Supporting Early and Scalable Discovery of Disinformation Websites

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Online disinformation is a serious and growing sociotechnical problem that threatens the integrity of public discourse, democratic governance, and commerce. The internet has made it easier than ever to spread false information, and academic research is just beginning to comprehend the consequences. In response to this growing problem, online services have established processes to counter disinformation. These processes predominantly rely on costly and painstaking manual analysis, however, often responding to disinformation long after it has spread.

We design, develop, and evaluate a new approach for proactively discovering disinformation websites. Our approach is inspired by the information security literature on identifying malware distribution, phishing, and scam websites using distinctive non-perceptual infrastructure characteristics. We show that automated identification with similar features can effectively support human judgments for early and scalable discovery of disinformation websites. Our system significantly exceeds the state of the art in detecting disinformation websites, and we present the first reported real-time evaluation of automation-supported disinformation discovery. We also demonstrate, as a proof of concept, how our approach could be easily operationalized in ordinary consumer web browsers.

1 INTRODUCTION

Disinformation has emerged as a serious and growing abuse of technology, and it threatens the integrity of public discourse, democratic governance, and commerce. Disinformation itself is not new—the practice dates to at least classical antiquity, and in the following millennia it has been a recurring instrument for international influence, domestic political advantage, and economic gain [78, 97, 19]. In recent years, the disinformation landscape has rapidly and radically shifted: The internet has made disinformation cheaper, easier, and more effective than ever before [58]. The same technologies that have democratized online content creation, distribution, and targeting are increasingly being weaponized to mislead and deceive. Russia notoriously deployed disinformation to interfere in the 2016 U.S. presidential election [90, 71, 105, 21, 47, 117], and political disinformation campaigns have also struck dozens of other nations [11, 10]. Additional disinformation campaigns have been economically motivated, driving valuable page views for advertising revenue, pushing products or services, or undermining competitors [66].

The major online platforms have not kept pace. Responses to disinformation mostly rely on user reports, manual analysis, and third-party fact checking, which are fundamentally slow and difficult to scale [7]. These responses give disinformation an asymmetric advantage, enabling it to spread and affect perceptions in the hours and days after it is first distributed—a critical period during which disinformation may be most effective [122].

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This paper presents Disinfotron, a sociotechnical system that uses automated detection to surface possible disinformation websites for human moderators. Disinfotron's design is motivated by prior work in the information security field that has demonstrated viable early detection for malware, phishing, and scams using machine learning and a combination of carefully engineered network-level and application-level features [43, 107, 102, 44]. Disinfotron uses similar insights to support discovery of disinformation websites, and it refines its predictions by taking advantage of features that become available at progressive stages of the website creation and distribution pipeline.

The design of Disinfotron is based on the intuition that there is a dichotomy between the human-perceived characteristics of a website and the technical configuration of the website. A website might *appear* to ordinary users as an authentic news outlet, but it might have distinct network-level and application-level properties that should raise red flags for human moderators. Disinfotron generates features from a website's domain, certificate, and hosting properties, then applies multi-label classification to categorize the website as disinformation, news, or other (i.e., lacking news content). We use a machine learning approach that facilitates interpretability so that Disinfotron can surface salient non-perceptual features for human moderators. Our evaluation shows that Disinfotron significantly outperforms the state of the art on historical data and is effective in a real-time pilot deployment.

In this paper, we make the following contributions:

- Identification of domain, certificate, and hosting features that distinguish disinformation, news, and other websites.
- Disinfotron, a sociotechnical system for discovering possible disinformation websites that can make a classification early in a website's lifecycle and can progressively improve its classification as the website becomes operational.
- Evaluation of Disinfotron's performance on both historical and real-time data, demonstrating that the approach is feasible, accurate, scalable, and inexpensive. We present what is, to our knowledge, the first successful deployment of real-time disinformation discovery supported by machine learning.
- Demonstration of how outputs from Disinfotron can be used in practice, including a proof-of-concept browser extension that warns users before visiting a disinformation website.
- Publication of the Disinfotron dataset, the largest public corpus of manually labeled disinformation and news websites, accompanied by an archive of domain, certificate, and hosting features for each website.

These contributions span multiple research areas. We add to the literature on computer-supported cooperative work, both from the perspective of platform moderators and ordinary users. We show that automation can support scalable human judgment for online disinformation, much like recent work has shown that automation can support scalable judgment about deceptive or manipulative e-commerce practices [67, 68]. We also demonstrate a plausible path for platforms and users to navigate the complex cooperative work problem of disinformation [98].

We contribute to the interdisciplinary literature on news and disinformation by significantly advancing the state of the art for automated detection of disinformation websites, demonstrating the value of a new class of infrastructure features for disinformation detection, and reporting the first instance of successful automation-supported discovery of disinformation websites. We also provide the most comprehensive dataset of news and disinformation websites to date, along with an archive of website features for future research.

In comparison to the information security literature, Disinfotron is the first system that leverages threat detection methods to address the growing challenge of online disinformation. We overcame
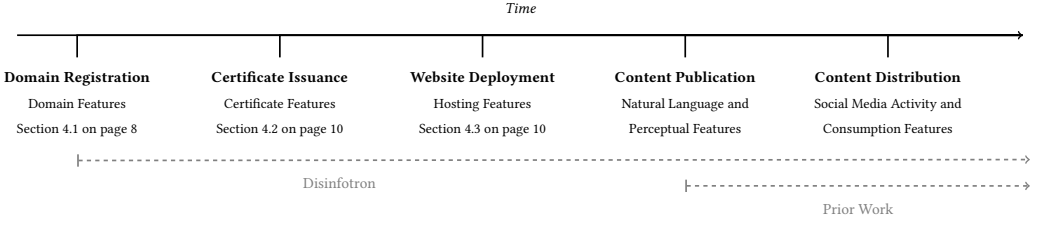
Fig. 1. The lifecycle of a disinformation website, from domain registration to content distribution. Disinfotron attempts to surface possible disinformation websites for human moderators as soon as the domain is registered, with progressively improving automated accuracy as the website deploys.

a number of significant technical challenges in adapting the combination of infrastructure features and machine learning to the disinformation problem domain, including: constructing a new real-time pipeline for surfacing possible disinformation websites and measuring associated infrastructure, rigorously refining infrastructure features (which produced a number of counterintuitive results), assembling the largest reported dataset of disinformation and news websites, and carefully structuring the machine learning problem to account for massive class imbalances.

The rest of the paper proceeds as follows. Section 2 describes our design goals and how we approach the problem of disinformation detection. Section 3 on page 5 describes how we developed a dataset of labeled websites for evaluating features and both training and testing automated website classification. Section 4 on page 6 presents our feature engineering for distinguishing classes of websites. Section 5 on page 12 presents our historical training dataset, Disinfotron's design, and an evaluation of the system's automated detection performance on historical data. Section 6 on page 13 applies Disinfotron to real-time feeds from domain registration, certificate issuance, and social media sharing, demonstrating that the system is effective in a real-time deployment. Section 7 on page 16 discusses operational considerations, including how Disinfotron contends with adversarial evasion. Section 8 on page 18 discusses related work, and Section 9 on page 19 concludes with a discussion of possible future directions.

2 DESIGN GOALS AND PROBLEM STATEMENT

We are motivated by the urgent sociotechnical problem of online disinformation, the need for new tools to assist human moderators in discovering disinformation campaigns, and the current asymmetric disadvantage in defending against disinformation [62]. Improving disinformation detection is essential for rebalancing the playing field, because detection must necessarily precede response processes and interventions by registrars, certificate authorities, hosting providers, social media platforms, search engines, browser vendors, extension developers, fact checkers, and journalists, among other internet stakeholders.

Our design goals for Disinfotron are *early detection*, since the adverse effects of disinformation appear to be concentrated in the period immediately following initial distribution, and *progressive detection*, recognizing that additional features become available during the lifecycle of a disinformation website (Figure 1). We also aim for detection that is *accurate*, *scalable*, and *low cost*, since the scale of new content on the web is vast and resources for countering disinformation—including human moderator capacity—are comparatively limited.

We envision Disinfotron as a system that uses automation to support human moderators in making judgments about potential disinformation websites. For example, a search engine might

deploy Disinfotron by ingesting crawl data, predicting whether a newly seen domain is disinformation, and triggering human moderation if red flags are present. Similarly, a social network might apply Disinfotron to shared links or a browser vendor might apply the system to domains that users navigate. The output from an instance of Disinfotron could also have value throughout the web ecosystem; it might trigger interventions by a platform or browser (like the proof-of-concept browser extension that we present).

We emphasize that, at least for the near term, we do *not* envision Disinfotron as a fully automated system. Disinformation is a complex sociotechnical problem that involves free speech, consumer protection, and competition considerations (among other societal priorities). We expect that online platforms will continue to require an exceptionally high degree of confidence and explainable evidence before categorizing a website as disinformation. We also expect that platforms will continue to rely on manual labeling for popular news and disinformation websites, which receive a disproportionately concentrated volume of web traffic [116]. Our goal is an automation-supported system that can discover new, comparatively less popular, or narrowly targeted disinformation websites, prompting manual review of a website's authenticity *before* it can become popular or have widespread negative effects. Human moderation also acts as a backstop, minimizing the adverse consequences of automated classification errors.

2.1 Scoping Disinformation

Definitions of disinformation vary in academic literature and public discourse [58]. Common components include intent to deceive about facts [54, 108, 27, 45], intent to harm [108], and intent to prompt distribution [62]. Many articles focus on "fake news," also with varying definitions and differing conceptions of how the category relates to disinformation [100]. For purposes of this work, we use the term *disinformation*, and we define a *disinformation website* as a website that appears to serve news about politics and current events, but that operates in a manner that is significantly inconsistent with the norms, standards, and ethics of professional journalism.[1] We define this category as distinct from the category of legitimate *news websites*, including those with a partisan bias, so long as they adhere to journalistic norms such as attributing authors, maintaining a corrections policy, and avoiding egregious sensationalism.[2] Our focus on websites related to current events and politics is motivated by recent results indicating that a significant proportion of the U.S. population has encountered these types of disinformation websites[37, 38, 5, 39, 4].

2.2 Website Domains as Granularity of Study

We study disinformation at the granularity of website domains, rather than individual articles, claims, advertisements, social media accounts, or social media actions (e.g., posting or sharing). Websites are a key distribution channel for disinformation and are often the subject of social media activity [37, 38, 5, 4]. There is also very limited prior work applying automated methods to surface disinformation at the domain level [8].

Focusing on domains has a number of benefits:

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[1]We decline to use the term "fake news," even though it may be a more apt description of the category of website that we study, because of the term's political connotations and because the system that we describe is generalizable.

[2]We note that a satire website can fall within our definition of disinformation if the satire is not readily apparent to users. This is an intentional definitional decision, since satire websites can (and often do) mislead users [25, 55], and since disinformation websites are increasingly relying on implausible small-print disclaimers that they are satire [75, 76]. Our goal is to identify websites where users might benefit from additional context or other interventions. We do not take a position on how internet stakeholders should respond to satire that risks misleading users, only that internet stakeholders should have the opportunity to make an informed decision about how to respond to such websites.

- **Early Warning.** It is possible, in principle, to identify disinformation websites before they begin to publish or distribute content.[3] Analysis of article content or social media activity, by contrast, can only occur much later in the disinformation lifecycle (Figure 1 on page 3).
- **Longer-Term Value.** Disinformation articles and social media posts have an inherently limited lifespan, owing to the rapid news cycle [122]. Disinformation websites, by contrast, can last for years.
- **Platform Independence.** Identifying disinformation domains is feasible without access to a major online platform's internal account or activity data.
- **Ecosystem Value.** A real-time feed of disinformation domains has value throughout the internet ecosystem, similar to existing feeds of malware, phishing, and scam domains [34]. Website data is immediately actionable for a diverse range of internet stakeholders.

In addition, websites are often a component of multimodal disinformation campaigns. Detection at the domain level can provide an investigative thread to untangle the rest of a disinformation campaign, including associated social media accounts and activities. And since false claims often spread between disinformation campaigns, identifying a subset of campaigns provides valuable features for identifying other campaigns.

There are drawbacks and limitations associated with focusing on domains. Some websites feature a mix of authentic and false news, complicating our labeling task (discussed in Section 3). We also recognize that disinformation websites are just one piece of the disinformation problem space, and that social media likely plays a comparatively greater role in exposing users to disinformation and inducing false beliefs. Our goal is to make tangible progress on a discrete subset of the disinformation problem space, highlighting a path forward for the broader field.

3 WEBSITE DATASET

We used both current and historical data to construct a dataset that includes three classes of website: disinformation, news, and other. We identified three classes, rather than just two classes of disinformation and non-disinformation, both to facilitate feature engineering and because we found that cleaner class separation improved classification performance. We sought to balance the three classes, ultimately including about 550 websites for each class.[4]

3.1 Disinformation Websites

We began by combining multiple preexisting datasets of disinformation websites that had been manually labeled by experts or published by news outlets, research groups, and professional fact-checking organizations. Specifically, we integrated the corpora from CBS [15], FactCheck.org [26], Snopes [60], Wikipedia [111], PolitiFact [33], and BuzzFeed [94, 95, 96]. We also included websites that have been labeled as "fake news" by OpenSources, a collaborative academic project that manually assigned credibility labels to news-like websites [121]. Additionally, we incorporated data from the NewsGuard browser extension [73], which provides credibility scores based on observations by a team of fact-checkers. Finally, we integrated the list of disinformation websites compiled by Allcott et al. for their study on the diffusion of disinformation on Facebook between

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[3]For example, the automated component of Disinfotron might spot a new domain registration that looks like a local newspaper name, but has infrastructure overseas. A human moderator might then investigate and find there is no local newspaper with that name.

[4]We first constructed the disinformation class, then constructed the other two sets with equal sizes for balanced training and testing. Class sizes changed slightly over the course of dataset construction, so the final datasets contain 551, 553, and 555 sites respectively. We recognize that the other website class would predominate in a real-time feed of domain, certificate, or social media events. Our rationale is that without balancing the dataset, the classifiers we develop would minimize error by simply labeling every website as other.

2015 and 2018 [5], which they also compiled from lists by fact-checking organizations and academic sources.

We then manually filtered the list of websites, leaving only the websites that satisfied our definition of disinformation (Section 2.1 on page 4). This step included removing obvious satire and hyperpartisan news, such as InfoWars and The Gateway Pundit. Our final dataset contains 769 disinformation websites. 582 (76%) of the websites are currently inactive: either unavailable, replaced with a parking page, or repurposed for other kinds of abuse (e.g., spam or malware distribution). This highlights the rapid turnover of disinformation websites in comparison to authentic news websites. Fortunately, we were able to reconstruct domain, certificate, and hosting features for 364 (63%) of these inactive websites (described in Section 4), resulting in a final set of 551 disinformation websites.

3.2 News Websites

We built a corpus of 553 authentic news websites, randomly sampling 275 from Amazon's Alexa Web Information Service (AWIS) [6] and 278 from a directory of websites for local newspapers, TV stations, and magazines [115]. From AWIS, we sampled websites categorized as "news," excluding the 100 most popular websites out of recognition that these websites likely have some distinct properties compared to the long tail of news websites (e.g., high-quality and customized infrastructure). From the local news dataset, we manually filtered to omit websites that did not prominently display news (e.g., TV station websites that primarily served as channel guides).

3.3 Other Websites

We built a set of 555 other websites by sampling from Twitter's Streaming API [104]. We filtered for tweets that contained a URL, extracted the domain name, and then used the Webshrinker classification service [109] to assign labels based on the Interactive Advertising Bureau's standardized website categories [52]. We excluded websites that belonged to the "News" and "Politics" categories.

4 FEATURE ENGINEERING

In this section, we detail and evaluate the features that the automated component of Disinfotron uses to classify disinformation, news, and other websites. We examine features in three categories:

- **Domain.** Features associated with registering and operating a domain name, including properties of DNS registration, domain names themselves, and nameserver configuration (Section 4.1 on page 8).
- **Certificate.** Features derived from TLS certificates, including certificate and certificate authority attributes (Section 4.2 on page 10).
- **Hosting.** Features related to web hosting infrastructure, including both network-level and application-level properties (Section 4.3 on page 10).

These three categories of features can be measured from a public internet host or acquired from commercial services, are inexpensive to obtain, and are available early in the lifecycle of a disinformation website (Figure 1 on page 3), consistent with our design goals (Section 2 on page 3). Additionally, because these features are related to a website's infrastructure rather than its content, they change (relatively) infrequently.

We are not able to extract every feature for every website. For example, some websites do not offer TLS certificates, and some certificates are incorrectly formatted. In such cases, we mark the type of data as missing through a boolean feature. Furthermore, some websites in our dataset were inactive. To obtain features for these websites, we began by locating the most recent Internet Archive Wayback Machine [53] snapshot from when a disinformation website was still active, and

Name	Category	Description	Rank	Data Type
News Keyword(s) in Domain	Domain	The domain name contains one or more keywords that imply it serves news (e.g., "herald," "tribune," or "chronicle").	1	Boolean
Domain Name Length	Domain	The number of characters in the domain name.	3	Numeric
"News" in Domain	Domain	The domain name contains the specific keyword "news."	8	Boolean
WHOIS Privacy	Domain	The domain registrant is using a WHOIS proxy service or registrar privacy option.	9	Boolean
Registrar Name	Domain	The organization with whom the domain was registered.	11	Categorical
Nameserver SLD	Domain	The second-level domain of the nameserver.	14	Categorical
Nameserver AS	Domain	The autonomous system of the nameserver's IP address.	16	Categorical
Registrant Organization	Domain	The organization of the registrant.	17	Categorical
Registrant Country	Domain	The country of the registrant.	19	Categorical
Time Since Domain Registration	Domain	The time elapsed since the domain was originally registered.	21	Numeric
Domain Lifespan	Domain	The time period between the domain's initial registration and expiration dates.	22	Numeric
Time to Domain Expiration	Domain	The time until the domain's registration expires.	23	Numeric
Time Since Domain Update	Domain	The time since the domain's configuration was updated.	25	Numeric
Nameserver Country	Domain	The country where the nameserver is located, using IP geolocation.	27	Categorical
Novelty TLD	Domain	The TLD is novelty (e.g., `.news`, `.xyz`, or `.club`).	29	Boolean
Digit in Domain	Domain	The domain name contains numeric characters.	30	Boolean
Hyphen in Domain	Domain	The domain name contains a hyphen.	31	Boolean
Domain Resolves	Domain	The domain name resolves to an IP address.	32	Boolean
SAN Count	Certificate	The number of domains in the Subject Alternate Name extension field.	2	Numeric
SAN Contains Wildcard	Certificate	The Subject Alternate Name extension field contains a wildcard entry for a domain.	7	Boolean
Expired Certificate	Certificate	The certificate is expired.	10	Boolean
Certificate Available	Certificate	A certificate is configured at the domain (i.e., a certificate is provided during a TLS handshake on the HTTPS port).	12	Boolean
Self-signed Certificate	Certificate	The certificate is signed by the domain owner, not a CA.	13	Boolean
Domain-validated Certificate	Certificate	The domain owner has proved ownership to the CA.	18	Boolean
Certificate Issuer Name	Certificate	The organization or individual who issued the certificate.	24	Categorical
Certificate Issuer Country	Certificate	The country where the certificate was issued.	26	Categorical
Certificate Lifetime	Certificate	The certificate's period of validity.	28	Numeric
WordPress Plugins	Hosting	WordPress plugins used by the website.	4	Categorical
Website AS	Hosting	The autonomous system of the website's IP address.	5	Categorical
WordPress CMS	Hosting	The website uses WordPress as its content management system.	6	Boolean
WordPress Theme	Hosting	The WordPress theme used by the website.	15	Categorical
Website Country	Hosting	The country where the website is located, using IP geolocation.	20	Categorical
Website Available	Hosting	A website is hosted at the domain (i.e., content is returned in response to an HTTP request for the base URL, following redirects).	33	Boolean

Table 1. Domain, certificate, and hosting features that Disinfotron uses to classify websites as disinformation, news, or other.

we retrieved raw HTML content that allowed us to generate hosting features. Next, we queried the DomainTools API [22] to retrieve historical DNS and WHOIS records from the time that the website was actively serving disinformation, enabling us to generate domain features. Finally, we used the `crt.sh` Certificate Transparency log database [89] to recover the TLS certificate from when the website was serving disinformation, allowing us to generate certificate features. Due to the incompleteness of the historical records we obtain, we are not always able to reconstruct every feature for inactive websites. In such cases, we mark the type of data as missing through a boolean feature.

Table 1 presents the complete set of features that Disinfotron uses to classify websites. We compute feature rankings by training a multi-class random forest model and computing mean

Rank	Disinformation	News
1	GoDaddy	GoDaddy
2	Enom	Network Solutions
3	Namecheap	MarkMonitor
4	FastDomain	CSC Corporate Domains
5	LaunchPad (HostGator)	Enom

Table 2. Top domain registrars used by disinformation websites and news websites in our historical data.

decrease impurity for each feature (Section 5.1 on page 12). The rest of this section examines the features that Disinfotron uses for classification.

4.1 Domain Features

Any public website with a domain name necessarily relies on the DNS infrastructure. The domain name itself provides information about the website, and the process of registering the domain reveals information about the registrar (the service provider where the domain name was registered), the registrant (the individual or organization who registered the domain), and the circumstances of registration (such as the initial date of registration). DNS also provides information about the authoritative nameservers used by the website. We use these domain properties to engineer a set of features that can distinguish disinformation, news, and other websites.

Registrar. We use the WHOIS protocol [49, 20] to identify the registrar for each domain in our labeled website dataset (Section 3 on page 5). We found that the vast majority of domains for each website class rely on a relatively small set of registrars. In particular, ≈84% of disinformation websites, ≈90% of news websites, and ≈82% of other websites use the top three registrars for their respective classes. The set of popular registrars is, however, somewhat distinct for each class. Table 2 presents the most common registrars used by disinformation and news websites. GoDaddy is the most popular registrar for all three classes of website, but certain other registrars have distinct usage patterns for each category. Namecheap and Enom, for example, are low-cost and consumer-oriented registrars; our dataset indicates that they are rarely used by news websites. By contrast, Network Solutions is a more expensive and business-oriented registrar, and both MarkMonitor and CSC are exclusively directed at businesses with valuable brands; we find that disinformation websites rarely use these registrars while they are common for news websites.

Registrant. We also use the WHOIS protocol to identify the registrant of each domain. Registrant data is not consistently available; it is often obscured by WHOIS proxy services [110, 48] or, increasingly, registrar privacy options.[5] Prior work has demonstrated that the DNS records for abusive websites often mask the registrant's identity [13, 14]. We find a similar pattern of WHOIS privacy adoption among disinformation websites; in our historical dataset, 57% of disinformation websites use WHOIS privacy.[6] News websites, by contrast, tend to include identifying information in domain registration records; only 9% of news websites use a WHOIS privacy service. We hypothesize that operators of disinformation websites use WHOIS privacy services to avoid culpability, similar to operators of other abusive websites. News websites, on the other hand, have an incentive to

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[5]ICANN recently implemented a specification that provides free WHOIS privacy, in order to comply with the European Union's General Data Protection Regulation [101, 24]. We note that this development is no more of an obstacle to Disinfotron than preexisting WHOIS privacy services, because the new specification allows ICANN, registries, and registrars to disclose WHOIS information for purposes of combating abuse.

[6]Our set of keywords for determining whether a domain registration uses a WHOIS proxy or privacy option will be available with our source code upon publication.
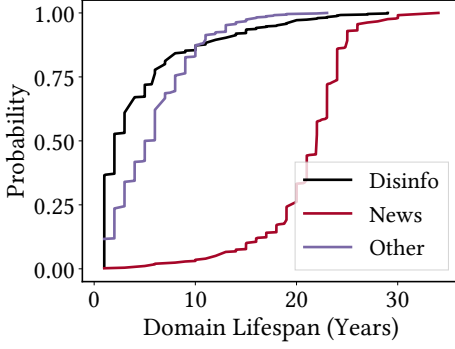
(a) The time period between the domain's initial registration and expiration dates.
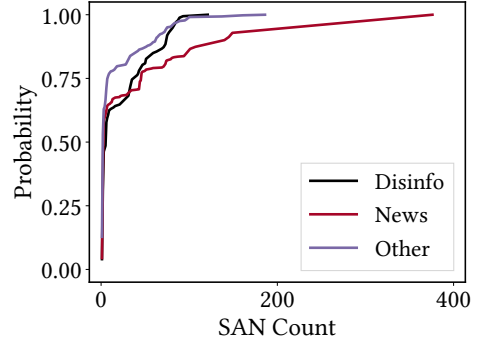
(b) The number of domains in the TLS certificate Subject Alternative Name extension field.

Fig. 2. Examples of features with differing distributions among disinformation, news, and other websites.

disclose registrant information both to demonstrate authenticity and to provide a technical point of contact in the event of a DNS configuration issue.

Registration. Information about a domain registration can also provide useful features about a website. For example, news website domains are often over a decade old—just like the associated news organizations. News websites also tend to have domain expirations far in the future, since news organizations plan to continue operations and do not want to inadvertently lose their domains. Disinformation websites, by contrast, often have recently registered domains because the websites are new fabrications. Disinformation websites also tend to have near-term domain expirations, presumably because the domain holds little inherent or long-term value—most traffic will originate from social media activity rather than recurring visits, and the website will foreseeably have to shut down or switch domains once it has been widely outed as disinformation. Figure 2 shows the distribution of the duration between initial domain registration and expiration for each class of website; news websites have domains with significantly longer lifespans.

Domain Name. The domain name itself, of course, includes valuable features for distinguishing classes of websites. The domain name of a news website often includes the term "news" and, since it tends to follow the name of the organization that operates the website, frequently includes news related keywords like "herald," "tribune," or "chronicle." News websites also tend to use a popular top-level domain; in our labeled website dataset, 83.5% of news websites have a `.com` domain. Disinformation websites also frequently use news keywords in their domain names, since they intend to appear as news websites. For example, 20 disinformation websites in the dataset used by Allcott et al. [5] are registered to domains following the convention `channel`**`xx`**`news.com`, where **`xx`** is a two-digit number intended to appear as an authentic television channel. We also observe that disinformation websites sometimes make use of newer TLDs, including `.news`, `.xyz`, or `.club`, where more domain names that have the appearance of news websites may be available.

Nameserver. Every public website has an authoritative nameserver (or set of nameservers) that resolves the website's domain name to an IP address. We perform DNS queries to both identify the first nameserver for a website and obtain that nameserver's IP address. Our dataset indicates that disinformation websites tend to use inexpensive and mass-market nameserver providers. These providers are often associated with the website's hosting platform, such as Cloudflare,

HostGator, or BlueHost, or the website's domain registrar, such as DomainControl (GoDaddy) or Namecheap. News websites also frequently use these providers, but they also use a distinct set of business-oriented nameserver providers such as NS1 or Qwest (CenturyLink).

4.2 Certificate Features

Websites are increasingly supporting encrypted and authenticated public access using HTTPS [80, 31]. Implementing HTTPS requires obtaining and configuring a TLS certificate; these steps inherently reveal properties of the issuing certificate authority (the service provider that validates the domain owner) and of the certificate itself (such as the period of validity and the extent of validation). The following features are exemplary of what we can extract from TLS certificates.

SAN Count. The Subject Alternate Name (SAN) extension in a TLS certificate enables sharing one certificate across multiple domains. In a conventional TLS deployment, the SAN field describes the set of domains that belong to a single organization. Increasingly, infrastructure providers use this field to efficiently facilitate hosting multiple domains with shared infrastructure. Cloudflare, for example, automatically includes dozens of customers in a shared certificate unless a customer pays extra for a dedicated certificate [80]. Our intuition was that news websites are more likely to manage their own certificates or purchase dedicated certificates, while disinformation and other websites are more likely to use convenient and inexpensive (or free) shared certificates.

Figure 2b on the previous page compares the distribution of the number of domains in a certificate SAN field between the three classes of websites. The results show that, contrary to our intuition, news websites are more likely to have a crowded SAN field than disinformation websites. We find that some parent news organizations have configured certificates that cover a large number of subsidiary news organizations.

Configuration Errors. We initially hypothesized that disinformation websites would be more likely to feature certificate misconfigurations, since they are not managed by professional news organizations. For example, the certificate for the disinformation website empirenews.net does not include that domain in the subject name or SAN field, and the certificate is also not signed by a trusted certificate authority. Both of these errors would cause a web browser to warn the user when navigating to the website.

We found that, contrary to our intuition, certificate configuration errors are similarly rare in all three classes of websites. This result may be because certificates are increasingly managed with automated platforms that avoid misconfiguration, or because certificate errors are easy to detect (a website becomes unavailable over HTTPS) and easy to correct.

4.3 Hosting Features

The third feature category that we examine relates to a website's hosting infrastructure. These features typically become available after a domain name is registered and a certificate has been issued, but before content is added or the website circulates on social media. We focus on hosting features related to where in the internet topology the server is located, where geographically the server is located, and how content is managed on the website.

Content Management Systems and Plugins. Many websites are built with content management systems (CMSes), application-level platforms that define the style and layout of the website and facilitate publishing and organizing content. Our intuition is that disinformation websites may be more likely to use a free CMS than authentic news websites, more likely to use CMS plugins for social media integration (rather than build the integration themselves) and search engine optimization (since disinformation websites are aggressive about content virality), and more likely

Rank	Disinformation	News
1	Cloudflare (13335)	Lee Enterprises (10668)
2	GoDaddy (26496)	Amazon (16509)
3	Google (15169)	Amazon (14618)
4	Unified Layer (46606)	Incapsula (19551)
5	Namecheap (22612)	Cloudflare (13335)

Table 3. Top autonomous systems used for hosting by disinformation websites and news websites in our historical data.

to use a variant of a stock CMS theme (rather than designing a new theme themselves). For example, the disinformation website `freeinfomedia.com` runs the free WordPress CMS, has added the `facebook-comments` plugin, and uses the inexpensive `mts-best` theme. We use CMS fingerprinting to detect whether a website is running WordPress, which popular plugins are installed, and which theme is active.[7]

We find, consistent with our intuition, that WordPress adoption is much more common among disinformation websites (82%) than news websites (20%). We also find that the distribution of WordPress plugins significantly differs between news and disinformation websites. Disinformation websites, for example, disproportionately use the `seo` (search engine optimization tools), `jetpack` (administrative tools), and `contact-form-7` (simplified contact forms) plugins, while news websites tend to not use popular WordPress plugins. WordPress themes had less value in distinguishing classes of website, since themes are often unique or renamed, but we did find that stock or inexpensive news-like themes (e.g., `Newspaper`, `mh-mag`, and `Newsmag`) were much more common among disinformation websites than news or other websites.

Hosting Provider and Location. We use DNS to resolve the IP address for each website in our labeled website dataset. We then use BGP routing tables to map the IP address to an autonomous system (AS) and the MaxMind GeoLite2 database to map the IP address to a country. Our intuition is that disinformation websites will disproportionately use hosting providers that are inexpensive and mass-market, or that are located outside the United States.

We find that a small proportion of ASes host the vast majority of websites across all three classes. In particular, ≈86% of disinformation websites, ≈84% of news websites, and ≈80% of other websites are hosted on the top three ASes for their respective classes. The prevalence of each AS, however, varies significantly by class. Table 3 presents the most common ASes for disinformation and news websites. Consistent with our intuition, inexpensive and mass-market hosting providers like GoDaddy and Namecheap are much more common among disinformation websites than news websites [72, 50]. By contrast, news websites make more frequent use of premium, business-oriented hosting providers like Incapsula [51]. We also find that some ASes are highly predictive of news websites. For example, the ASes for Lee Enterprises and Central Newspapers—a pair of news holding companies—are used almost exclusive for news websites [9, 63, 72].

We also find, contrary to our intuition, that geographic location of the hosting provider is not a particularly valuable feature. The overwhelming majority of websites in all three classes are hosted in the United States.

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[7]We additionally implemented CMS fingerprinting for Drupal and Joomla, but we found that those CMSes were rare in our dataset. We also implemented a test for reuse of Google Analytics IDs, hypothesizing that networks of disinformation websites might duplicate analytics code. We found, however, that only one pair of websites had identical Google Analytics IDs. We omitted all of these features from Disinfotron because of their low predictive value.

5   TRAINING AND TESTING WITH HISTORICAL DATA

(a) ROC Curves
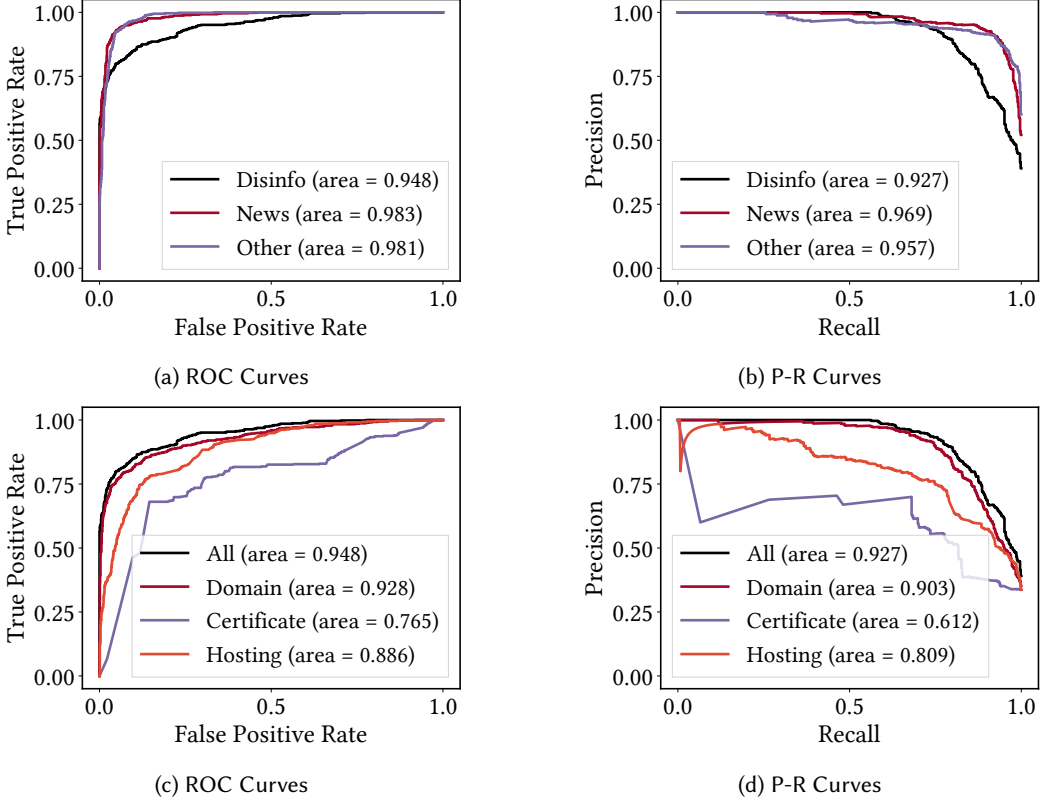
(b) P-R Curves

(c) ROC Curves

(d) P-R Curves

Fig. 3. Disinfotron performance on our training dataset. Figures 3a and 3b show performance on all three classes using all feature types. Figures 3c and 3d show performance on the disinformation class using subsets of features.

In the previous section, we examined domain, certificate, and hosting features that show promise for distinguishing disinformation, news, and other websites. In this section, we explain how we used the features to build a machine learning model. We describe our classifier and then we present an evaluation of the model's performance.

5.1   Classifier

The automated component of Disinfotron uses supervised machine learning to classify websites as disinformation, news, or other. We formulated the machine learning task as multi-class classification because human moderators might want to verify or label news websites in addition to disinformation websites, and because we found that cleaner class separation improved classification performance. We chose a random forest classifier so that results from Disinfotron are readily explainable to human moderators (see Section 7 on page 16).[8]

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[8]Other approaches to supervised machine learning, such as deep learning, can result in models that are difficult to interpret [61].

We set the hyperparameters for Disinfotron by conducting a randomized search over a wide range of values for each hyperparameter. We performed 250 iterations of 5-fold cross validation, selecting the hyperparameters that maximize average accuracy. We also conducted this search with each category of features, training a new model each time. We modularly built the classifier using `scikit-learn` to enable reproducibility and encourage future work [77].

5.2 Performance

We evaluate the performance of the automated component of Disinfotron based on the classifier's true positive rate (i.e., recall), false positive rate, and precision using mean values from 5-fold cross-validation.

First, we assess classification performance for each class of website. Figure 3a on the facing page presents the receiver operating characteristic (ROC) curve and area under the curve (AUC) for each class. Figure 3b on the preceding page presents the precision-recall (P-R) curve and average precision (i.e., the area under the P-R curve) for each class. We find that Disinfotron is able to effectively distinguish between the three classes of websites.

Our results significantly advance the state of the art in automated classification of disinformation and news websites. The most recent published work in the area used a combination of article text, URL, Twitter presence, Wikipedia presence, and web traffic ranking features, and it reported its most effective classifier as having a macroaveraged F_1 of 0.599 and accuracy of 0.655 [8]. While our results are not quite one-to-one comparable, since we use slightly different class definitions[9] and datasets,[10] for the primary purpose of detecting disinformation websites our classifier offers unambiguously far greater performance.

Next, we evaluate the importance of each category of features. Figure 3c on the facing page presents the ROC curve and AUC for each of the feature categories when detecting disinformation websites, as well as the ROC curve and AUC for all feature categories combined. Figure 3d on the preceding page presents the corresponding P-R curves and average precision scores. We find that domain features predominantly drive classification performance, which validates our design goal of enabling early warning for disinformation websites. Domain features are available early in a disinformation website's lifecycle, and domain registrars and registries (among other internet stakeholders) could plausibly intervene when a suspicious news-like domain name appears. We also find that hosting features can accomplish moderate classification performance. Certificate features, by contrast, do not appear to be as promising a direction for disinformation classification.

6 PILOT TEST OF REAL-TIME DISINFORMATION WEBSITE DISCOVERY

In this section, we present an end-to-end, real-time pilot test of Disinfotron. We show that the automated component of the system is capable of surfacing potential disinformation websites for human moderation, and that human moderators can rapidly respond to those flagged websites. This work is, to our knowledge, the first reported instance of a successful real-time disinformation detection system.

6.1 Implementation

The implementation of our Disinfotron pilot test operates in four stages: domain ingestion, feature extraction, classification, and human moderation (Figure 4 on the following page).

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[9]The prior work did not include a class of other websites, and it included three classes of website factuality rather than just news and disinformation.

[10]The prior work reused just one existing dataset, and it did not filter the dataset for consistency.
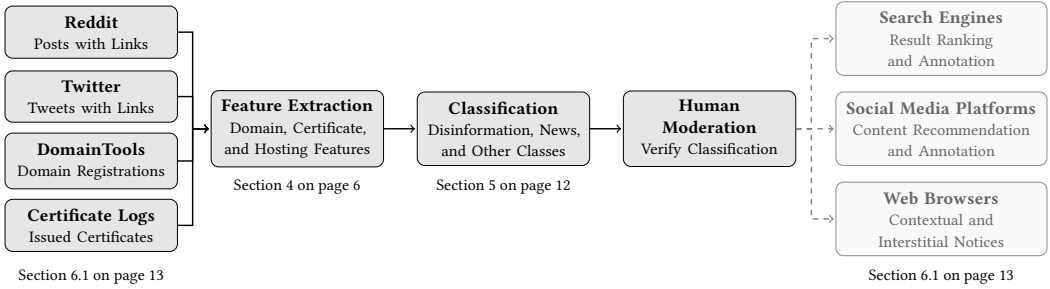
Fig. 4. The processing pipeline for our end-to-end pilot test of real-time disinformation website discovery, followed by example uses of the system's output.

Domain Ingestion. Disinfotron starts by ingesting live feeds of candidate domains. We have selected an initial set of feeds that span the early stages of a disinformation website's lifecycle: domain registration, certificate issuance, and website deployment (Figure 1 on page 3).[11] The earliest data source is DomainTools, which notifies Disinfotron when a domain with a news keyword is newly registered [22].[12] The next data source is CertStream, which alerts Disinfotron of newly issued TLS certificates [12]. The latest stage data sources are Twitter and Reddit [86], from which Disinfotron ingests posting activity that involves URLs.[13]

Feature Extraction. Next, our implementation of Disinfotron issues DNS queries, initiates a TLS handshake, and submits web requests to the candidate domain. The implementation uses the responses to those automated probes to generate the domain, certificate, and hosting features described in Section 4 on page 6. Our implementation archives the raw data and features for every website that it encounters, in order to facilitate human moderation, future refinement of the classifier (e.g., additional manual labeling), and longitudinal study (e.g., long-term trends in disinformation website volume, infrastructure, and content).

Classification. Our implementation next uses the extracted features as input to the classifier described in Section 5 on page 12, classifying the website at the domain as disinformation, news, or other.

Human Moderation. Finally, we manually reviewed a sample of classification output to simulate how an online platform might evaluate possible disinformation websites. We also reviewed samples of news class and other class websites for evaluation completeness.

6.2   Evaluation

We conducted our pilot test by running Disinfotron for five days with all four domain feeds. We split Disinfotron across two enterprise servers; one server ingested domains and extracted features, while the other performed classification. Each server had two 8-core, 2.6GHz CPUs (Intel Xeon E5-2640) and 128GB of RAM. Disinfotron processed 1,326,151 unique domains over the course of 1 week in February 2019.

In order to evaluate the automated components of the pilot implementation, we randomly sampled 100 websites from each detected class and labeled them manually. We only considered

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[11]Our pilot implementation of Disinfotron is easily extensible to additional feeds of candidate domains.

[12]We have omitted a link to our list of news keywords to preserve author anonymity. The list will be available with our source code upon publication.

[13]Tweets are from the Twitter Streaming API and are not filtered by language or geography. Reddit posts are from the Reddit API.
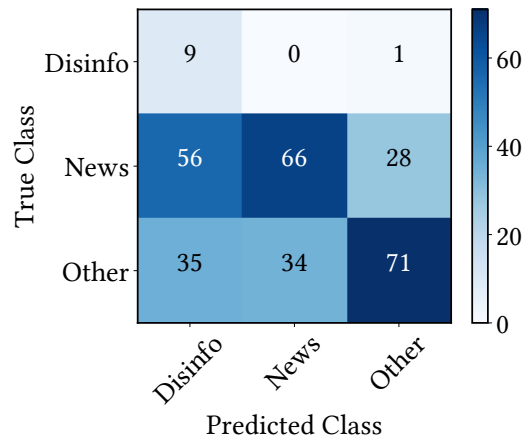
Fig. 5. Disinfotron automated performance on a manually labeled subset of real-time Twitter data.

websites sourced from Twitter for purposes of the evaluation, since we could most accurately label websites with all three sets of features.[14] Our methodology was also motivated by one of our intended use cases for Disinfotron—human moderators at a social media platform labeling websites that had been automatically flagged.

Figure 5 presents a confusion matrix for automated classification of the domains in our manually labeled Twitter sample.[15] We find that performance is radically degraded in comparison to our prior evaluation, which we hypothesize is attributable to two primary causes. First, there is massive class imbalance in the websites shared on Twitter; the overwhelming majority of websites are not in the disinformation class. Second, there is a risk of bias when assembling a historical dataset of news and disinformation websites. Those websites are often identified through commonalities (e.g., part of the same corporate family or network of websites), and those commonalities are susceptible to overfitting. Future work should carefully examine the differences between the historical disinformation classification task and the real-time disinformation discovery task.[16]

Nevertheless, despite the significant drop in performance, we found that the classifier's precision on the disinformation class (0.09) was sufficient to validate our system design. Our simulated moderators were able to rapidly evaluate the flagged websites and, just in the small-scale human moderation step of our pilot test, discovered 2 disinformation websites that had not been previously reported in any public venue.[17] Both websites featured overt false claims and misleading headlines, and both websites clearly satisfied our definition of disinformation (Section 2.1 on page 4).

Table 4 on the following page presents the overall automated classification results from the pilot test using three subsets of features, each reflecting a distinct stage of the disinformation website

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[14]In our envisioned deployment of Disinfotron, some sophisticated platforms might be able to make reliable determinations about a website's class even without hosting or certificate features. In most circumstances, a domain flagged on the basis of pre-content features would be subject to routine probes and would be reclassified when content appears.

[15]Our classifier predicts a class by calculating the highest mean probability across the trees in the forest.

[16]We note that prior work on disinformation has paid surprisingly little attention to machine learning task formulation, sample bias, and overfitting. For example, prior work on disinformation article classification tends to use articles from the same websites in training and test splits, and some work even explicitly encodes the website as a feature or in an embedding. These approaches are highly susceptible to overstating performance. We encourage the disinformation research community to join us in attempting realistic evaluation of research approaches.

[17]We conducted web searches for these domains and did not find any results identifying them as disinformation websites.

Lifecycle Stage	Disinformation	News	Other
Domain Registration	183,339 (13.4%)	95,578	1,088,141
Certificate Issuance	176,747 (13.1%)	111,667	1,061,747
Content Deployment	136,550 (10%)	120,168	1,069,433

Table 4. Classification results from a real-time deployment of Disinfotron over five days.

lifecycle. First, we demonstrate results on domain features, which would be available to a domain registrar or registry. Next, we show results on certificate and domain features, which would be available to a certificate authority when it issues a TLS certificate. Finally, we present results with all categories of features, which would be available to a browser vendor, search engine, or social media platform once a website has distributed content. The combination of our evaluation on manually labeled data and our overall classification results suggests—though we carefully note, it does not prove[18]—that a large number of disinformation websites have not yet been labeled in public datasets.

6.3 Proof-of-Concept Browser Extension

We anticipate that Disinfotron's output would be valuable to a broad range of internet stakeholders (Figure 4 on page 14). As one example, the system could be a basis for browser-based warnings to users.

We developed a proof-of-concept Google Chrome extension to confirm the ease of triggering user notification on the basis of Disinfotron's output. When a user who has installed the extension navigates to a website that Disinfotron has identified as potential disinformation (based on a dynamically updated domain list), the extension inserts an interstitial warning as shown in Figure 6 on the facing page. If the user clicks the "Learn more" option, the interstitial page explains that the website was identified as disinformation using a semi-automated disinformation detection system. Clicking "Details" will explain why the website was initially flagged as disinformation by the automated component of Disinfotron (specifically, the top three features for classification) and provide an option for the user to continue to the website. Clicking "Back to safety" will navigate the browser back to the previous website. The visual style of and user choices on the interstitial page are directly based on the Chrome warning for malware and phishing websites.

There are a variety of ways that this intervention could be improved, such as by adding more details about the classification or allowing users to offer feedback. We leave the question of how to optimize warning effectiveness open for future work; previous research on browser warnings for other security issues such as SSL errors [3] and malicious domains [23] may suggest fruitful directions.

7 DISCUSSION

In this section, we discuss our view on the role of human review in Disinfotron and the possibility of disinformation websites attempting to evade the automated components of the system.

Human Review. Content moderation has high stakes. Removing authentic news, satire, or political commentary—no matter how partisan or ideological—risks undermining free speech. And any classifier, including the classifier used in Disinfotron, will likely have a significant volume of false positives. Our view is that, at least for the foreseeable future, automated disinformation

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[18]Our manually labeled sample of websites is small, drawn only from Twitter, and not a random representative sample of websites.
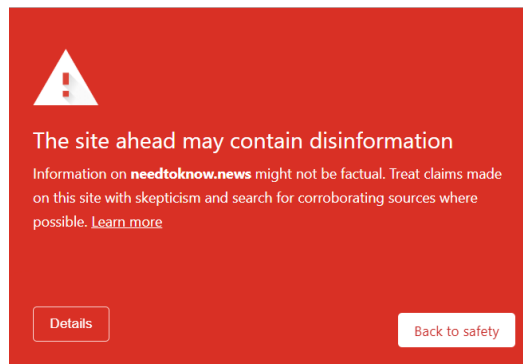
Fig. 6. The interstitial warning that the proof-of-concept browser extension displays to a user when visiting a disinformation website surfaced by the Disinfotron pilot test.

detection systems should not replace human moderators. Rather, automated systems should support moderators in making rapid, correct, and substantiated decisions.

In the Disinfotron design, we envision automated identification of potential disinformation websites early in their lifecycle, followed by periodic automated reevaluation of those websites for new features or more confident classification, and then eventual alerting for moderators if there is sufficient cause for concern. Our end-to-end pilot test suggests that this cooperative approach to disinformation website detection could radically reduce workload for human moderators.

Evasion. Disinformation websites will naturally be motivated to evade detection by major internet stakeholders. In other areas of online abuse, such as spam, phishing, and malware, new defensive measures are constantly developed and deployed to keep up with advances in adversary capabilities. We expect that disinformation will follow a similar cat-and-mouse pattern of defense and evasion.

The automated component of Disinfotron uses features that provide a degree of asymmetric advantage in identifying disinformation websites, since a website that seeks to evade detection must make changes to its infrastructure. Some features will be relatively easy to evade; for example, a website can easily change a WordPress theme or renew an expired TLS certificate. Fortunately, many of the most important features that Disinfotron relies on are difficult or costly to evade.

For example, one of the most predictive features is the lifespan of a website's domain. Evading that feature requires either significant advance planning or purchasing an established domain.[19] Evading certain other features incurs monetary costs, like purchasing a certificate from a reputable issuer, registering a domain for a longer time, switching to a more expensive non-novelty TLD, or migrating to a more trustworthy hosting provider. Evading other features incurs technical costs: obtaining and installing a correctly configured, reputably issued TLS certificate, for instance, imposes some operational cost and may not be possible if the domain has no reputation. Finally, evading many of Disinfotron's features might reduce the effectiveness of the disinformation campaign. For example, a top ranked feature is whether a domain contains news keywords. Removing those keywords from the domain name could diminish the credibility of the website and lead to less exposure on social media.

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[19]If an adversary were to resort to purchasing established domains, the natural countermove would be refining the domain lifespan feature by detecting when a website has changed ownership. This is exactly the type of cat-and-mouse pattern we envision.

8   RELATED WORK

There is prior work related to Disinfotron in the areas of disinformation measurement, detection, and labeling, as well as in the area of online abuse detection more generally.

Disinformation Ecosystem Measurement. Prior work has measured dimensions of the disinformation ecosystem. Starbird et al. presented a case study of online discussion of the Syrian White Helmets, and found that a small number of websites and authors generate most content [99]. Marwick and Lewis assessed internet subcultures that create and share disinformation [66]. Guess et al. examined the spread and reach of disinformation on social media in the U.S. during the 2016 election and found that one in four Americans visited a fake news website [39]. Fletcher et al. performed similar analysis on disinformation in Europe and found that the most popular disinformation website in France reached 1.5 million people [30]. Several research groups have developed methods for mining disinformation data to build reference datasets [92, 93, 91].

Automated Disinformation Detection. Previous publications have examined the textual content of articles to detect disinformation [82, 81, 46, 91, 74, 112, 16, 18, 88, 87, 119, 65]. Potthast et al. distinguished hyper-partisan news articles from mainstream articles, but could not distinguish disinformation from hyper-partisan news [79]. Similarly, Afroz et al. used stylometric techniques to identify disinformation articles with 96.6% accuracy [2] but achieved only 57.1% precision. These results illustrate the difficulty of detecting disinformation based on content.

Other previous projects on article classification relied on contextual features in addition to content [18], such as article appearance (e.g., number of references or length) [59], social network analysis (e.g., user relationships, hashtags, or interactions) [40, 120], information propagation patterns [114, 64, 113], and stylistic features such as the emotional tone of the writing [69, 85].

Another strand of scholarship has produced automated methods for identifying individual false statements, with limited success [106, 17, 35, 41, 103].

In the prior work that is most similar to Disinfotron, Baly et al. predicted the factuality of reporting from a given news outlet by examining articles, the outlet's Wikipedia and Twitter pages, its URL, and characteristics of its Web traffic for a combined accuracy of around 50% [8]. As described above, our implementation significantly exceeds this prior state of the art result.

Finally, there are parallels between disinformation detection and efforts to flag fake online reviews of products and businesses. Prior work has proposed classifiers using both lexical [28, 29] and contextual [112] features to address the problem.

We emphasize that, in comparison to prior work, Disinfotron is the first system to use infrastructure features. We also present the first reported evaluation of (and success at) disinformation detection on real-time data.

Disinformation Labeling. Zhang et al. convened journalists, fact-checkers, and researchers to develop a set of 16 indicators of article credibility [118]. The authors released a dataset of 40 annotated articles on climate science and public health, and they measured which labels correlated with article credibility. In the CREDBANK project, researchers trained Amazon Mechanical Turk workers to label the credibility of events discussed on Twitter [70]. The dataset includes over 1,000 events and 60 million tweets, but the study was specific to social sharing behavior and does not generalize to disinformation websites. We contribute to the literature on disinformation labeling with the largest reported dataset of news and disinformation websites.

Abuse Detection. Our approach of distinguishing malicious activity through infrastructure features has been used for abuse detection since at least 2006, when Ramachandran and Feamster

identified that spammers exhibit network-level behavior that is distinct from other types of legitimate email senders [83]. A key result from their work was that a disproportionate fraction of spam activity originates from a small number of autonomous systems. Subsequently, network-level features have also been used to distinguish spam from legitimate email [44], fingerprint botnets [36, 84], identify scam activity [56, 42], and detect websites that host unlawful content [57]. Most recently, Hao et al. demonstrated that spammer domain registration patterns can predict email scam campaigns, because domains used in email scams are often registered in batch and contain distinct lexical properties [43].

9 CONCLUSION

Online disinformation is a serious and growing societal challenge. Although the problem has attracted research and industry attention in recent years, existing approaches to automated or semi-automated disinformation detection have not seen much real-world adoption. We propose a new and viable approach to the subproblem of discovering disinformation websites: Disinfotron, a sociotechnical system that is fast, scalable, and inexpensive.

Our work demonstrates that disinformation websites rely on different infrastructure from authentic news websites, and that supervised machine learning can use that difference for automated identification. In our evaluation, we show that Disinfotron is both accurate on historical data and viable in an end-to-end, real-time pilot deployment. We are, to our knowledge, the first to report successful real-world results from a semi-automated system for discovering disinformation websites. We urge that future research on disinformation detection include similar realistic evaluation owing to the likely inconsistencies between historical classification tasks and real-time discovery tasks.

Future work on Disinfotron could include integrating additional infrastructure features, such as DNSSEC or email configuration, or analyzing longitudinal trends. Incorporating features derived from published content (e.g., natural language or perceptual properties) or extracted from content distribution (e.g., social media sharing or consumption patterns) would also be a natural extension to improve Disinfotron's performance in later stages of the disinformation website lifecycle.

Beyond the specific semi-automated detection approach that we explore, we believe that our work demonstrates a promising new direction for the disinformation problem domain. Our experience in developing Disinfotron has been that the challenges of identifying and responding to disinformation websites have deep parallels to the challenges of countering spam, malware, phishing, and other long-studied threats at the intersection of human-computer interaction and information security. Disinformation is not identical to these prior problems, to be sure, but we believe we are just scratching the surface of what the combination of HCI and information security can contribute to addressing this acute societal problem.

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