School of Phish: differentiating phishing pages via browser API usage

Anonymous authors

Abstract

Phishing kits, ready-to-deploy software packages for phishing web-sites, have proliferated the number of web phishing attacks launched daily. Last year alone, the Anti-Phishing Work Group reported over one million phishing pages. This volume presents new challenges for security researchers and analysts, as large quantities of pages employing behaviors of interest (data exfiltration, evasion, or mimicking techniques) can originate from a singular phishing kit while being deployed across different infrastructures throughout the year. At the same time, the whole ecosystem is examined page by page, and manual analysis is required to recognize static features for kit identification. This paper aims to aid researchers and analysts in automatically differentiating between collections of phishing pages from different underlying kits via the browser APIs executed and hierarchical clustering. We show an accuracy of 97% against a dataset of pages and kits collected from the wild. With a curated mapping of techniques to browser APIs and over 500,000 pages in which we identify 11,377 clusters, we explore what techniques are universal, widespread across kits, or kit-specific. Prior work has noted an increased complexity of client-side javascript included in phishing pages; overall, our methods and findings show that browser API usage can leverage this against adversaries to differentiate phishing pages originating from different kits and better understand the breakdown of behaviors in the ecosystem.

1 Introduction (1 page)

Web-based phishing attacks, where a web page, through mimicking or urgency, tricks the user into submitting personal information to an attack, have been increasing for the last 5 years[APWG]. While varying in delivery vectors, sent through email, SMS, or QR codes, they remain a successful attack for compromising individual accounts and enterprises. In 2021, the Cybersecurity and Infrastructure Security Agency (CISA) warned of phishing campaigns targeting NGOs and government workers which smuggled the HTML and Javascript of the phishing page through an attachment[https://www.microsoft.com/en-us/security/blog/2021/05/27/new-sophisticated-email-based-attack-from-nobelium/, https://www.cisa.gov/news-events/cybersecurity-advisories/aa21-148a]. Once an actor steals credentials, they sell them on illicit markets or leverage them to leak more data from the target, for example in 2024, joined with the Multi-State Information Sharing and Analysis Center, CISA reported that compromised former employee credentials were being used to access internal networks within the US government[https://www.cisa.gov/news-events/cybersecurity-advisories/aa24-046a].

Client-side javascript is a keystone in this profitable and effective family of attacks. This highly dynamic language, which has access to privileged functionality through browser APIs, enabled the attacks to obfuscate the true purpose of the web page (HTML/CSS and the javascript code itself) and effectively identify settings when a victim or a potential analysis framework is viewing the web page. [https://developer.mozilla.org/en-US/docs/Web/JavaScript, Crawl-Phish, Spartacus]. The javascript logic can range from a simple user-agent-based redirection to an AES-encrypted script that dynamically decrypts itself, identifying the browser through a series of API calls extracting information about the host's browser capabilities. The ability to distill information about the user via the browser's capabilities is referred to as browser fingerprinting. Prior work has studied it in both phishing and web-based advertising settings.

The Anti-Phishing Work Group (APWG) has reported over 1 million phishing attacks yearly since 2020. With the ecosystem full of pages, with Javascript reaching browser APIs to mimic the target page, cloak away from analysts, and exfiltrate data, we propose using browser API traces from these pages to study them at a layer of abstraction. kit We have crawled five phishing feeds for 401 days to answer the following research questions.

RQ1. **How indicative is a page's browser API trace of the underlying phishing kit? What differences do we see between the kits?** Having collected 4,448 pages from 526 distinct kits, we find that clustering based on the distance of browser APIs used is enough to identify if two pages share a kit behind the scenes, achieving an accuracy of 92% based on Fowlkes−Mallows index.

RQ2. **What does the clustering of all phishing pages collected look like?** By computing the density based cluster of these pages for a 4-week window, rolling it by 2 weeks, and merging these clusters by threshold of common pages, we get 27,833 total cluster for the span of 401 days. These clusters are very well formed with a silhouette score of 0.83 ($\sigma = 0.04$).

RQ3. **How are browser APIs being used in phishing? How are different techniques spread across clusters?** We find that 1.2 million pages (83%) of pages we observe execute JavaScript in a first-party context. We find no more then 15% use an obfuscation related browser API. We check API usage of techniques established by prior work and find a decrease in user-interactive permission pop-ups. We do see

that 1 in 3 pages calling out to a basic fingerprinting property (userAgent, cookie, or HTTP referrer). We observer that 1 in 4 pages makes a network request upon loading, some reaching out to IP identification URLs which allow free look-ups for the requesting machine, in this case that being the victims browser.

The rest of the paper will breakdown the necessary background regarding the phishing ecosystem and adversarial techniques, we will go over relevant work in studying the ecosystem in Section- 3. We will describe the methods we used to study the ecosystem in Section- 4 and go over what we found in Section- 5.

2   Background (1.5-2 pages)

In this section we provide a helpful background on current developments in phishing as a phenomenon and adverserial javascript techniques, as well as an overview of the parties involved in the phishing ecosyste.

2.1   Phishing as a phenomenon

Phishing is a form of social engineering where an adversary pretends to be a trusted entity to steal a user's credentials or gain access to a specific machine, network, or account to which the user has access. While delivery mechanisms vary, the most common way of phishing inevitably leads to a web page that requests some personal information (usually credentials) from the user.

While a basic phishing site is relatively simple to deploy and send through social media or email, the ecosystem has proven to be an ever-changing landscape. Workgroups tracking phishing saw an uptick in phishing domains in 202X, with a shift in what sectors are targeted throughout every year. In Q3 of 2020, the APWG reported SAAS and webmail services as the most targeted sectors, with 31% of all phishing attacks targeting them. In Q3 of 2021 it was the financial sector and in 2024 it is Social media[1]. In the 3rd quarter of 2024, the Anti-Phishing Working Group (APWG) reported 900,000 phishing attacks. Besides detection, to be able to identify trends in the ecosystem, security researchers need to be able to group a large number of pages through a higher level of abstraction.

As more organizations and academics turn to studying phishing websites and develop methods of trying to identify them, anti-analysis and anti-bot detection techniques have emerged in the ecosystem. These are no different from anti-debugging techniques found in malware; the end goal is to make detection and analysis of the page as tricky as possible. These techniques can be broadly classified into server-side and client-side techniques. Server-side techniques are stealthier; however, they rely on limited information. These can be studied by getting your hands on a zip bundle to set up the page (sometimes called a phishing kit). Most server-side techniques rely on pre-compiled denylists or allowlists of IP addresses, user agents, or referrers (the page from which the link is visited as identified by an HTTP header). The cloaking outcome can also vary; the page can redirect to a benign page, a long-dead phishing page, or send you off to an affiliate marketing page. Some pages may be simple checkpoints and choose to forward you to the actual phishing page should they decide you are not an analyst or a bot.

Client-side techniques, while allowing for much richer evasive behavior, are more detectable via instrumented tools. With the rise of fingerprinting on the web, driven by tracking scripts of advertisers and analytics companies, phishing pages turned to using browser fingerprinting APIs to identify real users and exfiltrating the fingerprinting to associate with the credentials harvested. Phishing pages utilize Browser APIs to trigger permission pop-ups to identify headless browsers (without a user interface usually used for crawling) and automated crawlers that can not interact with the full browser UI. Prior work has also identified captchas and click-through pages as a form of client-side cloaking, which requires more sophisticated crawlers to combat.

Even URL features of a phishing link contain techniques that have evolved to respond to anti-phishing research. Phishing pages frequently use URL shorteners (public or private) to obfuscate the final destination, landing pages requiring a user to follow hyperlinks to the actual page, and free web hostings with trustworthy TLDs.

2.2   Phishing as an ecosystem

As an ecosystem, phishing attacks have two major branches: cyber-crime as a service and credential sales. While you could develop a phishing page, set up hosting for it, adapt the latest cloaking techniques to your page, deliver the page through SMS, Email, or social media, and leverage the accounts for the financial game, the ecosystem as a whole has compartmentalized these into different segments. Phishing kits (bundles of software providing ready-to-deploy phishing pages) rose in popularity in illicit markets, varying in value, sophistication, and features. One stage higher from just selling kits is Phishing-as-a-service providers, which will do the majority of the technical challenges. Both of these enable massive phishing attacks with lower technical barriers to entry, so naturally, they attracted the attention of researchers and analysis studies. Prior work has shown that phishing kits are not above stealing from their costumers [11, 29], adapt and borrow features from others [18], and sometimes are tied to specific actors [3].

The credential sales part of the ecosystem has also adapted to modern MFA/2FA practices. With prior work showing that a browser fingerprint is sometimes enough to trick their protections[25], an actual cost is associated with executing javascript on the phishing page[42], as accounts with a browser fingerprint go for a higher value on elicit markets. While phishing pages can risk storing the credentials on servers that can be taken down, some have shown that they should be sent to chat channels for ingestion.

2.3   Adversarial JavaScript

The dynamic nature of javascript enables a variety of techniques for concealing from analysis and detection. Javascript obfuscation can transform a known malicious sample into an undetectable one. WebPack enables bundling benign and malicious scripts and wrangling them to make static analysis harder. The other side of obfuscation is evasions; while not nearly there to make code comprehension (via human or machine) harder, malicious actors have deployed time bombs, offloading parts of the malicious script to be read from the DOM or via a network request, and dynamic code generation to evade revealing the entire malicious behavior and thus detection.[38]

The research community has tried tacking these techniques by

developing deobfuscators, employing machine learning techniques from static features to identify similarities between known malicious and unknown samples, and developing force-execution engines, executing parts of the code that may trigger the malicious behavior or the next stage of an evasion.

3 Related Work

3.1 Phishing

Phishing detection: There is a wealth of research on phishing detection as the tug-of-war between adversaries and security professionals continues. Recently, Liu *et al.* and Abdelnabi *et al.* have deployed vison-based techniques to detect phishing pages [4, 27, 28]. [28] also presents over 6,000 phishing kits analyzed as part of the work. With adversarial attacks ensuring that the page looks different to crawlers and analysis, some have turned to extracting features from the URLs themselves, more recently via LLMs in [9, 20] and before via statistical models and machine learning in [22, 40, 45, 51]

Studying and combating adversarial techniques: Divakaran *et al.* in [12] reaffirms the need to keep up with the latest adversarial techniques to build detection systems for phishing better. Prominent work in this area includes [52] by Zhang *et al.*, which uncovered and categorized many novel client-side techniques by force executing phishing pages to trigger the cloaking behavior. Acharya *et al.* in [5] uncovered that phishing pages can successfully evade blocklists by knowing how to identify their crawlers, and Oest *et al.* in [33] demonstrated that cloaking from non-mobile based devices as a phishing page can ensure that your page goes unmarked by the blocklists for more than 48 hours.

Kondracki *et al.* in [21] uncovered a massive blindspot of the phishing detection ecosystem that was Man-in-the-middle phishing kits. Kits that would transparently forward your connection to the target page, mimicking brand logos on pages like Outlook without any configuration. Fortunately, the authors addressed the blindspot by demonstrating that these proxies remain fingerprintable using TLS fingerprinting. [50] proposed a similar attack, however, one that used javascript and NoVNC to trick the user into signing into their account through a VNC session in their browser.

With adversaries becoming creative with their evasions and obfuscation techniques, some novel defenses have also opted to think outside the box. Zhang *et al.* in [53] proposed a phishing defense solution that leverages the high likelihood of a phishing page cloaking away from a crawler to the defender's advantage. They demonstrated that a web browser configured to look like a crawler will trigger a cloaking response from phishing pages, ensuring that your users never see the page while maintaining compatibility with all of Alexa's Top One Million websites. Meanwhile, to combat phishing pages using captcha's [48] utilized vision-based models.

To better understand why, other than cloaking, phishing pages may choose to fingerprint, Lin *et al.* in [26] showed that browser fingerprints could be successfully used to bypass multi-factor authentication, a system meant to be a last line of defense against stolen credentials, for 10 out of 16 websites that provide popular services.

Phishing kits: Much can be studied about the phishing ecosystem via phishing kits. Cova *et al.* in [11] uncovered that most "free"

phishing kits contain a backdoor, effectively serving as a way to offload the deployment of a campaign to a 3rd party while siphoning off their stolen credentials.

Similar to our goals, [8] using a dataset of phishing kits gathered through **Kitphishr** and a collection of features extracted from the HTML DOM to classify websites into their matching kit. They achieved an F1 score 91 when classifying 2,000 pages (1,141 benign and 859) from features extracted from their kit. However, their multi-class classifier for identifying the kit only achieved an F1 score of 39. Merlo *et al.* in [30] further expanded on our understanding of phishing kit lineages by looking at over 20,000 phishing kits and identifying, via token similarity, most of them as clones of one another or previously encountered kits. Prominent work in extending our understanding of phishing attacks includes Han *et al.* in [17], where they monitor the deployment of phishing kits by adversaries that compromise vulnerable web servers by hosting a well-sandboxed honeypot. They collected 643 phishing kits and established that kits take minutes to install and test and can remain undetected for weeks. Using these kits, they were also able to identify evasion techniques used by these kits, like path randomization per visit, which back then was enough to bypass Google SafeBrowsing.

In [34], Oest *et al.* manually analyzed phishing kits to establish the taxonomy for server-side Cloaking, and in [7], Bijmans *et al.*, after collecting phishing kits by watching TLS transparency logs to identify Dutch brank phishing domains, manually creates a fingerprint from static features to analyze their prevalence in the wild.

More recently, Lee *et al.* in [23] provides a server-side script (PHP) level analysis of phishing kits, finding that dynamic generated URLs are still standard in the ecosystem and seeing seasonality in the kits they were able to obtain.

Extending the understanding of the phishing ecosystem:

Like our methods, Rola *et al.* in [42] deploy a modified Chromium browser to study a pre-selected browser API list on phishing websites for first and third-party scripts. They find that most of the most visited phishing pages (identified via browser telemetry data) deploy fingerprinting scripts, sometimes varying from the ones of the original brand they portray. At the same time, they accessed this at a script level, which reinforced our finding that phishing pages vary vastly from their original page.

Oest *et al.* in [35] demonstrates the full lifecycle of a phishing campaign by employing the fact that phishing pages often copy assets from the target domain and refer the victim back to the original page afterward. By collaborating with a significant financial institution, they developed a framework for leveraging this data to track a phishing page from its deployment to blocklists flagging the page as phishing. [35] observed all techniques highlighted by prior work, Cloaking, user-specific URL generation, Man-in-the-middle proxies, and short-lived bursty attacks. Expanding our understanding of the victim experience on a phishing website, Subramani *et al.* in [47] developed a crawler.

3.2 Dynamic analysis of web pages

This work shares methodology to dynamic analysis enabled by web measurement frameworks like OpenWPM[13] and VisibleV8[19].

Su *et al.* used VisibleV8 traces and taint analysis in [46] to discover emerging fingerprinting techniques. Sarker *et al.* used VisibleV8 to create an oracle for detecting obfuscation in [43]. Such an oracle was made possible by the observation that VisibleV8 marks the execution of an API at a given source line, At the same time, obfuscation techniques ensure that the API is not textually available there. And Pantelaios *et al.* in [38] used a combination of VisisbleV8 and force execution modifications to the chromium engine to identify and defeat javascript evasion techniques while also leveraging API traces and clustering to identify previously unlabeled malicious extensions.

4 Methodology (1 page)

This paper aims to study the evolution of browser API usage in phishing pages and leverage execution traces of these pages to identify which ones share an underlying kit. To accomplish this, we require browser API execution trances from phishing pages over a long period and a subset of pages where we know the underlying phishing kit. In the following section, we describe the experimental setup for gathering this data, the steps we took to aggregate and enrich the execution traces, how we identified anomalies and trends, and finally, the steps we took for clustering the data and evaluating them as an analog for phishing kits. A full overview of our crawling and analysis pipeline can be seen in 1.

4.1 Data Gathering

URL feeds: We gathered phishing pages from a diverse set of phishing feeds, monitoring OpenPhish[37], PhishTank[10], URLScan[44], SMS Gateways[32], PhishDB[31], and APWG[6], based on the availability of the feed and the level access we had at the time. Every hour, we checked these feeds for new urls (limited to the last 48 hours) and submitted them into two different crawlers: VisibleV8 and KitPhished.

VisibleV8: To get execution traces for every script loaded when visiting the page, we used an automated chromium-based crawler with VisibleV8 patches applied. The browser is being automated to visit the page and take screenshots with puppeteer[16], an NPM package by Google to help in UI/UX testing and browser automation. The patched chromium crawler uses puppeteer-stealth, a set of configurations to help mask the headless chrome and puppeteer itself from detection tools[36]. We initiated the crawls from a university network designated for research purposes and used Catapult[15], a man-in-the-middle proxy, to capture the entire HTTP archive for replayability. The crawler stays on the page for 45 seconds before taking a screenshot to allow scripts to load and start executing; this is consistent with prior work[13, 19].

KitPhisher: While not guaranteed, some malicious actors leave the zip files of the kits used in a discoverable folder on the same server that hosts the website (for example, the Apache document root). KitPhisher[2] is a go-based URL fuzzer that attempts to identify any left-over zip files on the server. Prior work[27, 34] establishes it as an excellent way to collect and analyze phishing kits. If it is successful, it will download the zip file and make a note of the domain from which kitphishr acquired it.

Brand's Original page: OpenPhish and APWG's eCrime Exchange report the brand that a phishing page targets. We selected 10 out of the top 100 brands targeted and collected VisisbleV8 logs for their home pages and, when applicable, their login pages. This is to assess how similar phishing pages are to their target pages. Lin *et al.* in [25] identified that phishing pages could effectively use browser fingerprints to bypass multi-factor authentication, and [42] found that phishing pages deploy a plethora of 3rd party fingerprinting scripts, which differ from the scripts of the original page, what is the simularity between browser API usage between the target brand's page, and the phishing counterpart.

4.2 Data enrichment and De-duplication

4.2.1 Enriching browser API executions. **Browser APIs and property accesses**: VisibleV8 has a default log-postprocessor set. These programs take the raw lags generated by the patched Chromium browser and convert it into an organized database, identifying duplicate scripts via sha3 hash, clearly marking the origin of each script that loaded and isolating which javascript API calls are browser API calls defined in the WebIDL file[1] generated during the while building the patched chromium. For our analysis, we use a tuple of the original page's URL, the script's URL, and a set (unordered) of APIs executed by this script.

First party API sets: To cut through the noise of cloaked pages and include third-party scripts like Google Analytics, known to be present in phishing pages[24], we isolate API sets executed by first-party scripts (from now on called first-party API sets). To do this, we establish the root domain as the domain submitted to the feeds and the origin as the domain from which the script is loaded. We consider a script first-party only if loaded from the domain we acquired from our feeds (root domain).

Browser APIs of interest: Even focusing on APIs that WebIDL marks, the total number of browser APIs exceeds 15,000 (depending in how you choose to categories inherited functions). We leverage Mozila Developer's network 150 WebAPIs categories when aggregating all the APIs used. MDN will mark which specification's (for example Web Crypto, Fetch, or HTML DOM) modify the implementation of a given method call, constructor, or property access. This can result in 'Window.fetch' falling both under 'HTML DOM', 'Fetch API', 'Streams API', and 'Attribution Reporting API'. To resolve this, we take in the ≈ 500 APIs that have multiple mappings and resolve them into a single category based on our prior knowlage of browser functionality.

However, we also look at prior work by Su *et al.* and Zhang *et al.* for categories of Browser APIs for fingerprinting and general cloaking, respectively. We use MDN's documentation to identify a list of 22 APIs that trigger a permission pop-up or validate permission. We should note that while *Permissions.query* is the only way to verify permissions, different WebAPIs like USB, clipboard, Geolocation, and Notification have their different APIs for requesting the pop-up

De-duplicating kit files: We crawl the URLs with KitPhisher to establish a ground truth dataset with URLs originating from the same kit. For zip files extracted via KitPhisher that have password-based encryption enabled, we use the SHA256 hash of the zip files to identify which domains yielded the same kit. For the remaining zip files, we further de-duplicate them into Kit-Families by looking at

---

[1]https://developer.mozilla.org/en-US/docs/Glossary/WebIDL
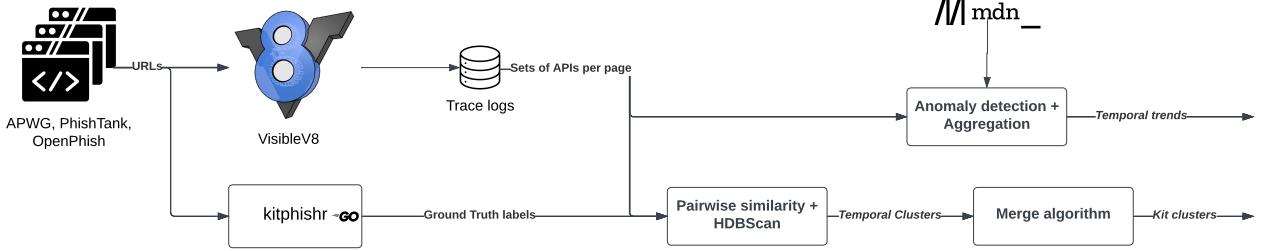
Figure 1: Crawling and Data enrichment infrastructure

Table 1: Manual criteria to identify cloaking behavior established by Zhang *et al.*

Cloaking Category	Required API calls
User Interaction	Any permission requesting API call
	FilePicker API calls
	HTMLElement event listeners
Fingerprinting	HTMLDocument.cookie
	HTMLDocument.referrer
	Navigator.userAgent
Bot Behavior	Crypto.getRandomBytes[3]
	Window.setTimeout + Performance.now

them as a set of SHA256 of source files[2]. If the Jaccard index-based similarity ($JI(A, B) = \frac{|A \cap B|}{|A \cup B|}$) of these sets is equal to or greater than 90%, we consider the two kits to be from the same family, and thus group all domains from both kits into the same group.

Adjusting for Cloudflare:: We find a high number of anomalies originate from cloudflare scripts on the same domain as the phishing pages. Since cloudflare scripts load from a url with a **'cdn-cgi'** in the url, for most of our analysis we do not consider scripts loaded from that endpoint. We however, do discuss the behaviors we were able to see from these scripts in Section- 5.

4.3 Identifying trends

Identifying anomalies: We use rapture[49] to detect change points in the time series of API calls. We use a linearly penalized segmentation algorithm (PELT), which combines a penalty parameter β and a cost function to quickly partition a time series based on points where it detects the series starts to change. For the cost function, we use **L1Cost**, which uses a deviation in the mean, and for the penalty parameter, we use $\beta = 2 \ln (n) = 12$ where n is the number of days in the timeseries. This aligns with the recommendation of Killick*et al.* in the paper introducing PELT to minimize the Bayesian information criterion. We normalize by our daily URLs ingested and look at a time series of the percentage of daily URLs that executed the given URL. To clear up the results from rapture,

we look at the change in the mean between segments. Any chance being less than 1%, we ignore and merge with the prior segment.

Identifying different traces from the same script: VisibleV8 will de-duplicate the same script loaded by multiple pages via the sha3 hash of the script. To establish if scripts have non-deterministic behavior, we pull the set of APIs executed by the script and compare the set of APIs executed by the same script on different pages. We use the Jaccard index to establish the similarity between the sets of APIs.

4.4 Identifying kits

We hypothesize that similarity in browser API execution means that the pages originate from the same phishing kit. We use the Jaccard index on the API sets that first-party scripts execute to establish this similarity. We use HDBScan, with a minimum cluster size of 10, to cluster the pages based on the Jaccard index. We then use the ground truth labels from KitPhisher to evaluate the clustering. When ground truth is available, we evaluate the clustering using the Fowlkes-Mallows Index (geometric mean between precision and recall)[14] and V-measure.

V-measure is a harmonic mean between completeness (all members in a cluster are from the right class) and homogeneity (all members in a cluster are from the same class). V-measure allows tuning a ratio β that prioritizes the score towards one vs the other. More importantly, looking at completeness and homogeneity scores lets you see how your clustering approach is getting things wrong[41]. We use sklearn's measure module to calculate all cluster evaluation metrics.[39].

For the much larger set of pages for which we do not have kit labels, we use silhouette score[4], a metric relative to how well packed and separated the clusters are, to evaluate the clustering when we do not have ground truth. As this would require clustering a total of more than 800,000 pages, we instead cluster a rolling window of 4 weeks, that we slide by 2 weeks. We then merge these temporal clusters if two clusters from different timezones have at least five common pages (same as our minimum parameter for HDBSCAN).

---

[2]Source files identified via libmagic

[4]While this metric is biased against non-convex clusters, based on our results, we do not see it necessary to switch to a density-specific cluster metric

5 Results (3-4 pages)

In this section, we will evaluate our clustering approach against the ground truth, inspect the distribution of ground truth pages in the final clusters, and report temporal patterns and the commonality of phishing behaviors across those clusters. In total, we crawled for 439 days collecting browser traces from 1,328,917 pages, out of which only 533,514 qualified for clustering by executing at least 8 APIs and 434,050 pages were not sorted by HDBSCAN into a cluster with no common APIs or placed as noise.

5.1 Cluster evaluation
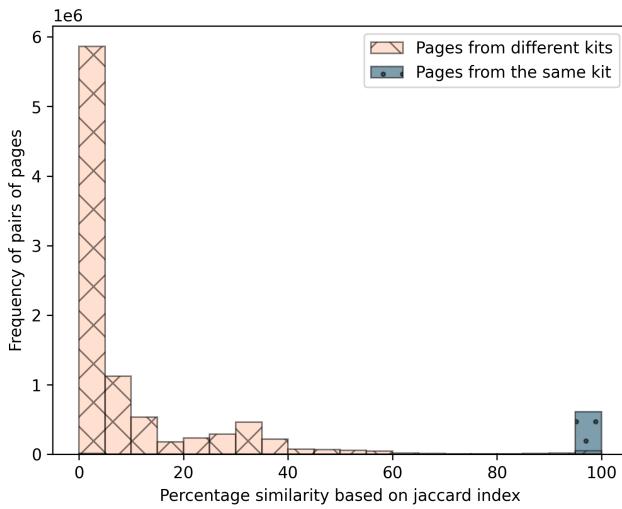
Figure 2: Histogram of the Jaccard index based simularity between any pair of pages belonging to the same kit, versus from different kits

Finding 1: *Pages from different kits employ vastly different APIs.* Figure- 2 shows the distribution of Jecard-based similarity between pages from the same kit versus different kits. We observe that while most pages with the same kit, as identified by KitPhisher, have around 90-100% similarity, pages from different kits, even ones with similar themes, rarely exceed 60% similarity. We leverage this in our clustering by treating $1 - JI(A, B)$ as a distance kernel of two pages.

Finding 2: *Browser API usage unique identify phishing kits apart from eachother.* Clustering pages from 4,448 pages across 521 kits, yeild 349. Evaluating these clusters against the ground truth labels for each page, we find that our clusters have an FMI-based accuracy of 0.93. The clusters have a V-Score of 0.86, which increases with a higher β, meaning the clusters tend to combine two kits into one instead of splitting pages from the same kit across multiple clusters.

Finding 3: *DOM APIs and property accesses play an essential role in identifying the underlying kit.* With 17,753 number browser APIs, feature reduction becomes an obvious goal. However, removing DOM-related APIs, or property reads, out of consideration drastically reduces the number of pages we can consider for ground truth evaluation, not increasing our overall accuracy. Evaluated our

same methodology described in Section- 4 with all HTML-DOM, SVG, and CSS APIs removed and observed FMI-based accuracy of 0.93 and V-Score of 0.86. When all property reads were removed (often used in finterprinting[Junhua]), we saw FMI and V-Score of 0.93 and 0.85, respectively. In both cases, we can cluster fewer pages and thus identify fewer kits.

Finding 4: *Clustering large quantities of phishing pages, based on their browser APIs, keeps pages deployed via the same kit together.* Pages with ground truth labels for originating kits remain appropriately sorted out in the clustering of the 434,050 pages, as out of the 3,505 pages clustered within the larger clusters, we maintain an FMI of 0.948 and a V-Score of 0.889, respectively. Manually inspecting the clusters, we observe that these clusters unique pages across deployment types (AWS, Cloudflare, DigitalOcean, etc.) and languages. For example, Cluster-e325887b comprises 487 pages across 5 unique tldr and contains pages engaging in voice-based phishing attacks (tech support scams) across Japanese, English, and German, varying phone numbers and errors in each. With over 400 APIs in common, it is clear that these pages' usage of keyboard intercepting APIs, Audio APIs, and Network APIs for IP intelligence caused the cluster to be formed.

5.2 Temporal patterns of clusters

With 11,377 clusters, we observe 4 temporal patterns: constant, abrupt, seasonal, and re-emergant.
Finding 5: .

5.3 Phishing Techniques across clusters

6 Discussion (1 page)

6.1 Why clusters?

6.2 Dynamic analysis combat evasions

7 Limitations and Future Work (.5 page)

7.1 Bias sampling

While most phishing pages have been shown to race the clock against being listed on a blocklist eventually, prior work has shown that these blocklists can have blind spots. Prior work has also shown a bias towards certain targets in different feeds[Citation needed]. While we follow best practices in diversifying our sources for phishing pages,

7.2 Limited Kit sophistication

The phishing kits in this paper were collected using KitPhishr; while this has been done in prior research, this requires a misconfiguration on the side of the deployer, thus the bias towards PHP, as it is relatively easy to miss-configure apache to allow downloading of the zip file if it is placed in the document root. However, modern backend web technologies, like ExpressJS, Flask, and even Go's built-in HTTP server, would nullify this weakness. The dataset of diverse phishing kits is hard to come by. It could only be obtained through gaining trust in communities where they are freely shared (i.e., Telegram groups, forums, or LinkedIn), direct purchasing, or honeypot setup similar to [17] but one that would enable deployment of any kits.

(a) Page variant in English

(b) Page variant in Japanese
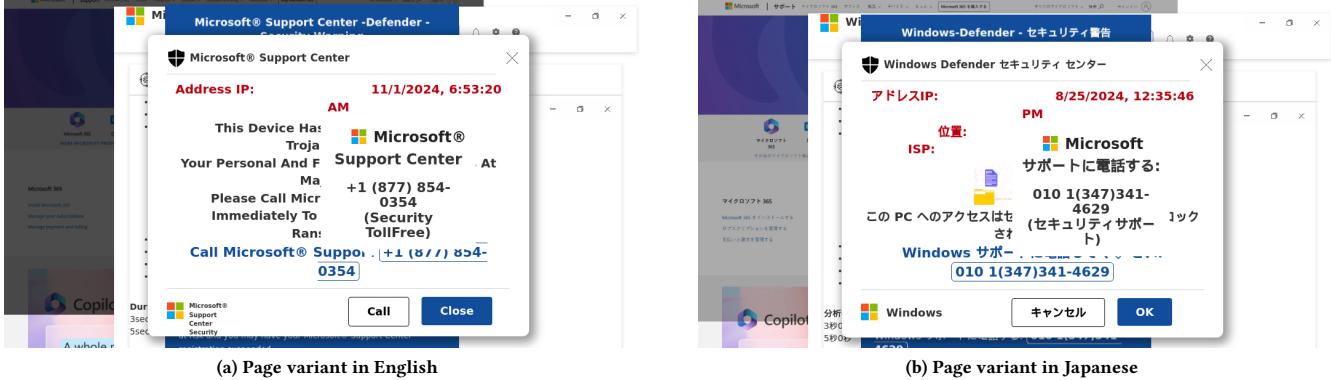
Figure 3: Cropped screenshots from Cluster-e325887b, IP addresses and location redacted to ensure anonymity of the authors.

7.3 Dataflow analysis

To avoid overfitting some pages and scripts, we look at overall sets of APIs used by phishing pages. However, future work can leverage ObjectID tags from VisibleV8 logs to effectively track the flow of some information between different browser APIs. Adding support for basic ES6 functions into VisibleV8 can also provide an avenue to identify complex client-side cloaking mechanisms, like setting a chain of timeouts and event handlers, and using the race condition as a trigger mechanism for redirection in an obfuscation-resilient way.

8 Conclusion (.25 page)

References

[1] APWG | Phishing Activity Trends Reports. https://apwg.org/trendsreports/.

[2] cybercdh/kitphishr: A tool designed to hunt for phishing kit source code.

[3] Unit 42. Threat Actor Groups Tracked by Palo Alto Networks Unit 42, June 2024.

[4] Sahar Abdelnabi, Katharina Krombholz, and Mario Fritz. VisualPhishNet: Zero-day phishing website detection by visual similarity. In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, CCS '20, pages 1681–1698. Association for Computing Machinery.

[5] Bhupendra Acharya and Phani Vadrevu. {PhishPrint}: Evading phishing detection crawlers by prior profiling. pages 3775–3792.

[6] Anti-Phishing Working Group (APWG). eCrime Exchange (eCX). https://apwg.org/, 2025.

[7] Hugo Bijmans, Tim Booij, Anneke Schwedersky, Aria Nedgabat, and Rolf van Wegberg. Catching phishers by their bait: Investigating the dutch phishing landscape through phishing kit detection. pages 3757–3774.

[8] Felipe Castaño, Eduardo Fidalgo Fernández, Rocío Alaiz-Rodríguez, and Enrique Alegre. PhiKitA: Phishing kit attacks dataset for phishing websites identification. 11:40779–40789. Conference Name: IEEE Access.

[9] Daiki Chiba, Hiroki Nakano, and Takashi Koide. Domainlynx: Leveraging large language models for enhanced domain squatting detection. *ArXiv*, abs/2410.02095, 2024.

[10] Cisco Talos Intelligence Group (Talos). Phishtank. https://phishtank.org/, 2025.

[11] Marco Cova, Christopher Kruegel, and Giovanni Vigna. There is no free phish: an analysis of "free" and live phishing kits. In *Proceedings of the 2nd Conference on USENIX Workshop on Offensive Technologies*, WOOT'08, USA, 2008. USENIX Association.

[12] Dinil Mon Divakaran and Adam Oest. Phishing Detection Leveraging Machine Learning and Deep Learning: A Review. *IEEE Security & Privacy*, 20(5):86–95, September 2022.

[13] Steven Englehardt and Arvind Narayanan. Online tracking: A 1-million-site measurement and analysis. In *Proceedings of ACM CCS 2016*, 2016.

[14] Edward B Fowlkes and Colin L Mallows. A method for comparing two hierarchical clusterings. *Journal of the American statistical association*, 78(383):553–569, 1983.

[15] Google Inc. Catapult. https://chromium.googlesource.com/catapult/, 2025.

[16] Google Inc. Puppeteer. https://pptr.dev/, 2025.

[17] Xiao Han, Nizar Kheir, and Davide Balzarotti. PhishEye: Live Monitoring of Sandboxed Phishing Kits. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, CCS '16, pages 1402–1413, New York, NY, USA, October 2016. Association for Computing Machinery.

[18] Microsoft Threat Intelligence. Franken-phish: TodayZoo built from other phishing kits. https://www.microsoft.com/en-us/security/blog/2021/10/21/franken-phish-todayzoo-built-from-other-phishing-kits/, October 2021.

[19] Jordan Jueckstock and Alexandros Kapravelos. VisibleV8: In-browser Monitoring of JavaScript in the Wild. In *Proceedings of the ACM Internet Measurement Conference (IMC)*, 2019.

[20] Koide, Takashi and Fukushi, Naoki and Nakano, Hiroki and Chiba, Daiki. Phishreplicant: A language model-based approach to detect generated squatting domain names. In *Proceedings of the 39th Annual Computer Security Applications Conference*, ACSAC '23, page 1–13, New York, NY, USA, 2023. Association for Computing Machinery.

[21] Brian Kondracki, Babak Amin Azad, Oleksii Starov, and Nick Nikiforakis. Catching Transparent Phish: Analyzing and Detecting MITM Phishing Toolkits. In *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*, CCS '21, pages 36–50, New York, NY, USA, November 2021. Association for Computing Machinery.

[22] Hung Le, Quang Pham, Doyen Sahoo, and Steven C. H. Hoi. Urlnet: Learning a url representation with deep learning for malicious url detection. *ArXiv*, abs/1802.03162, 2018.

[23] Woonghee Lee, Junbeom Hur, and Doowon Kim. Beneath the phishing scripts: A script-level analysis of phishing kits and their impact on real-world phishing websites. In *Proceedings of the 19th ACM Asia Conference on Computer and Communications Security*, pages 856–872. ACM.

[24] Kyungchan Lim, Jaehwan Park, and Doowon Kim. Phishing vs. legit: Comparative analysis of client-side resources of phishing and target brand websites. In *Proceedings of the ACM Web Conference 2024*, WWW '24, New York, NY, USA, 2024. Association for Computing Machinery.

[25] Xu Lin, Panagiotis Ilia, Saumya Solanki, and Jason Polakis. Phish in sheep's clothing: Exploring the authentication pitfalls of browser fingerprinting. pages 1651–1668.

[26] Xu Lin, Panagiotis Ilia, Saumya Solanki, and Jason Polakis. Phish in Sheep's Clothing: Exploring the Authentication Pitfalls of Browser Fingerprinting. pages 1651–1668.

[27] Ruofan Liu, Yun Lin, Xianglin Yang, Siang Hwee Ng, Dinil Mon Divakaran, and Jin Song Dong. Inferring phishing intention via webpage appearance and dynamics: A deep vision based approach. pages 1633–1650.

[28] Ruofan Liu, Yun Lin, Yifan Zhang, Penn Han Lee, and Jin Song Dong. Knowledge expansion and counterfactual interaction for {Reference-Based} phishing detection. pages 4139–4156.

[29] Heather McCalley, Brad Wardman, and Gary Warner. Analysis of Back-Doored Phishing Kits. In Gilbert Peterson and Sujeet Shenoi, editors, *Advances in Digital Forensics VII*, pages 155–168, Berlin, Heidelberg, 2011. Springer.

[30] Ettore Merlo, Mathieu Margier, Guy-Vincent Jourdan, and Iosif-Viorel Onut. Phishing kits source code similarity distribution: A case study. In *2022 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER)*, pages 983–994. ISSN: 1534-5351.

[31] Mitchell Krog and Nissar Chababy. PhishingDB. https://github.com/Phishing-Database/Phishing.Database, 2025.

[32] Aleksandr Nahapetyan, Sathvik Prasad, Kevin Childs, Adam Oest, Yeganeh Ladwig, Alexandros Kapravelos, and Bradley Reaves. On sms phishing tactics and infrastructure. In *2024 IEEE Symposium on Security and Privacy (SP)*, pages

169–169. IEEE Computer Society, 2024.

[33] Adam Oest, Yeganeh Safaei, Adam Doupe, Gail-Joon Ahn, Brad Wardman, and Kevin Tyers. PhishFarm: A Scalable Framework for Measuring the Effectiveness of Evasion Techniques against Browser Phishing Blacklists. In *2019 IEEE Symposium on Security and Privacy (SP)*, pages 1344–1361, San Francisco, CA, USA, May 2019. IEEE.

[34] Adam Oest, Yeganeh Safei, Adam Doupé, Gail-Joon Ahn, Brad Wardman, and Gary Warner. Inside a phisher's mind: Understanding the anti-phishing ecosystem through phishing kit analysis. In *2018 APWG Symposium on Electronic Crime Research (eCrime)*, pages 1–12. ISSN: 2159-1245.

[35] Adam Oest, Penghui Zhang, Eric Nunes, Jakub Burgis, Ali Zand, Kurt Thomas, and Adam Doupé. Sunrise to sunset: Analyzing the end-to-end life cycle and effectiveness of phishing attacks at scale.

[36] Berstend on Github. Puppeteer stealth plugin. https://www.npmjs.com/package/puppeteer-extra-plugin-stealth, 2025.

[37] OpenPhish. OpenPhish. https://www.openphish.com/, 2025.

[38] Nikolaos Pantelaios and Alexandros Kapravelos. FV8: A Forced Execution JavaScript Engine for Detecting Evasive Techniques. In *Proceedings of the USENIX Security Symposium*, August 2024.

[39] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[40] Ch. Chakradhara Rao, A.V.T. Raghav Ramana, and B. Sowmya. Detection of phishing websites using hybrid model. 2018.

[41] Andrew Rosenberg and Julia Hirschberg. V-measure: A conditional entropy-based external cluster evaluation measure. In *Conference on Empirical Methods in Natural Language Processing*, 2007.

[42] Iskander Sanchez-Rola, Leyla Bilge, Davide Balzarotti, Armin Buescher, and Petros Efstathopoulos. Rods with laser beams: Understanding browser fingerprinting on phishing pages. pages 4157–4173.

[43] Shaown Sarker, Jordan Jueckstock, and Alexandros Kapravelos. Hiding in Plain Site: Detecting JavaScript Obfuscation through Concealed Browser API Usage. In *Proceedings of the ACM Internet Measurement Conference (IMC)*, page 648–661, October 2020.

[44] SecurityTrails. Urlscan. https://urlscan.io/, 2025.

[45] Hossein Shirazi, Bruhadeshwar Bezawada, and Indrakshi Ray. "kn0w thy doma1n name": Unbiased phishing detection using domain name based features. *Proceedings of the 23nd ACM on Symposium on Access Control Models and Technologies*, 2018.

[46] Junhua Su and Alexandros Kapravelos. Automatic discovery of emerging browser fingerprinting techniques. In *Proceedings of the ACM Web Conference 2023*, WWW '23, page 2178–2188, New York, NY, USA, 2023. Association for Computing Machinery.

[47] Karthika Subramani, William Melicher, Oleksii Starov, Phani Vadrevu, and Roberto Perdisci. PhishInPatterns: measuring elicited user interactions at scale on phishing websites. In *Proceedings of the 22nd ACM Internet Measurement Conference*, IMC '22, pages 589–604. Association for Computing Machinery.

[48] Xiwen Teoh, Yun Lin, Ruofan Liu, Zhiyong Huang, and Jin Song Dong. {PhishDecloaker}: Detecting {CAPTCHA-cloaked} phishing websites via hybrid vision-based interactive models. pages 505–522.

[49] Charles Truong, Laurent Oudre, and Nicolas Vayatis. Selective review of offline change point detection methods. *Signal Processing*, 167:107299, 2020.

[50] Jonas Tzschoppe and Hans Löhr. Browser-in-the-middle - evaluation of a modern approach to phishing. In *Proceedings of the 16th European Workshop on System Security*, EUROSEC '23, pages 15–20. Association for Computing Machinery.

[51] Rakesh M. Verma and Avisha Das. What's in a url: Fast feature extraction and malicious url detection. *Proceedings of the 3rd ACM on International Workshop on Security And Privacy Analytics*, 2017.

[52] Penghui Zhang, Adam Oest, Haehyun Cho, Zhibo Sun, RC Johnson, Brad Wardman, Shaown Sarker, Alexandros Kapravelos, Tiffany Bao, Ruoyu Wang, Yan Shoshitaishvili, Adam Doupé, and Gail-Joon Ahn. Crawlphish: Large-scale analysis of client-side cloaking techniques in phishing. In *2021 IEEE Symposium on Security and Privacy (SP)*, pages 1109–1124, 2021.

[53] Penghui Zhang, Zhibo Sun, Sukwha Kyung, Hans Walter Behrens, Zion Leonahenahe Basque, Haehyun Cho, Adam Oest, Ruoyu Wang, Tiffany Bao, Yan Shoshitaishvili, Gail-Joon Ahn, and Adam Doupé. I'm SPARTACUS, No, I'm SPARTACUS: Proactively Protecting Users from Phishing by Intentionally Triggering Cloaking Behavior. In *Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security*, pages 3165–3179. ACM.