Tik-Tok: The Utility of Packet Timing in Website Fingerprinting Attacks

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Abstract
A passive local eavesdropper can leverage Website Fingerprinting (WF) to deanonymize the web browsing activity of Tor users. The importance of timing information to WF has often been discounted in prior work due to the volatility of low-level timing information. In this paper, we more carefully examine the extent to which packet timing can be used to facilitate WF attacks. We propose a new set of timing-related features based on burst-level characteristics as well as evaluate the effectiveness of raw timing information.

To summarize our findings: (i) we achieve 84.32% accuracy on undefended Tor using only our new timing features; (ii) using directional timing, we get 93.46% on WTF-PAD traffic, several points above the prior state-of-the-art; (iii) we get 68.90% accuracy against onion sites using only timing data, higher than using only directional data; and (iv) we get 0.98 precision and 0.92 recall on undefended Tor in the open-world setting using only raw timing.

These findings indicate that developers of WF defenses need to consider timing as a potential fingerprint for sites and protect against its use by the attacker. Additionally, in our study of timing, we implemented a prototype of Walkie-Talkie (W-T) defense and collected a new W-T dataset, on which we get accuracy results above 90%, far above the theoretical maximum accuracy for the defense of 50%. We discuss the reasons for these findings and challenges in Walkie-Talkie that still must be addressed.

1 Introduction

With over eight million daily users [1], Tor has become one of the most popular technologies to protect users’ privacy on the Internet. As shown in Figure 1, the user’s Tor client creates an encrypted circuit consisting of three nodes: a guard, a middle, and an exit. User traffic is then passed through these nodes before reaching its final destination. In this design, no single Tor node or eavesdropper should be able to link the user’s identity (i.e. IP address and location) with the websites she visits.

Unfortunately, previous work has shown that Tor is prone to a class of traffic analysis attacks called website fingerprinting (WF) [2, 3, 4, 5, 6, 7, 8]. The WF attack allows an attacker to learn information related to the client’s online activities even though the traffic is encrypted.

In a WF attack, a passive local eavesdropper collects side-channel information from the network traffic between the client and entry node, as shown in Figure 1. From the collected traffic, the attacker then extracts various features, such as packet statistics or bursts of traffic, and feeds this information into a machine learning classifier to identify which website the client has visited. Prior work has shown that this kind of attack is very effective, reaching up to 98% accuracy [8].

In response, the Tor Project community has become greatly concerned with designing new effective defenses against these WF attacks [9, 2]. The state-of-the-art attacks emphasize bursts as the powerful features used to classify the encrypted traces. Bursts are groups of consecutive packets going in the same direction, either outgoing from the client to the web server or incoming from the server to the client (see Figure 2). Thus, most WF defenses primarily seek to obscure these burst patterns.

However, this leaves the timing of packets as a largely untapped and unprotected resource for WF attacks. Moreover, prior work in WF either discounted timing as not being important [10] or found that some measures of timing information are not very important to classification [4]. The intuitive
In this work, we investigate new ways timing information can be used in WF attacks, and we find that timing offers significant value to classification. The key contributions of our work are as follows:

- We investigate the design of burst-level timing features to create new representations of timing information. These high-level representations achieve notable results against undefended traffic and help to further expand the community’s understanding of the power of handcrafted timing features.

- We show the effectiveness of our features using several different classifiers. With k-nearest neighbor (k-NN) and support vector machine (SVM) classifiers on Tor traffic, our timing features alone achieve 51% and 61% accuracy, respectively. When we apply a convolutional neural network (CNN) as the classifier, our feature set reaches up to 84.32% accuracy. This result indicates that timing information is useful for the WF attack.

- We investigate the use of raw packet timing information using the state-of-the-art WF attack, Deep Fingerprinting (DF) [8]. We propose a new representation of timing information by using the product of timing and direction (directional time) which results in a modest improvement in the performance of our attack. Using the DF model with only the raw timing information pushes the accuracy of the attack up to 96.54% against the undefended dataset and 84.97% against the WTF-PAD dataset. When we instead use our directional time representation, the attack attains 98.51% accuracy against undefended dataset and 93.46% against the WTO-PAD dataset. The result for WTK-PAD is several points higher than the previous highest result [8].

- We design and implement a prototype of the W-T defense for Tor that includes padding rather than simulating padding on collected traces. This platform allows researchers to more accurately evaluate W-T with real padding and packet timing. Upon acceptance of this paper, we will make the code for this prototype publicly available.

- Using our W-T platform, we crawl a new W-T dataset and use it to find that the DF model (with and without timing) achieves over 90% accuracy, much higher than both any previously reported result and the 50% theoretical maximum accuracy that would be achieved with a perfect padding mechanism. We describe in Section 7.1 why we get this result and the issues with W-T that must be addressed before it can be further evaluated and deployed.

- We extend our investigation to the application of WF attacks against onion sites. We show that WF using only timing information can attain 68.90% accuracy, significantly higher than using only packet direction at 53.30% accuracy for the DF model.

- To investigate our attack in a more realistic scenario, we evaluate the performance of WF attacks in the open-world setting. When we use only timing information, the DF model achieves 0.97 precision and 0.92 recall against undefended Tor. When applied against traffic protected by WTK-PAD, the direction time representation gets 0.98 precision and 0.75 recall, a modest increase over the state-of-the-art.

Overall, we find that timing information can be effectively used as an additional data representation to create an effective WF attack. Moreover, using timing along with packet direction further improves the performance of the attack, especially in the open world. These results indicate that developers of WF defenses need to pay more attention to timing features as another fingerprintable attribute of users’ traffic.
of times, capturing the network trace of each visit as a sample for that site. From this dataset, she extracts meaningful features and uses them to train the classifier. Once the classifier is trained, she can perform the attack. She intercepts the user’s encrypted traffic stream, extracts the same features as used in training, and applies the classifier on those features to predict the user’s website.

Due to the requirement of gathering samples of each site of interest, it is impossible to train the classifier to recognize any possible website the user might visit. The attacker thus trains the classifier on a limited set of websites called the monitored set. All other websites form the unmonitored set.

Based on these two sets, researchers have developed two different settings in which to evaluate the performance of the attack: closed-world and open-world. In the closed-world setting, the user is restricted to visiting only websites in the monitored set. This assumption is generally unrealistic [15] [2], but it is useful for evaluating the quality of ML models and potential defenses. In the more realistic open-world setting, the user may visit any website, including both monitored and unmonitored sites. This setting is more challenging for the adversary, as she must determine both whether the user is visiting one of the monitored sites and, if so, which one. Since it is difficult to produce a dataset covering the entire web, it is common to model the open-world setting by using a dataset with samples from many more unmonitored sites than the number of sites in the monitored set. Evaluation in the open-world setting provides more realistic assessments of the effectiveness of both attacks and defenses.

3 Background and Related Work

3.1 WF Attacks using Hand-crafted Features

Most prior WF attacks were based on applying ML with hand-crafted features. The adversary has to perform feature engineering, designing a set of effective features that can be used to train the classifier. Most of these works either ignore timing features or discount their importance to WF attacks.

Many WF attacks on HTTPS rely on packet size [11] [16], but this does not work on Tor, which has fixed-sized cells. Bissias et al. [17] propose an attack that uses inter-packet delays averaged over the training set as a profile of that site. The attack is not very effective and was not tested on Tor traffic. In our work, we propose timing features based on bursts of traffic instead of individual packet times.

Panchenko et al. proposed an attack with a number of features based on packet volume and packet direction [18]. They used a support vector machine (SVM) classifier and achieved 55% accuracy against Tor. Although the paper mentions the use of timing information, none of the features are based on timing, and packet frequency was mentioned as not improving their classification results. In 2012, SVM was also used by Cai et al., who proposed an attack using the Damerau-Levenshtein edit distance on simplified traffic traces that only indicated the direction of each packet [12]. The attack reached up to 87% accuracy on Tor.

WF attacks using hand-crafted features have been improved over a period of time with the set of better developed features with different ML learning algorithms. Several such attacks could attain over 90% accuracy and have been used as benchmarks for the subsequent research in WF attacks and defenses. At the same time, these attacks do not rely on timing information for their effectiveness. In the first part of our work, we have compared with these attacks to evaluate the utility of timing-based features.

$k-$NN. Wang et al. propose an attack using a $k$-nearest neighbor ($k$-NN) classifier on a large feature set [3]. In a closed-world setting of 100 websites, they achieved over 90% accuracy. This attack was the first to use a diverse set of features (bursts, packet ordering, concentration of the packets, number of incoming and outgoing packets, etc.) from the traffic information in a WF attack on Tor. A key set of features they identified is based on the pattern of bursts. Notably, the attack features have a limited amount of reliance on timing information.

CUMUL. Using a relatively simple feature set based on packet size, packet ordering, and packet direction, Panchenko et al. propose an attack using the SVM classifier [5]. This simple feature set, which did not include timing information, proved effective, with 92% accuracy in the closed-world setting.

$k-$FP. Hayes et al. propose the $k-$fingerprinting ($k$-FP) attack, which uses random decision forests (RDF) to rank the features before performing classification with $k$-NN [4]. This attack also achieved over 90% accuracy in the closed-world setting. Unlike the other attacks, their work did study timing features. They found that statistics on packets per second, e.g. the maximum number of packets sent in one second, were moderately helpful features in classifying sites. One such feature ranked ninth among all 150 features, with a fairly large feature importance score of 0.28, while most of the features ranked between 38 and 50 with feature importance scores of 0.07 and below. Statistics on inter-packet delays were also ranked relatively low, between 40-70. In our work, we explore a novel set of timing features based on bursts of traffic instead of fixed time intervals or individual packets. We also use histograms to capture a broader statistical profile than the maximum, minimum, standard deviation, and quartile statistics primarily used by Hayes et al.

Wfin. Yan and Kaur et al. have recently released a large feature set of 35k features in their Wfin attack [19] [20]. In their study, the authors evaluated the significance of features in seven distinct website fingerprinting scenarios, of which two of these scenarios (S4 and S5) model undefended and defended Tor traffic respectively. Wfin achieved 96.83% accuracy against encrypted tunnel traffic with MTU padding.
(undefended Tor), and 95.44% when that traffic was further defended by fixing the inter-arrival-time for packets (Tor w/ defended timing). When the authors investigated the feature importance ranking, several timing-based features appeared in the top 30 (six timing features within #11-30), and showed greater importance than the k-NN study. However, the results of S5 would suggest that the importance of their timing features are minor when it comes to the final classification decision. The significance of timing features alone was also not investigated.

### 3.2 WF Attacks using Deep Learning

Recently, deep learning (DL) has become the most effective ML technique in many domains such as image recognition, speech recognition, and so on [21]. A major advantage of DL over traditional ML techniques is an ability to automatically extract and learn features, rather than using manual feature engineering. This allows the classifier to learn some effective features that are not easily discovered or understandable by humans. DL has also proven to have higher performance than classifiers using hand-crafted features, especially in image recognition [22, 23]. This has motivated other research communities to adopt DL to improve classification performance in their work. In WF, there are three works that have examined the use of DL classifiers for attacks, where none of them have included timing information.

**SDAE.** Abe and Goto were the first to explore the effectiveness of deep learning (DL) in traffic analysis [6]. They propose a Stacked Denoising Autoencoder (SDAE) for their classifier. They used a simple input data representation composed of a sequence of 1 for each outgoing packet and -1 for each incoming packet, ordered according to the traffic trace. After the final packet of a trace, the sequence was padded to a fixed length with 0s. In the closed-world setting using the dataset from Wang et al.’s work on k-NN (100 instances per site) [3], they achieved 88% accuracy.

**Automated WF.** Rimmer et al. [7] investigate the use of DL to automate feature engineering in WF attacks. They comprehensively study three different DL models: SDAE, Convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM). Furthermore, they compare the DL models with CUMUL attack. The attacks were trained with very large dataset including 900 websites and 2500 traces each. As with Abe and Goto, they use a simple data representation of just packet direction. The results show that SDAE, CNN and CUMUL achieve 95-97% accuracy in the closed-world setting.

**DF.** Sirinam et al. propose the Deep Fingerprinting (DF) attack which utilizes a much deeper and more sophisticated CNN architecture than the one studied by Rimmer et al. [8]. They evaluated their model with a dataset containing 95 websites and 1000 traces each, again with the simple direction-only data representation. In the closed-world setting, the DF attack attains over 98% accuracy, which is higher than other state-of-the-art WF attacks. Moreover, they also evaluated the performance of their attack against two lightweight WF defenses, WTF-PAD and Walkie-Talkie. The results show that the DF attack achieves over 90% accuracy against WTF-PAD, the defense that is the main candidate to be deployed in Tor. In Walkie-Talkie, the attack achieved 49.7% accuracy and a top-2 accuracy of 98.4%.

### 3.3 Onion Sites

An onion service, formerly known as a hidden service, in which a website (an onion site) or other server is hosted that is protected by only being accessible through special Tor connections. A client who has the onion service’s onion URL makes a Tor circuit and requests to Tor to connect to the service. The client’s circuit is then linked up with another Tor circuit that leads to the service itself. Neither the Tor nodes nor the clients know the IP address or location of any given onion service. Onion services provide various kinds of functions such as web publishing, messaging, chat, and so on [24].

Onion services can be fingerprinted, however. Kwon et al. show that onion sites’ traffic can be discriminated from regular websites with with more than 90% accuracy [25]. Moreover, Hayes and Danezis [4] fnd that the onion sites can be distinguished from other regular web pages with 85% true positive rate and only 0.02% false positive from a dataset of 100,000 sites. Therefore, the adversary can effectively filter out the onion sites’ traffic from the rest of Tor traffic and apply WF attacks to determine which onion site is being visited. Since the number of onion sites is on the order of thousands, much smaller than the number of regular sites, the WF attacker only has to deal with a fairly small open world once she determines that the client is visiting an onion site. Since a smaller open world makes the attack easier, WF attacks on onion sites is a more serious issue compared to fingerprinting regular websites.

Recently, Overdorf et al. [26] collected a large dataset of onion sites, consisting of 538 sites with 77 instances each. They evaluated the k-NN, CUMUL, and k-FP attacks in their dataset. Their findings reveal the set of features that are significant for fingerprinting each site. Among timing features, packets per second was shown to be helpful for distinguishing between the smallest 10% of onion sites. Other timing features were not mentioned as being effective. In our paper, we explore the effectiveness of new timing features based on bursts on fingerprinting onion sites. Additionally, we are the first to apply more powerful DL-based attacks, both with and without timing information, to fingerprinting onion sites.
3.4 WF Defenses

In our work, we explore the effectiveness of WF attacks against the state-of-the-art defenses that have been shown to be effective with low bandwidth and latency overheads, namely WTF-PAD and Walkie-Talkie.

**WTF-PAD** Juarez et al. proposed WTF-PAD [27], an extension of the adaptive padding technique that was originally proposed to defend against end-to-end timing attacks [23]. WTF-PAD detects large delays between consecutive bursts and adds dummy packets to fill the gaps. The defense requires 54% bandwidth overhead without adding delays and could effectively reduce the accuracy of WF attacks using hand-crafted features to below 20% accuracy. Sirinam et al., however, show that several attacks including DF (90% closed-world accuracy) and k-FP (69%) perform much better against WTF-PAD [8]. In this paper, we study how timing information can be used to improve attack performance against WTF-PAD.

**Walkie-Talkie** Wang and Goldberg [10] propose the Walkie-Talkie (W-T) defense, which aims to make two or more websites look exactly the same to an attacker. First, W-T modifies the browser to use half-duplex communication, in which the browser requests a single element at a time. This creates a more reliable sequence of bursts compared with typical full-duplex communication, in which the browser makes multiple requests and then receives multiple replies. Given each site’s expected traffic trace through a half-duplex connection, which is expressed as a sequence of burst sizes, W-T essentially creates a supersequence of the two sites. This supersequence is composed of the maximum of the burst sizes from each site. For example, if site A has a sequence of two bursts, \{3, 4\}, and site B has the sequence \{5, 3, 1\}, then the supersequence will be \{5, 4, 1\}. Then, when the user visits either site, W-T will add padding packets to make the site’s burst sequence match the supersequence, e.g. adding 2, 0, and 1 packets to site A’s traffic. In theory, this ensures that both sites have the same traffic patterns and cannot be distinguished, guaranteeing a maximum attack accuracy of 50%. Wang and Goldberg report high effectiveness against attacks, along with reasonable overheads: 31% bandwidth and 34% latency. Sirinam et al. also report less than 50% accuracy for DF against W-T [8]. Both works, however, applied mold padding in simulation to W-T traces previously collected from a modified Tor client. In this paper, we examine the effectiveness of this defense more carefully with the first experiments on a full implementation of W-T including padding. Since W-T does not consider packet timing, we explore the effectiveness of packet timing in attacks. Also, based on our experiences building our W-T implementation, we report on major challenges in designing and practically deploying W-T.

**Fixed-Rate Padding** There exists another class of defenses which have shown to be effective against WF, albeit with significant bandwidth and latency overheads. This type of defense uses fixed-rate packet transmission to obscure fine-grained features. The first fixed-rate padding defense was proposed by Dyer et. al [13], and is known as BuFLO. Client and guard nodes operating the BuFLO defense send packets at a constant rate. All packets which enter the network queue are delayed to conform to the fixed transmission rate. If there are no packets in the queue when it comes time to send, a dummy packet is sent. In order to hide the end of the trace, BuFLO continues to send padding after a page has loaded until a minimum-time threshold has been exceeded. This defense aimed to decrease the performance of the attacks against BuFLO and Tamaraw defended traffic they found that these defenses can reduce the performance of all state-of-the-art WF attacks, including their DF attack, to less than 14% accuracy [8]. While this type of defense is very effective at obscuring packet sequence order and timing features, bandwidth and latency overheads range from 100% to 300%—which is often considered too costly for general Tor deployment. In this paper, we do not assess the effectiveness of our TickTock attack against this class of defenses. As packet timing is tightly controlled in these scenarios, we assume that our inclusion of timing-information in our attack would be of no benefit to the classifier’s performance.

4 Representing Timing Information

Prior work has explored using low-level timing features such as inter-packet delay [17] and second-by-second packet
computing MED. For $B_1$ and $B_2$, we get 0.10 and 0.50, respectively.

- Take the difference between two consecutive bursts’ medians. For $B_1$ and $B_2$: 0.50 – 0.10 = 0.4.

**IBD-FF.** This feature is the interval between the first packets of two consecutive bursts. For $B_1$ and $B_2$, we get 0.40 – 0.0 = 0.4.

**IBD-LF.** This feature is the interval between the last packet of one burst and the first packet of the subsequent burst. For $B_1$ and $B_2$, we get 0.40 – 0.20 = 0.2.

**IBD-IFF.** This features is the same as IBD-FF, but applied to two consecutive incoming bursts. $B_2$ and $B_4$ are the two incoming bursts in our example, so we get 0.75 – 0.40 = 0.35.

**IBD-OFF.** This feature is the same as IBD-IFF, but for outgoing bursts. $B_1$ and $B_3$ are the two outgoing bursts in our example, so we get 0.65 – 0.0 = 0.65.

### 4.1 Histogram Construction

| Dataset       | Number of Bins Tested | Selected |
|---------------|-----------------------|----------|
| Undefended    | 5, 10, 15, 20, 25,    | 20       |
|               | 30, 35, 40, 45, 50    |          |
| WTF-PAD       | 5, 10, 15, 20, 25,    | 20       |
|               | 30, 35, 40, 45, 50    |          |
| Walkie-Talkie | 5, 10, 15, 20, 25,    | 20       |
|               | 30, 35, 40, 45, 50    |          |
| Onion Sites   | 5, 10, 20, 25,       | 20       |

To create features that would be robust to changes from instance to instance, we further process the extracted timing features by constructing histograms (see Figure 5 for an overview). Just as having quartiles provides more information than just the median, histograms allow us to capture a broader range of statistics for each feature. Our feature processing operates in two phases: first, we produce a global distribution for each feature, and then we use these global distributions to populate the final feature sets for each instance.

**Global Distributions.** To compute the global distribution for each of our eight features, we begin by computing the raw values of that feature for all instances of every site. We then merge the raw data into a single array, which we sort. This array represents the global distribution for its respective feature. For each feature’s global distribution, we then split the data into a histogram with $b$ bins, such that each bin has an equal number of items. The lowest value and highest value
in each bin then forms a range for that bin. It is important to note that the width of each bin is not constant. For example, considering the MED feature which represents the median of each burst, there may be many bursts early in the trace. The range for the first bin is thus likely to be quite narrow, going from 0 up to a small value. In contrast, the last bin is likely to have a very wide range. We will use the ranges of the bins when we generate the final feature sets for each instance. In our evaluations, we compute these global distributions separately for our training, validation, and testing datasets so as to accurately model the attacker’s capabilities.

**Feature Sets.** Given the histograms created from the global distribution, we generate a set of features for each instance. For each of our eight extracted feature sets, we create new histograms of $b$ bins. The range for each bin is given by the bin ranges of the global distribution histograms. The count of the number of items in each bin is normalized to the range 0 to 1, and this is then a feature used in classification. The full feature set $F$ then includes $|F| = 8b$ features, $b$ for each of the eight timing feature types.

**Tuning.** The number of bins $b$ is a tunable parameter. Using many bins (large $b$) provides more fine-grained features, but it can lead to instability between instances of the same site. Using fewer bins (small $b$) is likely to provide consistent results between instances of the same site, but it does not provide as much detail for distinguishing between sites. We thus explore the variation in classification accuracy for varying values of $b$. We show the search range in Table 1. We finally select $b = 20$ for undefended, WTF-PAD, W-T, and the Onion Sites datasets.

### 4.2 Combining Timing and Direction Information

One of the efforts to use the timing and direction information is to use timing information with its associated packet direction’s sign. We call this the *directional timing* information. Since we represent outgoing packets with $+1$ and incoming packets with $-1$, we propose a directional timing representation generated by simply multiplying the timing information of each packet by its directional representation.

5 Datasets

#### 5.1 Undefended, WTF-PAD & the Onion Sites

For undefended and WTF-PAD traffic, we use the datasets developed by Sirinam et al. [8]. For onion sites, we use the dataset developed by Overdorf et al. [26]. The number of sites and the number of instances of each dataset are shown in Table 2.

#### 5.2 Walkie-Talkie Data Collection

##### 5.2.1 W-T Prototype

In order to accurately evaluate a defense against our timing-based attack, we require a dataset that contains realistic timestamp information. At the time the Walkie-Talkie (W-T) defense was proposed, Wang et al. did not consider attacks using timing as a credible threat against Tor traffic [10]. As such, their defense simulator did not calculate the timestamps of dummy packets in a realistic manner. To address this gap, we have developed a prototype of the W-T defense specification that runs directly on the Tor network, rather than simulating the padding.

The W-T prototype is designed as a Tor Pluggable Transport (PT) module, as an extension of the WFPadTools Framework [31]. We developed our own implementation of the W-T padding algorithm to use in this PT. The PT is deployed on both the client and the guard node. Figure 6 shows how the W-T PT operates in the context of the Tor network. Our prototype is intended to be used in tandem with the Tor Browser Bundle configured with the half-duplex patch used in Sirinam et al.’s evaluation of W-T [8].

We faced several implementation challenges, and we describe our solution to each in turn.

**Burst Identification.** Implementing W-T padding requires the defense to know which burst the stream is currently on so it knows how much padding is required. So it is necessary to correctly identify when a new W-T burst had begun. In W-T, a burst begins when the client initiates new connections; the burst then ends when all of the newly formed connections have died or become idle. Since the PT sits atop the Tor process, however, it does not have knowledge of the state of the circuit.

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1. We call the application of directional timing in the DF classifier as the "TickTock attack," as it is the most powerful attack we have overall.

2. The WFPadTools Framework operates on a Tor bridge node, but we have the bridge act as a guard so as to not add a node to the length of the circuit.
browser’s requests. To remedy this issue, we have modified the half-duplex patch such that the browser sends a signal to the PT whenever a new burst is about to begin. This allows the PT to identify which burst number the session is currently on. This information also needs to be communicated to the co-operating guard node. To address this problem, we configured the client to send a control message piggybacked on the first packet sent out in the burst. With these mechanisms, both the client PT and guard PT are able to remain synced to the current position in the burst sequence.

**Padding.** The next issue we had to address is how the guard can identify when a burst ends and the next burst begins. This is important for determining when to add padding – the guard cannot wait until the end of a burst to add padding, because by that time the next burst has often already been started by the client. We address this by adding padding to the start of the burst. This behavior is similar to what Wang and Goldberg describe in Section 4.4 of the W-T paper [10]. Since the guard does not know how much real traffic will be in the burst, it assumes that the burst pattern will follow the expected pattern, which is derived from a reference trace of the site. For each site, we derived these reference traces by performing a single undefended half-duplex crawl. Note that the site’s pattern may not match the expected pattern, which can lead to a mismatch in the output trace. In our experiments, we saw moderate variation in both the number of bursts and size of bursts within a website. We were unable to identify a solution to address this concern.

**Tail Padding.** Fake bursts need to be added to the trace when the real burst sequence is shorter than the burst sequence of the decoy site. The W-T specification gives no guidelines as to when in the burst sequence to add these bursts. For our implementation, we simply add the fake bursts at the end of the real communication, which we identify based on when the Tor browser closes its connection to the proxy application.

### 5.2.2 W-T Dataset

Using our W-T prototype, we performed a new crawl of 110 websites to collect a new closed-world W-T dataset. In a closed-world setting, the W-T defense creates pairs between two or more different websites and performs padding to make the two sites look the same in terms of their packet sequence. Wang and Goldberg’s dataset keeps the pairings the same for the full dataset. Unfortunately, this does not accurately model the attack. While a client should indeed use the same pairings all the time, the attacker should not know what those pairings are in advance.

Consequently, an attacker cannot train on a dataset that contains only the correct pairings. The attacker must instead train on all possible pairings of real and decoy sites. With this understanding, we designed our closed-world crawl. We first divided our monitored websites into two groups of equal size: group A and group B. For each website in group A, we collected 10 instances for each possible pairing with a website in group B. This pairing scheme is depicted in Figure 7. The same was done for the websites in group B. This results in a dataset where every possible pairing between the two groups is represented. The attacker trains on the traffic paired with different other sites’ traffic and tests on the paired traffic. Based on the W-T defense, a client chooses the decoy site. In a realistic setting, the paired traffic between the actual website and the decoy can be variously different among different users. Hence, an attacker needs to train the classifier with traffic paired with variety of other sites. In this way an attacker can test on W-T traffic of any user.

**Figure 7: Walkie-Talkie Website Pairing Strategy.**

Our crawl was performed using a modified variant of the Tor Browser Crawler [32] so as to accurately represent the browsing behavior of the Tor Browser Bundle. The crawlers were configured to use version 7.0.6 of the Tor Browser Bundle, patched so as to operate in half-duplex mode. We deployed our W-T defense prototype as Tor guards on vir-
tual private servers hosted by Amazon Web Services. Our crawlers were then configured to connect to these servers as their guards. We collected our data in batches in which each site was visited once. Between each batch, the decoy site to which each real site was paired was changed, following the pairing scheme discussed above.

Upon completion of the crawl, we examined the data for potentially faulty traces. We discarded any traces with fewer than 50 packets. Sites which had fewer than 460 instances were also removed from the dataset. Finally, the number of instances per each site was trimmed so that each site’s representation was of equal size. This resulted in a total of 100 classes with 460 instances each represented in our closed-world W-T dataset.

6 Experiments

6.1 Model Selection

In order to select an effective model for our feature design, we performed experimental evaluations using models seen in previous state-of-the-art WF attacks. To evaluate the effectiveness of our custom feature set we selected the $k$-NN and the SVM due to their effectiveness as shown in prior works. We explain our custom timing features in Section 6.3.

We have used the deep fingerprinting (DF) model for our experiments with direction, raw timing information (see Section 6.4), and directional timing (see Section 6.5). We selected the DF model because of its state-of-the-art performance.

Model Architecture The DF model has eight convolutional layers and three dense layers. The last dense layer is the classification layer that returns the probability of each class using softmax regression. Batch normalization is used as the regularizer for both the convolutional and first two dense layers. The model has max pooling layer after each two subsequent convolutional layer. The model has dropout layer after each two subsequent convolutional layers with dropout rate of 0.10. For the first two dense layers, the dropout rate is 0.70 and 0.50, consecutively. The model uses both exponential linear unit (ELU) and ReLU activation functions. ELU is used for the first two convolutional layers, while the remaining convolution and dense layers use ReLU. For a more detailed review, please reference the original paper by Sirinam et al. [8] in which the model was defined.

For the experiments with direction information, we reproduced the results reported by Sirinam et al. [8] keeping all the hyperparameters as the same. For the experiments with raw timing and directional timing, we do not change any hyperparameters. When training, we increase the number of epochs for the experiments of timing features to 100. We believe this allows the model to better learn the complex patterns which exist due to the greater amount of information present in the input of our experiments. For the experiments with raw timing information, we tuned the dropout rate to 0.40 for both dense layers in order to increase the performance of model learning. All other parameters were left unchanged.

6.2 Splitting Data based on Circuits

For the undefended and WTF-PAD datasets, Sirinam et al. explained that they collected the datasets in batches within which each website was visited 25 times. The website crawler which they use is designed to rebuild Tor circuits at the start of each batch. Thus the number of batches used to collect the dataset corresponds to the number of different circuits on which that data was collected. The crawler is also configured to use different entry nodes for each circuit. The datasets have 95 sites with 1000 instances each and were collected over 40 batches. To correctly model the variance in timing information, we split our dataset based such that the circuits used in the training, testing, and validation sets are mutually exclusive. In this way, our tests better model a realistic attacker who does not have access to the same circuit as the victim. We split based on 8:1:1 ratio which means instances of first 32 circuits (32 x 25 = 800 instances) are for training, instances for the next 4 circuits (4 x 25 = 100 instances) for validation, and instances for the remaining 4 circuits (4 x 25 = 100 instances) are for testing.

For the onion sites dataset, Overdorf et al. mentioned that their crawler creates a new circuit for each visit to crawl their dataset. So, it is not necessary to manually split the dataset based on the circuits as the traffic of each instance was collected from different circuits. We use the 8:1:1 ratio to split into training, validation, and testing set for the onion sites dataset. In order to collect the Walkie-Talkie (W-T) dataset, we use the defense prototype mentioned earlier. Like the crawl performed by Overdorf et al., our crawler also creates a new circuit in each visit. So, we did not need to split data based on circuits, and we again use the same 8:1:1 ratio to split into training, validation, and testing sets.

6.3 Classification Value of Timing Features

Table 3: Closed-World: Attack accuracy of timing features with $k$-NN and SVM against the undefended dataset.

| Features         | MED | IMD | IBD | Combined |
|------------------|-----|-----|-----|----------|
| $k$-NN           | 41% | 20% | 18% | 51%      |
| SVM              | 56% | 24% | 29% | 61%      |

We selected and extracted eight types of burst-level timing features in a five-step process as shown in Figure 5 and explained in Section 4 and Section 4.1.
We first evaluate our eight features against the undefended dataset. Table 3 shows our evaluation results for the $k$-NN and SVM models when used with our features. We also examined the performance of each feature separately to identify the most effective features. Our initial findings demonstrated that the most effective combination was three features – MED, IMD, and IBD – when used with $b = 20$ bins. As shown in Table 3, MED, IMD, and IBD all provide different levels of classification accuracy. Combining these features together, the accuracy reaches 61% with the SVM on undefended Tor traffic. This indicates that this combination of timing features is more effective than using a particular feature alone.

We next apply our features with a deep learning model. In particular, we adopt the DF model proposed by Sirinam et al., which is very effective for WF attacks [8]. In our experiments, we combined all of the eight features together as the input to train the DF model. The results show that the attack is effective, attaining 84.32% accuracy against undefended traffic in the closed-world setting (see Table 4).

Against the WTF-PAD and W-T defenses, the attacks achieved accuracies of 56.08% and 55.80%, respectively. Moreover, using a combination of timing features could achieve beyond the theoretical maximum accuracy claimed by W-T, which supports further investigation of timing information against the W-T defense. However, against onion sites, the attack was held to just 12.86% accuracy. We believe that a lack of training examples and the large number of websites are responsible for this result.

6.4 Raw Timing Information

From the previous section, we see that using a combination of timing features provides reasonably effective WF attacks using traditional machine learning (ML) and especially with deep learning (DL). It is well known that one of the major advantages of using DL is end-to-end learning, in which the classifier can directly learn from the raw input, and this has been shown to provide better performance compared to traditional ML with hand-crafted features [33]. Thus, we explore how WF attacks, especially with DL, could effectively perform the attacks by using only raw packet timing.

In our experiments, we extracted the raw timing information from our datasets and fed them to train a WF classifier using the DF Model. In the undefended dataset, the attack could effectively attain 96%. Against defended datasets, using only timing information, they achieve fairly effective results against WTF-PAD and W-T datasets with almost 84% and 74% accuracies, respectively. Furthermore, in the Onion Sites dataset, we got 15% higher accuracy using only raw timing information compared with using only direction information (see Table 4).

As with DL in other domains, WF attacks using DL trained with only raw timing information had better accuracy compared to our hand-crafted timing features. In the undefended, WTF-PAD, and W-T datasets, the attack’s respective accuracies improved 10-20%. For Onion Sites, we find over 40% improvement.

Overall, our results suggest several takeaways:

- Using end-to-end learning with the raw timing data, the WF classifier can effectively and directly learn more fine-grained information from the input, leading to higher performance of the classification.
- Even if the raw timing data is noisy, the timing information leaves fingerprintable information that can be effectively extracted by DL.
- Even if an attacker cannot use the direction information because of the pattern distortion caused by a defense, she can still use the timing information for the attack.

6.5 Directional Time

Next, we further investigated how to improve the use of timing information in WF attacks using DL. We have learned from the previous work [6, 7, 8] that packet direction is a powerful data representation for WF attacks. We evaluated different methods to combine timing and direction, such as using timing features and direction together, raw timing and direction together, and directional time. We find that directional time provides the most effective results.

With the directional-timing data representation, we experimented with WF attacks and show the key results in Table 4. Using directional timing provides slightly higher accuracy than that of either using only direction or only raw timing in the undefended and W-T datasets. Impressively, the attack against WTF-PAD could attain 93.46% accuracy.
Table 5: **Open-World**: Results when tuned for precision and tuned for recall

| Dataset     | Tuned for Precision | Tuned for Recall |
|-------------|---------------------|------------------|
|             | Precision | Recall | Precision | Recall     |
| Undefended  | Only Direction | 0.991  | 0.938   | 0.932  | 0.985   |
|             | Only Timing  | 0.969  | 0.922   | 0.857  | 0.980   |
|             | Directional Time | 0.988   | 0.948   | 0.908   | 0.989   |
| WTF-PAD     | Only Direction | 0.961  | 0.684   | 0.667  | 0.964   |
|             | Only Timing  | 0.972  | 0.609   | 0.640  | 0.942   |
|             | Directional Time | 0.979   | 0.745   | 0.740   | 0.957   |

Figure 8: **Open World**: Precision-Recall curves. Note that both axes are shown for 0.5 and above.

which is significantly higher than that of either direction or raw timing. In the onion sites dataset, directional timing had 12% higher accuracy than using only direction information, though the accuracy is slightly lower than using only timing information.

### 6.6 Open-World Evaluation

Having explored the quality of our models and baseline comparisons of attacks in the closed-world setting, we now evaluate these in the more realistic open-world setting.

The performance of the attack is measured by the ability of the WF classifier to correctly recognize unknown network traffic as either a monitored or an unmonitored website. True positive rate (TPR) and false positive rate (FPR) have been commonly used in evaluating WF attacks and defenses in the open-world setting [3, 4, 7]. These metrics, however, could lead to inappropriate interpretation of the attacks’ performance due to the heavy imbalance between the respective sizes of the monitored set and unmonitored set. Thus, as recommended by Panchenko et al. [18] and Juarez et al. [15], we use precision and recall as our primary metrics.

In our experiments, we use the standard model, in which an additional class label for the unmonitored set is trained on and then used in predicting test traces. This helps the classifier to better distinguish between the monitored and unmonitored sites. An alternative to the standard model was proposed by Rimmer et al. [7], in which the unmonitored set is predicted when the classifier shows low prediction confidence. While both models have been applied in ML applications, the standard model has been more common in the previous work on WF [3, 4, 5, 8].

We trained the WF classifier by using the DF attack [8] as the base model with different data representations in both undefended and WTF-PAD datasets, including only-direction, only-timing, and directional time. We did not evaluate the W-T defense in the open-world setting, as it remains a major challenge to obtain an open-world W-T dataset (see Section 7).

Finally, we note that the attacks can be flexibly tuned with respect to the attacker’s goals. If the attacker’s primary goal is to be highly confident that a user predicted to be visiting a monitored site truly is doing so, the attack will be tuned for precision, reducing false positives at the cost of also reducing true positives. On the other hand, if the attacker’s goal is to widely detect any user that may be visiting a monitored website, the attack will be tuned for recall, increasing true positives while accepting more false positives.

**Results.** Figure 8 shows precision-recall curves for the attacks in the open-world setting, while Table 5 shows the results when the attack is tuned for precision or tuned for recall. For the undefended datasets, the results show that all data representations can effectively be used to attain high precision and recall. The attacks consistently performed best on the only-direction and directional time data representations, with 0.99 precision and 0.94 recall when tuned for precision. Timing alone, however, is also very effective. On all three WTF-PAD datasets, we see reductions in both precision and recall. Nevertheless, all three datasets show over 0.96 precision and 0.60 recall when tuned for precision. Interestingly, Figure 8 shows that directional time outperforms only-direction on WTF-PAD data. Timing information appears to improve classification of monitored versus unmonitored sites for traffic defended with WTF-PAD.
7 Discussion

7.1 Deployment Challenges for W-T

Padding. As noted in Section 5.2, the guard is unable to identify when a burst ends and the next burst begins. We addressed this by adding padding to the front of the burst, but this means that we must guess the real burst size based on prior data instead of measuring the number of real cells. This is a serious problem when we consider that in the real-world the burst sequences vary between visits of the same site. This is particularly prevalent due to the ubiquitous presence of dynamic content on the web. The effect of this is that the results of the padding may not produce a perfect collision, which inevitably leaks features that the classifier can leverage.

Tail Padding. As described in Section 5.2, the W-T specification does not indicate at what point the defense should create a fake burst. The difficulty of adding a fake burst is that the timing of the packets within the burst should resemble that of a real burst. Otherwise, the attacker needs only to identify and filter out likely fake bursts to greatly improve their classifier’s performance. This issue is magnified if the fake bursts are left until the real traffic ends, as done in our implementation. If the attacker can identify one fake burst the attacker can prune the trace to the last suspected real burst.

7.2 Closed-world Results for W-T

The experimental results show that W-T is effectively undermined by DF with over 90% using both packet directions and timing information. This contradicts the theoretical maximum accuracy in the closed world that should be at most 50% according to Wang and Goldberg [10].

We note that both the original W-T dataset created by Wang and Goldberg and the dataset developed by Sirinam et al. used traces of half-duplex network traffic and simulated the padding [10]8. Given this controlled and simulated condition, the traffic from the two websites can be formed into a supersequence via an algorithm that is strictly followed without dealing with other factors, such as the effect of padding on the network connection, the processing time on the Tor nodes, and unexpected changes to the burst sequence.

In contrast, our W-T dataset was directly crawled from our W-T prototype, which was built to work with padding on the Tor network. This not only allowed us to evaluate W-T with realistic timestamps, but also uncovered the issues discussed above in Section 7.1. The instance-to-instance changes we observed in the traces would have led to different burst sequences than expected by the algorithm, exposing fingerprints that could be detected by the DL classifier. We note that W-T has lower bandwidth overhead than WTF-PAD and maintains a lower classification accuracy against the attacks we tested, so it appears that the supersequence-based padding does offer a more efficient defense. At our reported accuracy levels, however, it cannot be recommended.

The effects we find from realistic conditions raise the questions about the actual performance of defenses. While simulated padding is useful for gathering an initial idea about a defense’s effects, padding should be evaluated experimentally before confident judgments can be made about its design.

7.3 Open World Challenge of W-T

The fundamental concept of W-T in the open-world setting is to attempt to confuse the classifier by creating a supersequence between a monitored website and an unmonitored website [10]. This simple idea, however, is not easily implemented nor tested for a few main reasons:

- Since each attacker selects his own monitored set, we cannot expect to know what the monitored sites are. Supposing that the W-T algorithm pairs some sites that are more likely to be monitored (sensitive sites) with those that are less likely (non-sensitive sites), one must still test how attacks perform when the attacker monitors sensitive sites, non-sensitive sites, and a mix of both.
- Each user may have a different idea of what sites are sensitive and not sensitive and should be paired together. If pairing is random, a sensitive site might be paired with a particularly unlikely decoy site, greatly reducing its effective protection. So finding a good approach to pairing sites is an open challenge.
- When W-T pairs a real site A and a decoy site B, this pairing must be kept the same for all future visits of site A. Otherwise, the attacker will see site A paired with different sites and can eventually infer that A is being visited, while the other sites are decoys. Further, the pairing must be symmetric, such that if the user actually visited the decoy site B, the site A must be selected as its decoy. This could be achieved by locally storing the mapping of decoy and real sites, but this would need to be done carefully to avoid leaving a record of the user’s Tor activity on the client. Alternatively, every possible site the user could visit could be paired up in advance, but this is an enormous list of sites. Note that W-T also requires a database of traffic traces for every possible site, so it is already a problem before pairing is considered.

These issues must be carefully addressed before a realistic study of W-T in the open-world setting could be conducted.
Furthermore, the issues with the site-pairing algorithm remain major problems to address before W-T could be deployed.

8 Conclusion

In this study, we investigate the use of timing information as the features to perform effective WF attacks. We proposed the eight new burst-level timing features that could be effectively used to perform WF attacks with both traditional ML and DL. These features are robust over multiple noisy instances and provide meaningful classification power. With timing features, the closed-world results show that the attacks could reasonably perform well on undefended traffic and against the WTF-PAD defense with 84% and 56% accuracies, respectively.

Moreover, we evaluate the use of the raw timing information and find it to provide very useful data for classification using DL. Using only timing information, the attack can achieve 96% accuracy on the undefended dataset. Against WTF-PAD and W-T defenses, the attacks attain almost 84% and 74% accuracies, respectively. In the Onion Sites dataset, the accuracy of the attack is significantly higher than the one that applies timing features. Moreover, we proposed the use of directional timing formulated by taking the product of timing and direction data, and we show that this improves the performance of the attacks. In more realistic open-world experiments on undefended traffic, using only raw timing information, the attack attains 0.97 precision and 0.92 recall. Against WTF-PAD, it reaches 0.97 precision and 0.61 recall.

In summary, our study shows that timing information can be used as an additional input to create an effective WF attack. Furthermore, developers of WF defenses need to pay more attention to timing features as another fingerprintable attribute of the traffic. Finally, we show through our evaluation of W-T that it is a significantly weaker defense in practice than previously reported, and we discuss the key challenges to address before it can be evaluated further or deployed.

Availability

The code and datasets will be released upon the publication of this paper.

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