. Given that the same device generates 21 hashes/second, the time required to make 1 XMR is approximately 52 years, while the energy consumed is many orders of magnitude more costly (note that the calculations here are quite theoretical; to mine 1 XMR, it would take $\approx 321,543$ battery charging cycles, each of which would cost 0.41 cent (total of $\approx 1318$). In Table VII, we report all the results obtained from the experiment for each device used in for our experiments in the dynamic analysis, along with the amount of time required for each device to mine 1 XMR.

B. Cryptojacking and Online Advertisement

In-browser cryptojacking is being argued as an alternative to online advertisement. To understand the soundness of this argument, we performed an experiment to analyze and compare the monetary value of in-browser cryptojacking as a replacement to online advertisements.

We select Alexa’s top 10 websites [40]. For each website, we obtained the average number of visitors and the time they spent on those websites during March 2018. We use this information and our model from section VI-A to measure the potential profit those websites could have made using cryptojacking. We assume that visitors on these websites have the potential profit those websites could have made using cryptojacking.

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Table VIII: Monthly Profit earned by top websites by applying cryptojacking. GR denotes global rank, CR denotes the country rank, visits are in Billions, average time duration of visits is in mm-ss, and P-CJ is profit earned by cryptojacking and P-Ads is revenue earned through ads. “——” denotes the revenue of the companies that we could not find online.

| Website          | GR  | CR  | Visits | Time  | P-CJ  | P-Ads |
|------------------|-----|-----|--------|-------|-------|-------|
| google.com       | 1   | 1   | 47.09  | 07:23 | 2.41 M | 7.94 B |
| youtube.com      | 2   | 2   | 26.22  | 20:05 | 3.65 M | 291 M  |
| baidu.com       | 3   | 3   | 19.08  | 08:56 | 1.18 M | 234 M  |
| wikipedia.org    | 4   | 6   | 6.55   | 03:51 | 0.17 M | 160 M  |
| reddit.com       | 5   | 4   | 1.69   | 10:38 | 0.12 M | —      |
| facebook.com     | 6   | 3   | 29.87  | 13:28 | 2.80 M | 3.3 B  |
| yahoo.com        | 7   | 7   | 5.21   | 06:19 | 0.22 M | 250 M  |
| google.co.in     | 8   | 1   | 5.33   | 07:46 | 0.29 M | 1.1 B  |
| qq.com           | 9   | 2   | 3.66   | 04:02 | 0.10 M | —      |
| taobao.com       | 10  | 3   | 1.73   | 06:25 | 0.08 M | —      |

use those figures to examine the potential of cryptojacking as an advertisement alternative at scale. For that, we first obtain a monthly revenue figure for each website by dividing the annual revenue by 12. We compare those numbers to the cryptojacking alternative highlighted above. The results are shown in Table VIII, where it can be seen that the revenue earned by operating cryptojacking is negligible compared to the revenue earned through online advertisements. For example, if Google is to switch to cryptojacking, it will make $2.41 million USD per month, at most. In contrast, Google earns ≈$7.94 Billion USD monthly from online advertisement.

To estimate the revenue by cryptojacking websites, we conducted the same experiment on the top-10 websites in our dataset and computed the estimated profit earned by them, shown in Table IX. We notice that the maximum profit, earned by firefoxcina.cn is ≈$2,747 USD. Although, the ad revenue for these websites is not available online, we still suspect that $2,747 USD per month is far too low for a website that has 87.24 million monthly views, each with an average duration of 4 minutes and 32 seconds, as compared to the potential revenues for online advertisement. Those findings are in-line with recent reports indicating that an adversary who compromised 5,000 websites and injected his own cryptojacking scripts was only able to make $24 USD [42].

We conclude that in-browser cryptojacking is not a feasible alternative for online advertisement since it generates negligible revenue compared to the existing model. Also, as with most PoW-based systems, the economical analysis of cryptojacking as a model highlights a huge $P$ and $L$ negative gap, making it impractical as a revenue source.

VII. COUNTERMEASURES

In-browser cryptojacking is relatively a new phenomenon therefore, not much attention has been paid to its use, effects and countermeasures. In this section, we will survey the existing countermeasures available at the browser level to prevent cryptojacking. For the existing countermeasures, we will evaluate their usefulness by performing experiments on our test websites. Furthermore, we will point out new directions for effectively countering cryptojacking based on our results and analysis.

A. Existing Countermeasures

At the browser level, existing countermeasures include web extensions such as No Coin, Anti Miner, and No Mining [43], [44], [45]. Each of these web extensions maintains a list of uniform resource locators (URLs) to block while surfing websites. If a user visits a website that is blacklisted by the extension, the user is notified about cryptojacking. However, we show that blacklisting is not an effective technique to counter cryptojacking since an adaptive attacker can always circumvent detection by creating new links that are not found in the public list of blacklisted URLs (proxying).

To further explore that, we set up these extensions on chrome and evaluated them on our cryptojacking test website. All the extensions detected cryptojacking by reading the WebSocket requests generated by website to Coinhive. However, in the next phase, we removed the binding key of our script shown in Listing 1. In the absence of the key the website establishes the WebSocket connection but does not perform cryptojacking as it cannot verify itself with the server without the key. However, when we tested that on the extensions, all of them wrongly signaled the presence of active cryptojacking. Since extension-based blacklisting does not read the data frames exchanged between WebSockets, therefore, even the presence of an outdated key or a broken link is falsely labeled as cryptojacking which highlights a major limitation in the detection approach of the existing countermeasures.

1) Evading Detection: An attacker, knowing the blacklist, can always evade detection by setting his own third party server to relay data to and from cryptojacking server. The cryptojacking website can establish an innocuous WebSocket connection to a third party server and send data frames and keys to the server. Since anti-cryptojacking extensions will not have the address of third party server blacklisted, they will not be able to prevent the connection and cryptojacking. In Figure 10, we show how the current countermeasures for cryptojacking can be circumvented by an adaptive attacker. To practically demonstrate that, we set up a test website using Coinhive script and installed a local relay server. We installed four chrome extensions that block the in-browser cryptojacking, namely No Coin, Anti Miner, No Mining and Mining Blocker. In the first phase of the experiment, we installed the Coinhive script and ran the website. Each extension detected the WebSocket request and blocked it. To mimic an adaptive attacker, we configured our relay server to act as a proxy and receive socket
requests from the browser and relay them to Coinhive server. In the Coinhive script, we modified the code and replaced the Coinhive socket address with our server address. Next, when we visited the website, it started cryptojacking on the client machine and no extension was able to detect it, concluding it is possible to circumvent detection through a relay server.

2) Countering Adaptive Attacker: To counter an adaptive attacker and overcome the limitation of existing countermeasures, a better approach is message-based cryptojacking detection in web extensions. Instead of blocking specific URLs, the extensions can monitor the messages exchanged between the user and the server during cryptojacking session. If the messages follow the sequence of web frames that we have illustrated in Listing 2, the extension can flag them as cryptojacking. This will prevent cryptojacking even if WebSocket requests are relayed through a third party.

To experimentally demonstrate that, we developed a chrome web extension that detects the strings of web frames shown in Listing 2, and notifies the user when the website starts cryptojacking. To test our extension against the existing countermeasures, we deployed a proxy server that relayed the data between our test website to the dropzone server as shown in Figure 10. We installed four chrome extensions that detect cryptojacking: No Coin, Anti Miner, No Mining, and Mining Blocker. Since all of these extensions take a blacklisting approach for detection, they failed to detect cryptojacking in the presence of the relay server. However, when we installed our newly developed web extension, it immediately flagged cryptojacking upon reading the actual data exchanged between the browser and the relay server. Therefore, in our view, the blacklisting approach is insufficient to counter cryptojacking. In contrast, better countermeasures can be developed by deeply inspecting the traffic exchanged between the WebSockets.

B. Long-term Countermeasures

Based on the results of our static and dynamic analysis, a fine-grained detection tool can be built at the browser level to address cryptojacking. As we have observed in (§V), there are features inherent to the code of cryptojacking scripts that distinguish them from malicious and benign scripts. Moreover, the performance of client machine during cryptojacking is unique in comparison to the performance of the device under normal operation. Based on these features, an accurate detection system can be developed that can detect cryptojacking websites during web browsing. These classifiers can be further used by search engines and web crawlers to identify cryptojacking websites and effectively notify the users about them, or plug them in “safe-browsing” lists.

C. Discussion

By showing a huge negative profit/loss gap, we settle the argument that cryptojacking is not a viable alternative for online advertisement at the moment, and with the current cryptocurrency price. Moreover, the associated negative reputation may also be a factor to discourage users from visiting a website that is known to perform cryptojacking on its visitors. To that end, we do not see browser-based cryptojacking transforming into a popular and ethical way of generating revenues for online web service. This conclusion is also supported by the low prevalence of cryptojacking sites among the top websites in the world, as shown in Table IX.

Although the scope of the ethical use of cryptojacking is limited, it is likely that the unethical use may increase as the cryptocurrency market grows and the websites remain vulnerable to JavaScript injection attacks. Cryptojacking might not be a suitable revenue source for web service providers, it however, may still provide lucrative incentives for adversaries who can make “easy money” by compromising vulnerable websites and targeting their visitors. Malicious website owners may combine both cryptojacking and online advertisements to increase their overall revenue from websites.

Results from our dynamic analysis (§V) show that cryptojacking is highly resource intensive, as it causes excessive battery drainage of the target device. As such, cryptojacking attacks can be launched solely to abuse devices of visitors on a specific website, thereby influencing the reputation of the website and its ability to attract users and traffic. Therefore, cryptojacking provides multiple attack avenues for miscreants and we cannot ignore the potential threat of these attacks or their likelihood of becoming more prevalent in the future.

As demonstrated in §VII-A1, the existing countermeasures for cryptojacking, based on the blacklisting approach, can be easily circumvented by using relay servers to proxy cryptojacking payload. With the increasing threat potential, and the limitations of defense mechanisms, there is a need for strong countermeasures in the web community to prevent websites from becoming an attack vector for cryptojacking. Web hosting platforms and ISPs can use the methods outlined in our static analysis (§IV) to keep a check on the spread of cryptojacking code across websites and notify websites’ owners and visitors.

Moreover, as a direct result of our dynamic analysis, we argue that web browsers must shield their users from cryptojacking by analyzing the WebSocket payload (§V) and reporting fraudulent behavior to the users. We provide a direction towards such improved countermeasures by developing a chrome extension that reads cryptojacking payload during WebSocket communications, and notifies the users (§VII-A2). With such collaborative efforts and effective defense mechanisms, cryptojacking can be stalled in its early stages from becoming a major threat in future.

VIII. RELATED WORK

In-browser cryptojacking has gained a lot of attention recently, although not treated with any systematic study that
Covers all major dimensions. In the following, however, we review the related work.

**Cryptojacking:** Concurrent to this work, Rüth et al. [46] (to be published in ACM IMC 2018; Fall 2018) carried out a measurement study to observe the prevalence of cryptojacking among websites. Towards that, they obtained blacklisted URLs from the No Coin (§VII-A) web extension, and mapped them on a large corpus of websites obtained from the Alexa Top 1M list. In total, they found 1491 suspect websites involved in cryptojacking. However, as shown in §VII-A1, blacklisting approach to detect and prevent cryptojacking has major limitations, and may yield insufficient results to accurately measure prevalence. This perhaps explains a smaller size of their dataset (1491 sites) compared to the dataset used in our analysis (5703 sites). Concurrently, Eskandari et al. [47] also looked into the prevalence of cryptojacking among websites and the use of Coinhive as the most popular platform for cryptojacking. Although these two studies, carried out in parallel to ours, highlight the issue of cryptojacking through measurements, and highlight the emerging use of cryptojacking as an alternative to online ads, they, however, stop short of conducting any code analysis towards detection, nor analyzing the economical arguments for cryptojacking as an alternative online ads, two directions which we pursue in detail in this paper.

Tahir et al. [48] studied the abuse of virtual machines in cloud services for mining digital currencies. They used micro-architectural execution patterns and CPU signatures to determine if a virtual machine in cloud was being illegally used for mining purposes, and proposed MineGuard, a tool to detect mining. Bartino and Nayeem [49] highlighted worms in IoT devices which hijacked them for mining purposes, pointing to the infamous Linux.Darloo worm that hijacked devices running Linux on Intelx86 chip architecture for mining [50]. Krishnan et al. [51] studied a series of computer malware, such as TrojanRansom.Win32.Linkup and HKTL_BITCOINMINE, that turned host machines into mining pools. Sari and Kik [52], used Open Source Intelligence (OSINT) to study vulnerabilities in mining pools with Mirai botnet as case study.

**Malicious JavaScript:** Malicious JavaScript code and their impact on web browsers and client machines has been studied. Cova et al. [53] used machine learning techniques to identify anomalous JavaScript code in web applications. Their system also detected obfuscated code, and generated detection signatures for signature-based systems. Classification techniques have been commonly used to detect obfuscated code that appears benign in nature but performs malicious activities [54], [55], [56]. Jovanovic et al. [57] used static analysis involving context-sensitive data-flow analysis to study vulnerable points Web application programs. Vogat et al. [58] used dynamic data tainting and static analysis to counter Cross-site scripting (XSS) attacks involving code injection during application launch. Tzermias et al. [59] combined static and dynamic analysis techniques to detect malicious JavaScript code in vulnerable PDF files. Curtsinger et al. [28] presented a JavaScript malware detection tool called “Zozzle” that used Bayesian classification and abstract syntax tree to identify code elements linked to malware.

**Battery Drain Attacks:** Battery is a useful resource in laptops and smart devices, and recently people using smart phones have outnumbered the people using canonical PCs. As a result, the targeted energy-based attacks on smart phone batteries have increased. Fiore et al. [60] studied the energy-based attacks on smart phones and their effect on the battery drainage. Martin et al. [61] explored three major attacks namely service request power attacks, benign power attacks, and malignant power attacks that can be used to drain the battery of pervasive computing devices. A number of other attacks on battery exhaustion have been discovered in mobile phones and laptops that exacerbate the usage of battery sensitive applications and cause swift battery drain [62], [63].

**IX. Conclusion**

In this paper, we take a systematic look at in-browser cryptojacking through the lenses of characterization, static analysis, dynamic analysis, and economics analysis. In order to that, we collect a dataset of cryptojacking websites and perform static analysis that unveils unique code complexity characteristics and can be used to detect cryptojacking JavaScript code from malicious and benign code samples with an accuracy of more than 96%. We explore, through dynamic analysis, how in-browser cryptojacking uses various resources, such as CPU, battery, and network, and use that knowledge to reconstruct the operation of cryptojacking scripts. We also study the economical feasibility of cryptojacking as an alternative to advertising, highlighting its infeasibility. By surveying prior countermeasures and examining their limitations, we highlight long-term solutions, capitalizing on the insights from our static and dynamic analysis, as well as clustering findings.

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