School of Phish: Differentiating Phishing Pages via Browser API Usage

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***Abstract*—Phishing kits, ready-to-deploy software packages for phishing websites, have proliferated numerous 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. Our system has an accuracy of 97% on 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. **Alex:** ▶Is accuracy and number of clusters the only numbers we want to report in the abstract?◀

I. Introduction

Web-based phishing attacks, where a web page, through mimicking or urgency, tricks the user into submitting personal information to an attacker, have been increasing for the last 5 years [12]. While varying in delivery vectors, sent through email, SMS, or QR codes, phishing attacks remain successful in compromising individual accounts and enterprises. In 2021, the US Cybersecurity and Infrastructure Security Agency (CISA) warned of phishing campaigns targeting Non-governmental organizations (NGO) and government workers that smuggled the HTML and JavaScript of the phishing page through an attachment [26], [6]. 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, together 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 [7].

JavaScript is one of the cornerstones in evasive behavior of phishing pages. Evasions are critical for phishing pages because they extend their lifetime (delta time between deployment and discovery) and hinder follow-up analysis of the whole campaign. JavaScript allows access to privileged functionality through browser APIs, which enables the attacks to obfuscate the true purpose of the webpage and effectively identify differentiating factors when a victim or a potential analysis framework is viewing the webpage [61], [63]. The JavaScript logic can range from a simple user-agent-based redirection to an AES-encrypted script that dynamically decrypts itself, identifies the browser through a series of API calls, and renders the page after confirming the victim is using a real browser.

In this paper, we leverage the complexity of the client-side code in phishing web pages to automatically reduce the space of phishing by viewing pages at a layer of abstraction. Figure 1 shows the how much the volume of the phenomena is reduced through clusters of browser API usage of pages. With a peak of over 60,000 pages in a month, this paper aims to aid researchers and analysts in automatically differentiating between collections of phishing pages from different underlying kits or common techniques. Overall, we offer the following contributions:

C1. We create a phishing kit groundtruth dateset with 4,448 pages from 526 distinct kits and observe a Jaccard index based similarity for the JavaScript APIs used of 0.011 for pages from the same kit, and 0.916 for pages from different kits. We find that clustering based on the distance (1 - similarity) of browser APIs used is enough to identify if two pages share a kit behind the scenes, achieving an accuracy of 92% based on the Fowlkes-Mallows index. These clusters are more homogeneous then complete, meaning that clustering may split pages from the same kit into few clusters, or combine two similar kits into a single cluster, but will less often break kits apart into multiple kits.

C2. By computing the density-based cluster of these pages for a 4-week window, rolling it by 2 weeks, and merging these clusters, we get 11,377 total clusters for the span of 439 days. These clusters are very well formed with a silhouette score of 0.6. These clusters provide a dramatic reduction in space for the overall traffic observed; we find that the top 50 clusters alone account for 40.7% of the pages in Figure 1. We also find that the majority of the clusters are short-lived (72%), being observed for less than a month, and map to a single brand (80%). This could suggest that mass phishing campaigns gravitate towards low-quality, non-modular, and cheap or free kits. We find an example of a cluster from a open-source kit that is now sever years old, as well as over 10,000 USPS pages from the same kit that we are able to extract on 40 different occasions using KitPhishr.

C3. By creating an enumerated mapping of browser API to

different phishing techniques, presented in Table I, we identify basic user agent and cookie-based fingerprinting, and UI-interactivity to be near universal across clusters, being present in 91% and 85% of the clusters respectively. We find that browser fingerprint exfiltration, obfuscation, and timing-based bot detection is present in around 1 of every 3 clusters and that compared to prior work, pop-up based obfuscation techniques have declined, and while present in low numbers on the phishing feeds, we draw attention to client-side IP reputation checking and Cloudflare Turnstile embedded clusters, both of which can potential identify scanning tools.We find that with a small number

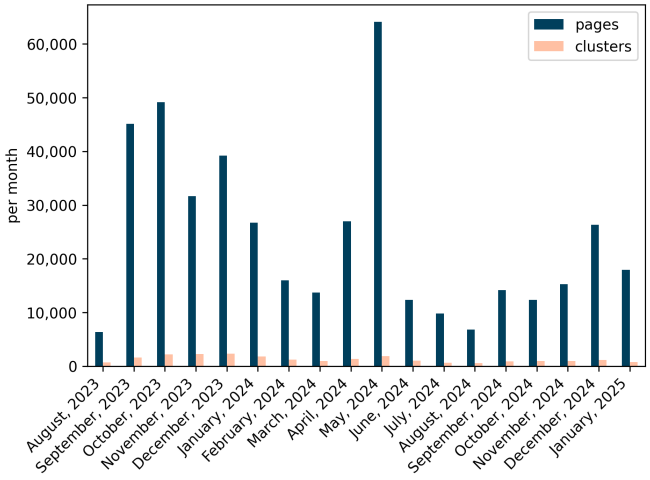

Fig. 1: Comparison between monthly pages observed vs the monthly clusters observed based on dynamic behaviors. We observe a drastic, non-linear reduction of phenomena needed to investigate monthly.

II. Background

In this section, we provide a background on current developments in phishing as a phenomenon and adversarial JavaScript techniques, as well as an overview of the parties involved in the phishing ecosystem.

A. 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 web page 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 the 2020s, with a shift in what sectors are targeted throughout every year. In Q3 of 2020, the Anti-Phishing Working Group

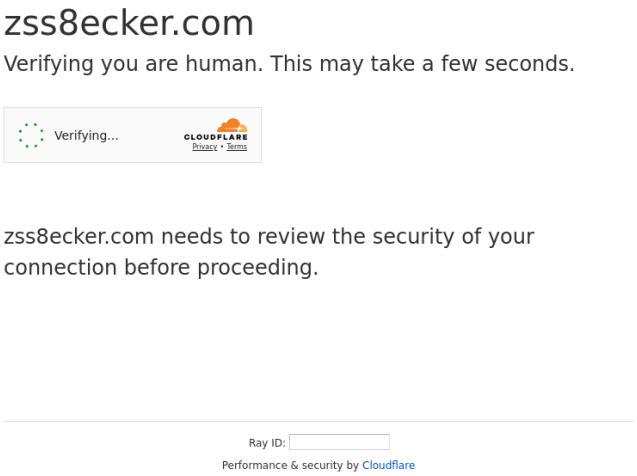

Fig. 2: Example of a phishing page in our dataset that embedded Cloudflare Turnstile verification on a non-cloudflare domain

(APWG) reported Software-as-a-Service (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; in 2024, it is Social media [1]. In the 3rd quarter of 2024, the 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 developing methods of identifying them, anti-analysis and anti-bot detection techniques have emerged in the ecosystem. These techniques are no different from anti-debugging techniques found in malware; the end goal is to make detection and analysis of the page difficult. The techniques can be broadly classified into server-side and client-side techniques [43]. Server-side techniques are stealthier; however, they rely on limited information and can be studied by acquiring a zip bundle to set up the page (sometimes called a phishing kit). Most server-side techniques rely on precompiled deny-lists or allow-lists 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 if your browser does not meet the criteria the attacker requires (e.g., crawling bot, not a mobile user, not in a specific country).

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 [51]. 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. Cloaking also inherits behaviors from bot-detection and abuse prevention, recently, phishing pages have opted to use Cloudflare Turnstile, a popular widget for obuse prevention, in order to offload the engineering work required to accuratly identify automated browsers. Figure 2 shows an exmaple of a non-cloudflare domain, using a Cloudflare Turnstile as seen from the viewpoint of our automated crawler.

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 hosting with trustworthy top level domains (TLDs).

B. Phishing as an ecosystem

As an ecosystem, phishing attacks have two major branches: cybercrime 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[Citation needed]. 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 and have been researched. Prior work has shown that phishing kits are not above stealing credentials from their customer's kit deployments [19], [37], adapting and borrowing features from other kits [27], and that they are sometimes are tied to specific actors [9].

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 [**?**], an actual cost is associated with executing JavaScript on the phishing page [**?**], 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.

C. 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; in addition to making 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. [47]

The research community has tried tackling 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.

III. Methodology

This paper provides a methodology for reducing the space of phishing pages, evaluating how closely the clusters resemble underlying phishing kits, and describing how widespread different adversarial techniques are in the ecosystem. The building blocks of our system are browser API execution traces from phishing pages and a ground-truth dataset 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 Figure 3.

A. Data Gathering

Our crawling infrastructure aims to ingest phishing URLs from upstream providers and output execution traces from the page, as well as a potential kit used for that page.

URL feeds: We gathered phishing pages from a diverse set of phishing feeds, monitoring OpenPhish [46], PhishTank [18], URLScan [53], SMS Gateways [41], PhishDB [39], and APWG [12], based on the availability of the feed and the level of 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 [24], 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 [45]. We initiated the crawls from a network designated for research purposes, for which the ISP would register as 'educational' for any IP intelligence API and used Catapult [23], a man-in-the-middle proxy, to capture the entire HTTP archive for replayability. The crawler stays on the page for 45 seconds

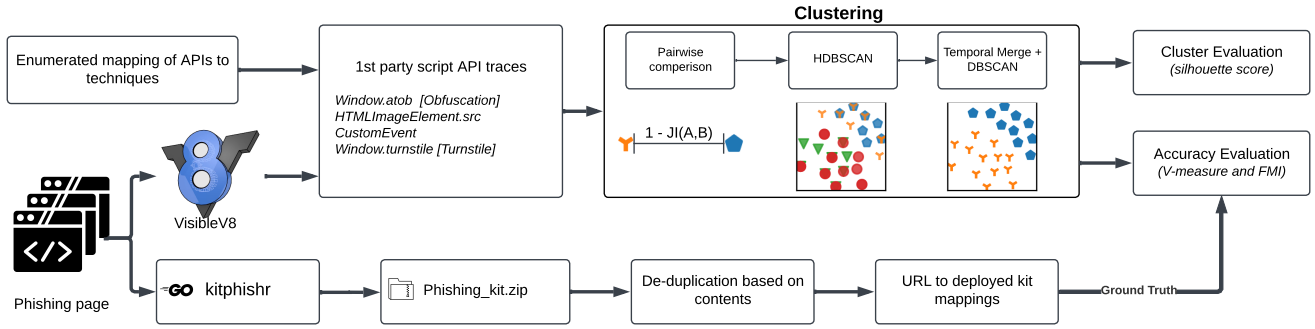

Fig. 3: Crawling and clustering infrastructure

before taking a screenshot to allow scripts to load and start executing; this is consistent with prior work [28], [21].

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 leftover zip files on the server. Prior work [35], [43] establishes a method to collect and analyze phishing kits. If successful, it will download the zip file and make a note of the domain from which kitphishr acquired it.

B. De-duplication

Once we have collected browser API traces and potential phishing kits, we will post-process the traces into a set of APIs executed in a 1st-party context per page and deduplicate the phishing kits based on archive file similarity.

1) Trace postprocessing: 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 an unordered set of APIs executed by this script.

To not introduce artifacts into our clusters from cloaked pages and 3rd-party scripts like Google Analytics, known to be present in phishing pages [33], we isolate API sets executed by 1st-party scripts (from now on called 1st-party API sets). 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 1st-party only if it is loaded from the domain we acquired from our feeds (root domain). The only exception is when we identify which pages embed a Cloudflare Turnstile script. As some of the Turnstile scripts can be hosted on 'Cloudflare.com.'

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 them as a set of SHA256 of source files[2]. If the Jaccard index-based similarity ($JI(A,B) = |A \cap B|/|A \cup B|$) 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. However, we discuss the behaviors we could see from these scripts in Section-IV.

C. Data enrichment

In addition to data from our phishing feeds, we compile API usage from brand's original pages in order to discuss the differences between phishing pages and the login pages they are targetting in Section-V and we present a mapping of different adversarial technique employed by phishing pages mapped to different API usages.

Technique to Browser API mapping: Client-side JavaScript can engage in data harvesting (exfiltrating information dynamically and not through form submission), evasion (conditional dynamic behavior aimed at hiding functionality or contents), obfuscation (unconditional behavior meant to hinder static analysis), and mimicking (dynamic behavior to make the page more believable, for example, false loading pages, stage by stage data extraction). Based on prior work by Su *et al.* and Zhang *et al.* and manually identifying APIs from the Mozila Developers Network (MDN) documentation, we present a table mapping standard phishing techniques to browser APIs in Table-I.We leverage the presence of these APIs in the execution traces as a signal of the technique being present in the page. If the page falls within a certain cluster, we mark the entire cluster as using that technique. This is done

[1]https://developer.mozilla.org/en-US/docs/Glossary/WebIDL

[2]Source files identified via a python libmagic module [5]

because we observe phishing pages load scripts that engage in non-deterministic behavior, as well as the difference in the load on our infrastructure, can cause different amounts of work (lines of code) to be executed between different visits. For Cloudflare turnstiles embedding, we use a non-browser API as our detection metric, as Cloudflare's native turnstile script will read the value of `Window.Turnstiles`. For Client-side IP checks, we manually looked through every `Window.fetch` and `XMLHttpRequest.open` argument URL that were present in more than 50 pages, and manually identified 15 that were IP reputation APIs.

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 52 brands targeted and collected VisibleV8 logs for their home pages and, when applicable, their login pages, to assess how similar phishing pages are to their target pages. Lin *et al.* in [**?**] identified that phishing pages could effectively use browser fingerprints to bypass multi-factor authentication, and [**?**] found that phishing pages deploy a plethora of 3rd party fingerprinting scripts, which differ from the scripts of the original page, what is the similarity between browser API usage between the target brand's page, and the phishing counterpart.

D. Identifying kits

We hypothesize that similarity in browser API execution means that the pages originate from the same phishing kit. In order to test this, we ingest API sets from pages we were able to identify phishing kits for, and output a potential clustering of those pages, checking how well the clustering maps back to the ground truth information.

To establish this similarity, we use the Jaccard index on the API sets that 1st-party scripts execute. We use Hierarchical Density-Based Spatial Clustering of Applications with Noise [14] (HDBSCAN), with a minimum cluster size of 2, to cluster the pages with the Jaccard distance as our distance kernel. With HDBSCAN requiring minimal fine-tuning out of the box, and requiring no prior knowledge of the number of clusters we need to look for, we 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** [22] 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 [50]. We use sklearn's measure module to calculate all cluster evaluation metrics. [48]. For the much larger set of pages for which we do not have kit labels, we use **silhouette score**[3], a metric for how well packed and separated the clusters are, to evaluate the clustering when we do not have ground truth.

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

To process 533,514 pages in one go, we divide the pages into small time windows and first cluster them into smaller local clusters. Figure 3 shows the breakdown of our methodology. But we first divide our data using a 3-week rolling window; we roll by 2 weeks. However, pages now may exist across two clusters, so once we cluster these chunks using HDBSCAN, with no hyperparameter tuning and a minimum cluster size of 2, we merge any 2 clusters with at least one page in common across the sliding window. We refer to these clusters as 'local clusters'. However, these clusters can not represent phenomena like the re-emergence of clusters, if it happens after 2 weeks. To resolve this, we use the set intersection of APIs (representative API set for the clusters) from every page within a local cluster. We use DBSCAN with a conservative $\epsilon = 0.05$ to merge them. Intuitively, this ϵ represents the maximum dissimilarity you are willing to tolerate between clusters. We selected this ϵ value by experimenting on the clusters of pages from the ground truth set. When it comes to merging local clusters, $\epsilon = 0.04$ yields fewer clusters and a better silhouette score; however, to avoid data-peeking, as we use the silhouette score to describe the shape of the final clusters, we chose not to determine the value based on the final clusters. We present the clustering metrics from both local clusters and final clusters in Section-IV. To avoid calculating a distance matrix on the over four hundred thousand pages successfully clustered, we use the representative set from each local cluster to compute the silhouette score on the final clusters. We separate local clusters labeled as noise in the 2nd cluster step (with DBSCAN and $\epsilon = 0.05$) into single clusters.

E. Identifying trends

We attempt to identify temporal anomalies in every API's time series to discuss the differences between a singular API changes over time and a clustering of pages via their API sets. We also discuss here how we chose to quantify the lifetime of clusters and the deployment diversity of different clusters.

Identifying anomalies: We look at the overall anomalous patterns for a timeseries of every browser API we observe. We use rapture [58] 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. If we are less than 3%, we ignore and merge with the prior segment.

Cluster lifetime and deployment diversity: Throughout this work, we refer to cluster lifetime as the time range between when the first page belonging to the cluster is observed on the

TABLE I: Manual mapping of Phishing techniques to browser APIs

Technique	Category	Identifying markers
Fingerprinting extraction	Credential Harvesting	10 Fingerprinting API calls and an exfiltration related API call from [55]
Client-side IP check	Evasion	`Window.fetch` `XMLHttpRequest.open`
Timing bot detection	Evasion	`Performance.now + Timeout`
Encryption	Obfuscation	`Subtlecrypto.decypt`
Encoding	Obfuscation	`TextDecoder.decode` `window.atob`
Dynamic script Evaluation	Obfuscation	`eval`

Basic fingerprinting	Evasion	`HTMLDocument.cookie`
		`HTMLDocument.referrer`
		`Navigator.userAgent`

Dynamic script creation	Evasion	`HTMLScriptElement.text` `HTMLScriptElement.innerHTML`
Cloudflare Turnstiles	Evasion	`Window.turnstile`

feed and when the last page belonging to the cluster is observed on the feed. We pull and crawl URLs from the phishing feeds every two hours, meaning that this is an approximation of when the URLs appear on the feeds, with an error of two hours. We measure deployment diversity of the phishing pages by looking at the effective 2nd-level domain (e2LD) for the URLs. Using the e2LD instead of the entire hostname ensures that pages deployed on 'pages.dev' or 'blogger.com' are considered a single deployment form.

IV. Results

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. Furthermore, 99,464 pages were clustered as noise by HDBSCAN or formed a cluster where all the pages had no common APIs. As shown in Figure 1, in contrast to the number of pages we observe monthly, we can substantially reduce the scope of the phishing ecosystem based on common behaviors.

A. Characteristics of clusters

Finding 1: *Multiple deployments of the same kit use the same sets of APIs, on average have XXX% simularity*. Figure 4 shows the distribution of Jecard-based similarity between pages from the same kit versus different kits. We observe that pages from different kits, even ones with similar themes, rarely exceed 60% similarity, while most pages with the same kit have around 90-100% similarity. We leverage this in our clustering by treating $1 - JI(A, B)$ as a distance kernel of HDBSCAN.

Finding 2: *Browser API usage unique identify phishing kits apart from each-other*.Clustering pages from 4,448 pages across 521 kits, yield 349 clusters. 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 are homogeneous. In the ground truth data, this resolves into clusters comprising a few kits being mixed together, as opposed to pages from the same kit being split across multiple clusters. In the larger clusters, we find that this results in pages that appear to be from the same kit forming 3-4 clusters.

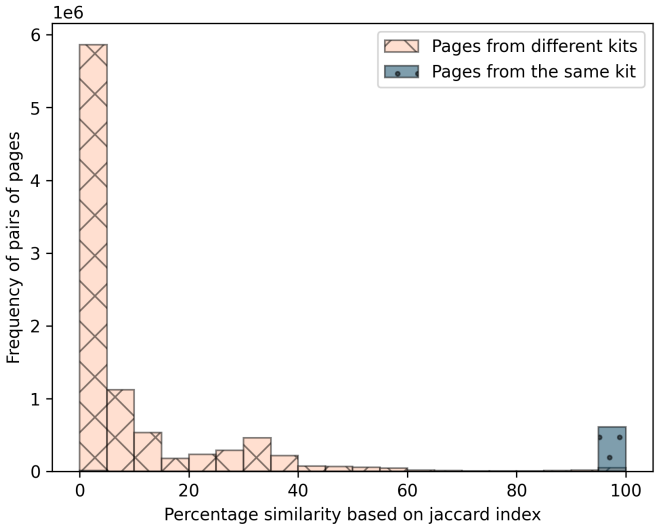

Fig. 4: Histogram of the Jaccard index based similarity between any pair of pages belonging to the same kit, versus from different kits

Pages with ground truth labels for originating kits remain appropriately sorted out in clustering the 434,050 pages. We maintain an FMI of 0.95 and a V-Score of 0.89, respectively. After manually inspecting the clusters, we observed that these clusters have unique pages across deployment types (AWS, Cloudflare, DigitalOcean, etc.) and languages. For example, Cluster-e325887b comprises 487 pages across five unique e2TLDs and contains pages engaging in voice-based phishing attacks (tech support scams) across Japanese, English, and German, varying phone numbers and error messages in each, shown in Figure 10. 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. Figure 5 shows two different clusters, with example screenshots pulled from both. One cluster is from a

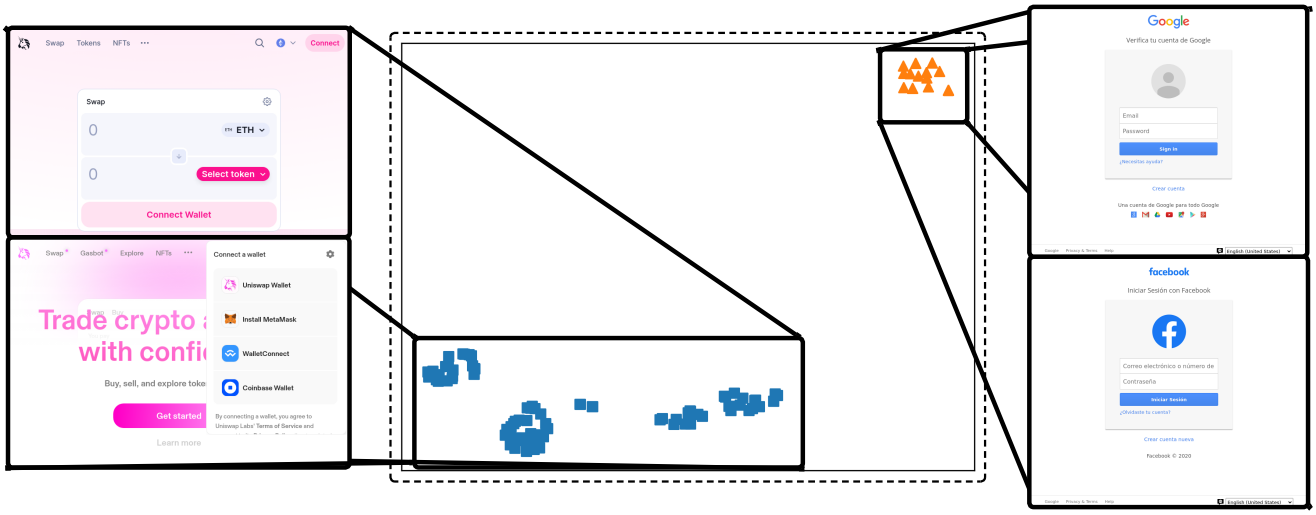

Fig. 5: Example of pages from two different pages and embedding between them. We useed t-distributed stochastic neighbor embedding to visualize the distance matrix between all of the pages in a 2-d plain. The clusters presented here are from an Etherium wallet pages with a few variations of the landing page (▲) and pages that decend from an open-source phishing kit discussed in Seciton-IV (■)

deployment we can tie to a public GitHub repository (discussed in Finding-11), and the other is a collection of crypto-wallet targeting pages. The figure shows a t-distributed stochastic neighbor (t-SDN) embedding for the distance matrix between all the pages from the two clusters to illustrate better how the pages are separated.

Finding 3: *Dismissing DOM APIs and property reads as noise does not measuably increase accuracy, while reducing the number of pages that can be considered for clustering*. With 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, without increasing our overall accuracy. Evaluated our same methodology described in Section-III 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 (which are often used in fingerprinting [55]), 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. Figure 6 shows the distribution of the silhouette score of the local clusters. With an average score of 0.8, these clusters are incredibly well formed and, on average, pages inside a cluster contain 64 APIs in common.

Finding 4: *80% of clusters contain urls only marked by a single target brand by our threat intel sources*[4]. 534 clusters (15%) had two brand labels. However, the most popular combination of these was "Meta/Facebook", "National Police Agency JAPAN/Facebook", and "Facebook/Instagram", keeping

[4]We did not include clusters in this count that had no brand-labeled urls in them

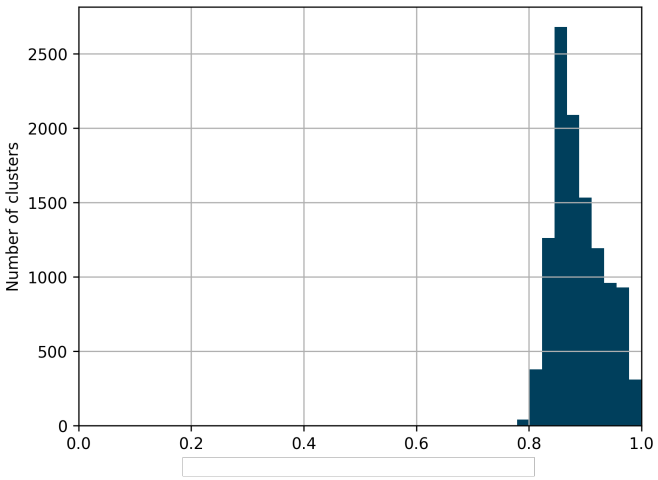

Fig. 6: Histogram of the silhouette score of local clusters. This score is calculated including the noise cluster, pages of which are not considered for the merge algorithm

the parent organization of the target the same in the majority of the cases. Manual examination of clusters with "National Police Agency JAPAN/Facebook" brand labels revealed shopping pages in Japanese to be marked with that label incorrectly from our data feeds. The cluster with the most diverse set of brand labels had 14 unique brand labels, which was a cluster with 12,467 pages with simple sign-in pages that exfiltrated information using client-side registered event listeners to exfiltrate data using client-side JavaScript. Furthermore, we find that 16,100 pages (3% of the pages observed spanning 313 clusters) come from phishing kits collected using Kitphisher;

however, we could not pull the kit from the URL in all pages.

B. Temporal patterns of clusters

Finding 5: *Majority of phishing pages that execute JavaScript originate from the same 50 clusters*. 40.7% pages of pages that executed JavaScript in a first-party context (533,514) are sorted into one of the 50 top clusters. The 10 clusters by page count are 20.8% of the total pages alone. We provide a breakdown of these clusters along with manual labeling of what campaigns they correspond to in Figure 8. We note that one of the clusters, which we labeled dynamically generated, turned out to be a noisy cluster of simple pages that dynamically generate part of their page, without any sophisticated client-side behavior. The E-commerce cluster shown in Figure 8 has a significant seasonality as lags 7, 14, and 21, meaning the appearance of the clusters on the feeds happens every week. However, further investigation showed that the majority of seasonal clusters are similar e-commerce phishing clusters, with vastly different dynamic behavior, allowing us to conclude that the seasonalality in the majority of the clusters is due to regular reporting by threat-intelligence sources to our feeds, and not seasonal deployments of kits.

Finding 6: *72% of the clusters (144,695 pages), and by extension kits, are only seen for a single month by phishing feeds*. 15% of the clusters (14,555 pages) we observe are only seen for one day, along which were brandless bank pages, and phishing page impersonating the government of Korea. Meanwhile, 1,282 clusters (11%) have lifetimes longer than 100 days. Some clusters with a lifetime greater than 100 days still only deploy a few pages (less than 1 page every 10 days). We use this as a heuristic to identify 251 clusters 're-emergence' through our observation period. It should be noted that every day, there is a new cluster that appear on the phishing feeds based on behaviors, however, from Figure 1, the total number of clusters active on all of our phishing feeds is much more manageable, especially when considered that the clusters can be queried based on their dynamic behaviors.

C. Phishing Techniques across clusters

Finding 7: *UI interactivity and fingerprinting are a near-universal behavior across clusters*. Multi-stage phishing pages are very well documented in prior work, and we find that the majority of clusters (91%) register a click event listener using JavaScript. Though this could be as simple as submitting credentials using JavaScript, this highlights the need for researchers to augment their crawlers in the future to extract better and more complete execution traces from websites. As mentioned in Section-III, we split fingerprinting into two categories, basic and advanced. Basic fingerprinting, which follows the list of APIs identified by Zhang *et al.* in [62] was present in 80% of the clusters (over 300,000 pages), and Advance fingerprinting (measured by at least 5 APIs idenfied by Su *et al.* in [55]) show up in 70% of the clusters. Together, 85% of clusters (9,572 clusters, 313,212 pages) exhibit some kind of fingerprinting.

TABLE II: Breakdown of the obfuscation techniques observed in our dataset

Obfuscation techniques	Pages	Clusters
Window.atob	61,125	1,455
eval	14,561	982
Textdecoder.decode	11,113	534
SubtleCrypto.decrypt	1,185	36

```
await this.$http({
  method: "get",
  url: "https://api.ipregistry.co/?key=" +
    ↪ this.key
}).then(e => {
  const s = e.connection.type,
      c = ["cdn", "hosting", "education"];
    /*omitted for brevity*/
    if (c.indexOf(s) != -1)
        /*Redirect*/
})
```

Fig. 7: Example of IP-based cloaking by using a 3rd-party reputation API. The following example specifically cloaks away from educational networks like ours.

Finding 8: *Fingerprint exfiltration, obfuscation, and bot detection are widespread phishing clusters*. While fingerprinting is near universal, we find that a smaller fraction of the clusters employ obfuscation, fingerprint exfiltration, and timing for bot detection. We present the breakdown of all these techniques in Table II. We find that 22% of clusters call out use `Performance.now` in conjunction with setTimeout, enabling delta time measurement for bot detection. 46% of pages call at least five advanced fingerprinting APIs, followed by an exfiltration-related API.

31% of clusters (2,395) employ some form of obfuscation. A full breakdown of different obfuscation forms is in Table II and as we can see, eval and Base64 encoding were the most popular ways of obfuscation. Despite the best recommendations [8] to web developers, JavaScript's eval function remains a favorite for obfuscation and evasions [47]. Sometimes, a script is executed via 'eval()', which evaluates yet another script itself; we measure this phenomenon as a level in **eval-depth**. We find that 48 clusters have pages that go to eval-depth 3. However, this seems to be a side-effect of embedding the phishing pages (mainly ones targeting Facebook) in Blogger.com pages.

Finding 9: *While rare, client-side IP reputation checks are present across multiple clusters*. While only present in 504 clusters (19,869 pages), we identify 15 unique IP reputation APIs used by phishing pages as soon as the page loads. We present a full breakdown in Table III. While not the most popular, *api.ipregistry.co* presents an interesting case study, as it enables the identification of educational networks. Manual examination of pages from these clusters reveals snippets similar to Figure 7

Finding 10: *Pop-UP APIs are declining*. We see only 104 clusters (1,323 pages) call out to pop-up requesting APIs.

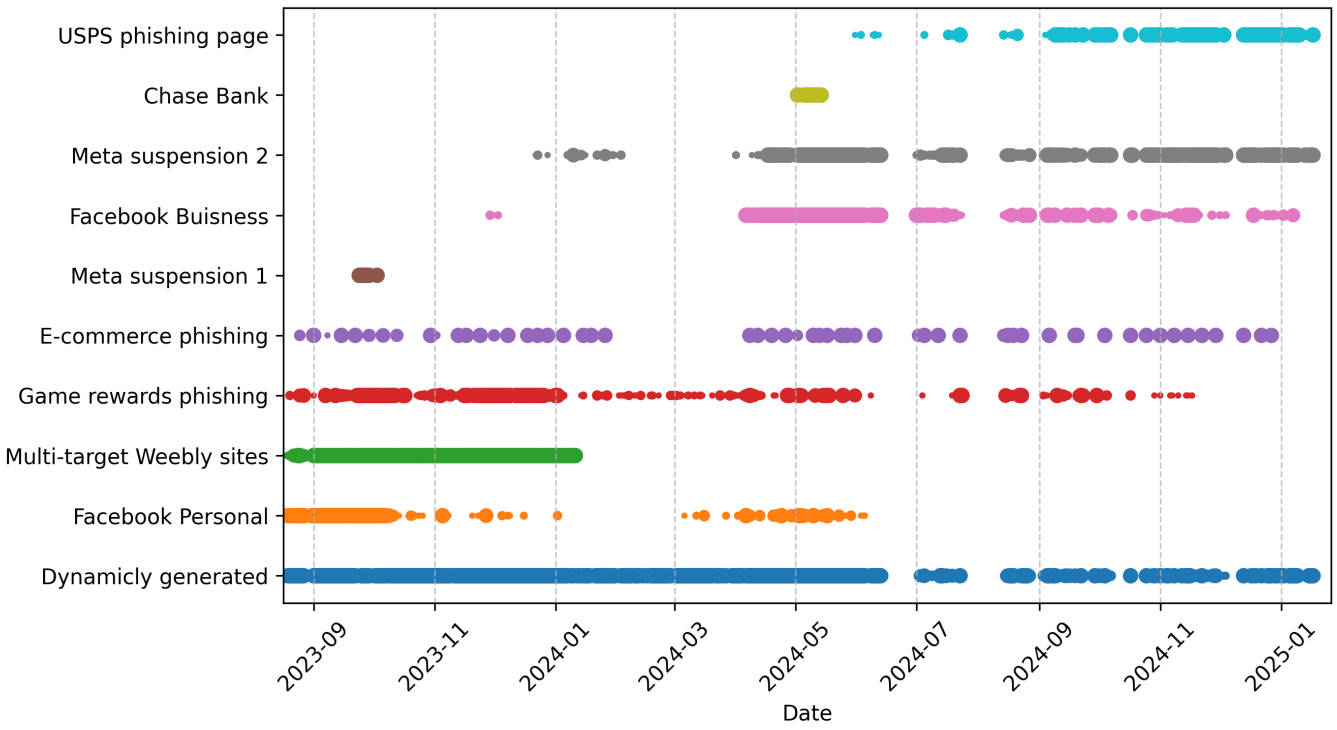

Fig. 8: Timeline of the top 10 clusters

API url	clusters	pages
api.db-ip.com	40	3,124
api.geoapify.com	3	63
api.ipapi.com	5	143
api.ipgeolocation.io	21	96
api.ipify.org	177	7,417
api.ipregistry.co	9	3,995
freeipapi.com	38	6,444
geolocation-db.com	14	492
geolocation.onetrust.com	37	364
get.geojs.io	14	753
ipapi.co	106	735
ipinfo.io	65	1,963
ipwho.is	47	798
pro.ip-api.com	20	101

TABLE III: List of all API endpoints that client-side code reaches out for IP intelligence.

Among these, Geolocation.getCurrentPosition (55 clusters) was the most popular. While requiring a pop-up to interact with, this API can also play a crucial role in cloaking, as any VPN or proxy does not mask the results.

We observe a smaller fraction of the ecosystem (16 clusters, 148 pages) than [**?**] employs this cloaking technique, especially when it comes to triggering a notification pop-up to verify user interaction. This could be a result of Firefox, citing low engagement with the notifications, started requiring user interaction to trigger the popup [40] at the end of November 2019, when crawlphish's data collection ended. Chrome has since discussed modifying the notification API to make the request less disruptive to the user experience [3]. The lack of pop-up requests could also be explained by our **Finding-9** regarding usage of Fetch and XMLHttpRequest or by the overwhelming amount of the pages (67%) registering at least one HTMLElement event handler, which would be classified as a *Click-through* by Crawlphish's taxonomy. We report a full breakdown of APIs related to the Crawlphish categorization of client-side cloaking in Table V.

Finding 11: *Mouse Detection API calls and Cloudflare Turnstile embedding are specific to a small group of clusters*. While supported by most modern browsers, we see a very rare use of Mouse Detection APIs. Only 35 clusters employ mouse detection-related APIs. Two of these clusters[5] are from an open-source phishing kit, leveraging botguard, are from a public GitHub repository, which was last updated in 2017[6]. We see these clusters deploy across 17 unique domains, starting from 2023-10-07 all the way to 2024-07-19. **7 clusters (181 pages)** embed a Cloudflare turnstile check in their page; some of these domains are not hosted on Cloudflare. It should be noted that in the case of redirection, while we discussed the presence of WebAssembly-based captchas for bot detection, embedding a Cloudflare Turnstile check allows the phishing kit authors to offload bot detection to a well-established ecosystem. Recently, analyses have identified high-value phishing kits with this behavior [4].

Figure 9 shows the confusion matrix between the techniques

[5]Split due to infrastructure inability causing crashes in early crawls
[6]https://github.com/ashanahw/Gmail_Phishing

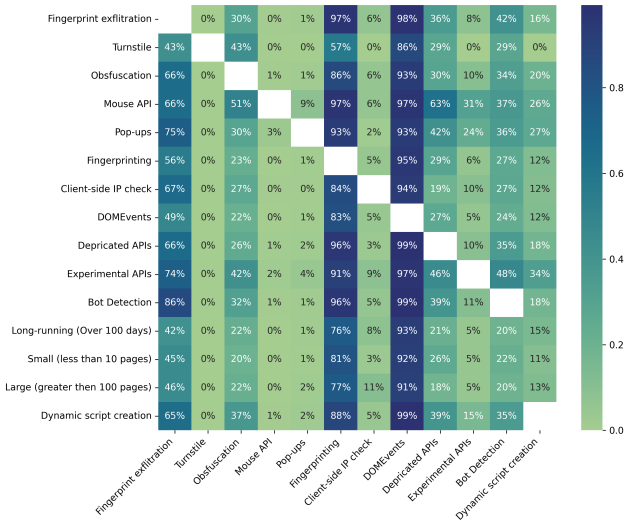

Fig. 9: Confusion matrix between all of the techniques enumated and cluster lifetime characcteristics, normalized by row.

we enumerated and the size of the clusters. We see no noticeable difference between small and large clusters when it comes to cluster size, with the exception of a higher percentage of large clusters using client-side IP checks. We also observe that pages that employ experimental APIs also tend to include a deprecated API call, which is in line with their usage for browser fingerprinting.

Finding 12: *The phishing ecosystem consists of clusters that utilize both cutting-edge, experimental browser APIs, and extremely deprecated APIs*. We find 421 clusters (8,270 pages) that utilize *NavigatorUAData.getHighEntropyValues* for fingerprinting and *Keyboard.lock* to restrict user input, APIs not fully supported by Firefox and Safari. We identified 10 clusters across 4,433 pages that used *Scheduling.isInputPending*, however, upon closer inspection, these were not pages using a novel kit, but rather pages that used Google Sheets to construct their landing page. On the other hand, 25% of the clusters spanning (47,001) pages use a deprecated API. While not experimental, WebAssembly is still a relatively modern web practice. We find a total of 199 clusters (5,107 pages) that use WebAssembly related APIs. Upon manual inspection of 33 unique WASM modules present on these pages, we identify bot-detection, in most cases, by using FriendlyCaptcha, as the most common use case for WebAssembly in phishing.

V. Discussion

A. Why clusters?

As we have shown in the examples in this paper, phishing feeds can be a noisy data source for studying the overall ecosystem. From e-commerce pages to mass-spammed USPS and EZ-parking phishing pages, differentiating between a handful of pages of varying sizes becomes crucial for efficiency. This paper demonstrates that browser API usage can closely proxy the phishing kit (providing commonality for the page's origin) as best, and group via standard client-side techniques as worst.

Furthermore, kit identification lets you infer server-side behavior about a particular page as long as a kit is identified and analyzed for one of the pages. As established by Oest *et al.*, Phishing kits thrive on including up-to-date IP blocklists. However, this blocklist is not always included in the client-side code. Being able to link pages to the same kit without any anti-evasion techniques like dynamic execution will allow better triaging of failed detections from phishing feed crawlers, something prior work established can be done by prior profiling [11]. Write:I feel like this is where we gotta hammer home that AT WORST, you get a cluster of pages that all did the same thing using their javascript when you crawled the page (for example, Cloudflare captcha, cloaked away because of the user agent, use Squarespace for hosting, etc. etc...)...

Finding 13: *Changes to the daily usage of individual API are due to either an introduction of a new cluster, or changes in dependencies used*. Write:Still working on this one...

B. What makes a kit identifiable?

Sets of browser APIs used are not the most granular method to describe pages; however, without many degrees of freedom in choices, the more sophisticated the phishing kit becomes, the easier it is to spot by just the browser APIs it uses. In plain JavaScript, without browser APIs, a page can not reach out to a C2 server, gather browser fingerprints, dynamically generate or cloak page contents, or request browser pop-ups without calling out to a browser API. In the case of the pages clustered in Figure-10, the APIs *Keyboard.lock*, *HTMLDocument.onkeydown* for keyboard locking, *Window.atob* for obfuscation, and a handful of fingerprint APIs and DOM APIs for dynamic content generation, set these pages apart from the other clusters.

Finding 14: *Phishing pages vary wildly from the brand that they are mimicking*. We collect browser API traces from Facebook, USPS, Meta, Microsoft, and IRS login pages and compare them to their phishing counterparts. The average similarity of the APIs executed by the phishing page and the original page is 11%, indicating that browser APIs do not relate to the target page. We found no pages where the original page's API set was a subset of the phishing page's API set, and in 5% of the cases, the phishing page executed at least half of the APIs from the original page. We report per-brand findings in Table- IV and note that the least similar brand was USPS, which could be the result of USPS phishing pages being multi-stage pages requiring user interaction and targeting credit card information [16].

This, however, does not indicate that browser API usage alone is a good indicator of maliciousness. All of the techniques described in Section-III are common throughout the web. However, phishing pages are singular in their purpose, and their choice to engage in these techniques sets them apart.

TABLE IV: Comparison of phishing page metrics across different brands

Brand	Phishing pages observed	Avg % Similar	Std Dev (%)	Perfect Subset	50%+ Match
Facebook	338,686	11.6	9.6	0	24,039
USPS	66,692	10.3	10.5	0	53
Meta	51,969	12.4	7	0	2,605
Microsoft	3,768	11.8	8.7	0	419
IRS	1,207	11.5	9	0	61

C. Dynamic analysis combats evasions

While dynamic analysis suffers from drawbacks we will discuss in Section-VII, it allows us to sidestep any sophisticated obfuscation techniques effectively in JavaScript. Even something as nuanced as an AES encrypted script will show up in VisisbleV8 as long as the behavior is triggered. While not incorporated by our work, prior work has shown forced execution [47], [**?**] to ensure that dynamic analysis effectively extracts all behaviors.

VI. Related Work

A. 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 vision-based techniques to detect phishing pages [36], [10], [35]. [36] 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 [17], [29] and earlier via statistical models and machine learning in [54], [31], [49], [60]

Studying and combating adversarial techniques: Divakaran *et al.* in [20] reaffirms the need to keep up with the latest adversarial techniques to build better detection systems for phishing. Prominent work in this area includes [**?**] by Zhang *et al.*, which uncovered and categorized many novel client-side techniques by forcing the execution of phishing pages to trigger the cloaking behavior. Acharya *et al.* in [**?**] uncovered that phishing pages can successfully evade blocklists by knowing how to identify their crawlers, and Oest *et al.* in [42] 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 [30] 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 blind spot by demonstrating that these proxies remain fingerprintable using TLS fingerprinting. [59] 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 [**?**] 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 CAPTCHAs [57] utilized vision-based models.

To better understand why, other than cloaking, phishing pages may choose to fingerprint, Lin *et al.* in [34] 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 [19] 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, [15] 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 0.91 when classifying 2,000 pages (1,141 benign and 859 phishing) from features extracted from their kit. However, their multi-class classifier for identifying the kit only achieved an F1 score of 0.39. Merlo *et al.* in [38] 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 [25], 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 [43], Oest *et al.* manually analyzed phishing kits to establish the taxonomy for server-side cloaking, and in [13], Bijmans *et al.*, after collecting phishing kits by watching TLS transparency logs to identify Dutch brank phishing domains, manually created a fingerprint from static features to analyze their prevalence in the wild.

More recently, Lee *et al.* in [32] provides a server-side script (PHP) level analysis of phishing kits, finding that dynamically generated URLs are still standard in the ecosystem and observing seasonality in the kits they were able to obtain.

Extending the understanding of the phishing ecosystem:

Similar to our methods, Rola *et al.* in [**?**] deployed a modified Chromium browser to gather data and analyze phishing website browser APIs utilizing a pre-selected API list focused on first and third-party scripts for phishing pages. They find that the majority 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, reinforcing our finding that phishing pages vary vastly from their original page.

Oest *et al.* in [44] 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. [44] 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 [56] developed a crawler.

B. Dynamic analysis of web pages

Our work shares a methodology for dynamic analysis enabled by web measurement frameworks like OpenWPM [21] and VisibleV8 [28]. Su *et al.* used VisibleV8 traces and taint analysis in [55] to discover emerging fingerprinting techniques. Sarker *et al.* used VisibleV8 to create an oracle for detecting obfuscation [52]. 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.* used a combination of VisibleV8 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 [47]. Iqbal *et al.* used OpenWPM to capture execution traces from tranco top 100K URLs of Tranco, training a classifier on a mixture of dynamic and static features extracted from the JavaScript's AST and execution traces, respectively, to achieve a 99.8% accuracy in identifying fingerprinting scripts online.

This work stands apart from prior research, as we attempt to deferentitate pages via all of their browser APIs executed, instead of a pre-existing list of APIs. Compare to the F1-score of 39.54% from [15] we are more successful in differentiation via execution traces, we create the notion of clusters entirely automatically, using the entire executation trace, compared to [20], and provide insignts into dynamic behaviors and techniques as opposed to static resource usage presented in [33].

VII. Limitations and Future Work

A. Variance

We collect API traces from these pages by remaining on these pages for 15 seconds. While this is in line with what prior work employs, the lack of force execution, page interactions, and different system loads between runs introduces noise into our measurement. As highlighted by other work [56], modern phishing pages include a multi-step user experience, and future work can aim to extrapolate the techniques used by pages at different stages via instrumented crawlers that interact with the pages.

B. 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,

C. Limited Kit sophistication

The phishing kits in this paper were collected using Kit-Phishr; 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, Flagitsk, 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 a honeypot setup similar to [**?**] but one that would enable deployment of any kits.

VIII. Conclusion

In this paper, we provide a workflow for researchers and analysts to automatically differentiate between a collection of phishing pages, based on common underlying kits or shared techniques, if the behaviors are too generic. 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.

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IX. Ethical consideration

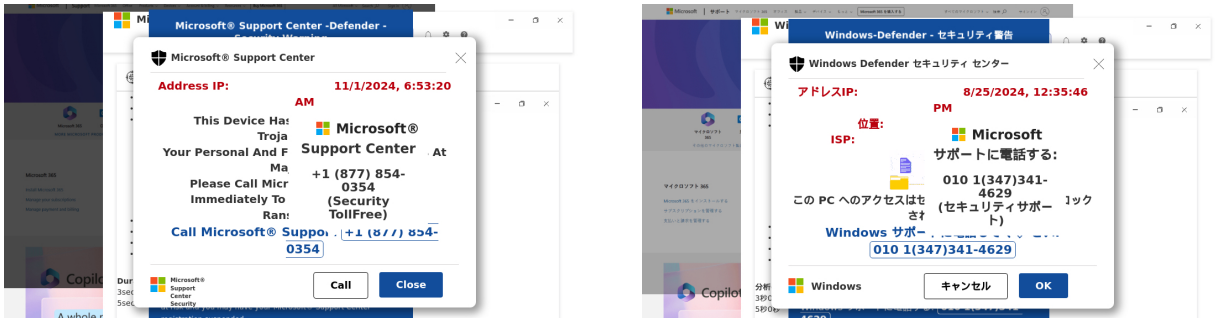
This research relied on publicly and commercially available URLs detected using proprietary methods to be phishing websites. No additional threat intelligence is attached to the URLs we are planning to release, and to ensure that any confidential information is not accidentally leaked through the URLs (like GET parameters that are indications of a test submission before the URL was submitted to the feeds), we will blind the get parameters of the URLs we visited upon release.

We did not collect or store any identifiable information about the individuals behind phishing kits or the pages, and we did not conduct any live testing of their networks, as we only visited at most twice upon ingestion.

Appendix A

TABLE V: Summary of all API calls that match to a category identified by Crawlphish

Category	Clusters	Pages
User-Interaction		
Pop-up (Total)	104	1,323
Accelerometer	7	63
Clipboard.readText	1	2
Geolocation.getCurrentPosition	55	479
Gyroscope	4	10
MediaDevices.getUserMedia	5	55
Notification.requestPermission	16	148
Window.alert	22	581
Mouse	35	62
DomEvents	10,402	362,700
Fingerprint		
Total	9,131	289,014
Navigator.userAgent	8,641	266,126
HTMLDocument.cookie	4,664	124,110
HTMLDocument.referrer	2,175	39,344
Bot Detection		
Timing	2,528	78,202



(a) Page variant in English

(b) Page variant in Japanese

Fig. 10: Cropped screenshots from Cluster-e325887b, IP addresses and location redacted to ensure anonymity of the authors.