Towards Effective and Efficient Padding Machines for Tor
The good, the bad, and the ugly. November 30, 2020

TOBIAS PULLS, Computer Science, Karlstad University, Sweden

Tor recently integrated a circuit padding framework for creating padding machines: defenses that work by defining state machines that inject dummy traffic to protect against traffic analysis attacks like Website Fingerprinting (WF) attacks. In this paper, we explore the design of effective and efficient padding machines to defend against WF attacks. Through the use of carefully crafted datasets, a circuit padding simulator, genetic programming, and manual tuning of padding machines we explore different aspects of what makes padding machines effective and efficient defenses. Our final machine, named Interspace, is probabilistically-defined with a tweakable trade-off between efficiency and effectiveness against the state-of-the-art deep-learning WF attack Deep Fingerprinting by Sirinam et al. [14]. We show that Interspace can be both more effective and efficient than WTF-PAD by Juarez et al. [7], the padding machine that inspired the design of Tor’s circuit padding framework. We end this paper by showing how Interspace can be made less effective, identifying the promising tactic of probabilistically defined padding machines, and highlighting the need to further explore this tactic in more complex defenses.

1 INTRODUCTION

Tor [4] recently integrated a circuit padding framework for circuit-level defenses in the form of padding machines1. The framework is thoroughly documented 2 and a simulator for the framework has been developed3. Moving forward, we expect that researchers will use the circuit padding framework to build new padding machines with the goal of defending against a range of traffic analysis attacks. One such attack—that was one of the motivations behind the design of the framework—is a Website Fingerprinting (WF) attack [3, 15, 6, 8, 5, 12]. In a WF attack, a passive local eavesdropper (e.g., a guard relay or an ISP) observes the encrypted traffic between a Tor Browser client and the Tor network and attempts to infer the destination based on patterns in the encrypted network traffic.

This paper is dedicated to the evaluation of WF attacks and defenses involving padding machines in the circuit padding framework and accompanying simulator. We present a dataset and evaluation method for the circuit padding simulator structured for webpage-to-website fingerprinting, building upon the work of Cai et al. [2] and Panchenko et al. [11] (Section 2). Using the state-of-the-art Deep Fingerprinting (DF) attack by Sirinam et al. [14], we show that DF is highly successful in webpage-to-website fingerprinting, that the safest security level for TB is quite different from the others, and that the start of traces is the most useful for DF (Section 3).

Using genetic programming together with the circuit padding simulator, we evolved padding machines from February until June 2020, where the best machine achieve 0.57 max recall4 with 0.52 precision and 206% overhead (Section 4). Next, we refine the evolved machines by manual pruning and tuning, resulting in two machines: Spring and Interspace. Spring is a simplified machine from the best evolved machine. Interspace in turn is based on Spring with the main change of being a probabilistically defined machine, similar to how ScrambleSuit (and obfs4) works [16]. The Interspace machine has a max recall slightly above 0.3 with 230% overhead. In the same setting, the WTF-PAD defense by Juarez et al. [7]—that inspired the design of Tor’s circuit padding framework—has a max recall of about 0.7 at 178% overhead. Interspace is tweakable, allowing an

1https://gitweb.torproject.org/torspec.git/tree/padding-spec.txt
2https://gitweb.torproject.org/tor.git/tree/doc/HACKING/CircuitPaddingDevelopment.md
3https://github.com/pylls/circpad-sim
4We focus on max recall because of the results of Pulls and Dahlberg [13], assuming that an attacker can use so-called website oracles to reduce the false positive rate of its WF classifier.
effectiveness-efficiency trade-off. At the same overhead as WTF-PAD, Interspace has a max recall of 0.5, and can provide 0.7 max recall at 150% overhead (Section 5).

Section 6 discusses the good, the bad, and the ugly of our results. The good was earlier mentioned: Interspace is an effective machine in our setting, tweakable, and built for Tor’s circuit padding framework. In terms of the bad, we are basically brute-forcing the design of the machines against a particular deep learning attack through simulation. Also, we completely ignore time, since DF does not use time and time in the simulator is unrealistically accurate. For the ugly, we show that the effectiveness of Interspace could be reduced by significantly increasing the training data available to DF through repeated simulation of its defense on our collected traces (in a sense, changing our experimental setting), reaching a max recall above 0.6.

We conclude this paper in Section 7. Interspace, being a probabilistically defined machine, could be made less effective with more training data. However, we show (again) that DF struggles once deprived of being able to train on the exact defense used by a target. This tactic should be further explored for more complex defenses.

2 THE GOODENOUGH DATASET

We set out to create a dataset that better reflects the challenges of an attacker than the typical datasets used in the evaluation of WF attacks. The dataset consists of 10,000 monitored samples and 10,000 unmonitored samples (balanced, so not taking into account client or network base rate). The monitored samples represent 50 classes of popular websites taken from the Alexa toplist (all within Alexa top-300 at the time of collection). For each website/class, we selected ten webpages of that website to represent that class, hence webpage-to-website fingerprinting. For example, for the website reddit.com, we selected ten URLs to popular subreddits such as r/wholesomememes and r/Wellthatsucks/. Similarly, for wikipedia.org, we selected articles such as https://en.wikipedia.org/wiki/Dinosaur and https://en.wikipedia.org/wiki/Fossil. The full list of websites and webpages are available as part of the dataset. We collected 20 samples per webpage, resulting in 50x10x20 = 10,000 monitored samples.

Now to the key idea of the dataset: to evaluate WF attacks based on classifiers that need training, we split the dataset into training, validation, and testing with a 8:1:1 ratio. This split is done per webpage, such that the classifier never gets to train on the same webpage as is used for validation or testing. This trains the classifier to identify the common structure that makes up different webpages belonging to the same website/class.

Figure 1 visualizes the structure of our dataset, including the unmonitored samples, which consists of 10,000 unmonitored webpages collected from reddit.com/r/all (top last year). We made sure to exclude webpages of monitored websites, which include self-hosted images at Reddit. We also excluded direct image links, since they are too distinct to the monitored webpages, and links to YouTube and Twitter that have a tendency of sporadically blocking access from the Tor network.

2.1 Security Levels

The dataset exists in three versions with one for each security level in Tor Browser: standard, safer, and safest. The security level determines if a number of features in the browser are enabled or not, where one of if not the most notable feature is JavaScript. JavaScript is completely disabled at the safest security level. Three versions of the dataset allows us to better take into account another important aspect often overlooked in the evaluation of WF attacks and defenses.
2.2 Key Collection Details

All samples in the final dataset were gathered with Tor Browser 9.0.2 in February, 2020, from Karlstad University, Sweden (connected to SUNET\(^5\)) using freely available tools\(^6\) with ample compute and network resources. We also collected the full dataset in December, 2019, and January, 2020. No differences in results between the three different points in time were noticed, beyond having to update a few webpages that disappeared (primarily news articles). We therefore opt to only use the February dataset for the rest of this paper unless stated otherwise.

Each sample consists of one log and two traces. The log is the modified tor log from Tor Browser using the circpad-sim\(^7\) modifications, generated by having 140 concurrent docker containers of headless Tor Browser visiting webpages for one minute. In Tor Browser, we disabled guards (UseEntryGuards 0) and altered the security level. Each visit used a dedicated copy of Tor Browser with a fresh copy of the consensus (to reduce the load on the network). Therefore, each sample was collected on its own circuit.

From each log, we generated the client trace from circpad-sim using torlog2circpadtrace.py\(^8\) with default parameters (note the 10,000 maximum length per circuit to extract). We also include corresponding simulated relay traces, generated using simrelaytrace.py\(^9\) with default parameters. Please note that accuracy of the timestamps in the traces are unrealistically accurate for any possible network attacker. This is because the timestamps are generated by tor with nanosecond precision before the cells are ultimately packaged into TCP/IP packets (inside a TLS record) and transmitted.

We made efforts to try to ensure that the monitored logs and traces actually correspond to the intended webpages, discarding any traces where tor/Tor Browser may have used two or more circuits to load content for the visit (for unknown reasons). Less care was taken for unmonitored samples to better represent realistic background traffic (that may use multiple circuits for unknown yet sporadically observed reasons).

2.3 Related Work

Both the work of Panchenko et al. [11] and Cai et al. [2] inspired how our dataset is structured and its implied method of use. Both works use traditional machine learning techniques with manually engineered features, significantly reducing the effectiveness of attacks in their evaluations.

---

\(^5\)https://www.sunet.se
\(^6\)https://github.com/pylls/padding-machines-for-tor/tree/master/collect-traces
\(^7\)https://github.com/mikeperry-tor/tor/commits/circpad-sim-v4
\(^8\)https://github.com/pylls/circpad-sim/blob/master/torlog2circpadtrace.py
\(^9\)https://github.com/pylls/circpad-sim/blob/master/simrelaytrace.py
Cai et al. differentiate between websites and webpages, where an attacker’s goal is to identify a visit to any webpage of a website. They note that webpages of websites commonly share structure (“templates”), and that an attacker can attempt to detect that structure regardless of exact webpage visited by a victim. This is identical to our work. However, their dataset is small, consisting of two monitored websites, with an unclear number of unmonitored websites (open world is stated though). They also focus more on modelling complete browsing sessions by victims, at a time when many of the advances in WF attacks were still to see the light of day.

Panchenko et al. also differentiate between websites and webpages, but in general, train on the same webpage as they later classify. They did note one attempt of only training on a subset of the webpages later used for testing, in the closed world, where the performance of their classifier degraded significantly. This is our default setting, but in the open world. We used reddit to gather our unmonitored dataset, while Panchenko et al. in part used Twitter.

In gist, how our dataset is structured and its method of evaluation is based upon the work of Panchenko et al. [11] and Cai et al. [2], but our results and extended experiment design benefit from the recent advances in automatic feature engineering using deep learning.

3 RESULTS USING DEEP FINGERPRINTING

For all the following results, we extracted the first 5,000 cells of the 10,000 maximum events extracted from logs, as noted in Section 2.2. We use the state-of-the-art Deep Fingerprinting (DF) attack by Sirinam et al. [14], ported to the PyTorch library. Deep-learning based attacks (like DF) free us from the burden of manual feature engineering and have been shown to be superior to traditional machine-learning WF attacks in many settings [1, 10, 14].

Because the dataset is of modest size—20,000 traces per security level—it is feasible to perform ten-fold cross-validation when using DF and a modern GPU. For each fold, we change the webpages used to train, validate, and test the monitored websites as well as the unmonitored webpages deterministically, never training on any webpage used for validation or testing.

3.1 Webpage-to-Website Fingerprinting

Figure 2 shows the results of performing webpage-to-website fingerprinting for all three security levels of Tor Browser. Each dot represents a possible precision-recall trade-off—based on the probability threshold for the monitored classes from the final softmax in DF—for ten-fold cross-validation. The DF attack is highly successful. We see slightly better protection offered by the safest security level on average (note the axes), with no difference between standard and safer.

Fig. 2. 10-fold cross-validation with 16 thresholds for the three different security levels in Tor Browser.

Note that cells make up a subset of the 10,000 maximum events extracted from logs, as noted in Section 2.2.
3.2 Classification Across Security Levels

Figure 3 shows the impact of cross-level classification, where a model trained on a dataset generated by one security level of Tor Browser is used to classify all three levels. We see a significant difference when it comes to the safest security level: the impact on webpage-to-website fingerprinting is huge. There is no significant difference between standard and safer, similar to the results in Figure 2.

![Fig. 3. Precision-recall metrics on datasets collected using the three security levels in Tor Browser, when the model is trained on data belonging to a particular security level.](image)

3.3 Estimating Defense Priorities

We can estimate the relative importance of different parts of a trace by zeroing cells, removing a variable amount of information from the attacker. In the following analysis we only consider the maximum recall by setting the threshold in DF to 0 for each of the ten-folds per measurement.

Starting from an empty trace, Figure 4a includes increasingly more cells in traces. Note the logarithmic x-axis. The figure shows a steep increase in recall with a few hundreds of cells, needing only about 100 cells to hit 0.5 recall. No significant difference between security levels, with the exception of a small dip for standard and safer around 1,500 cells.

Figure 4b starts with a full trace and excludes increasingly more cells. Note the linear x-axis. Comparing the results to Figure 4a, it is clear that the start of a trace has the most utility for an attacker: the first 100 cells are about as useful as the last 3,000 cells for standard and safer security levels. This is in line with the results of Mathews et al. [9]. However, the most striking result is the impact on the safest security level. By excluding the first 1,000 cells the maximum recall is cut to about 0.25, approximately a third of the recall for the other security levels.

![Fig. 4. The maximum recall when including or excluding increasingly more cells of traces. Based on the dataset collected in January (took about a week to produce with ten folds, cannot justify costs when no other scenario offers any noticeable difference).](image)
The degree to which the safest security level stands out in Figure 4b can be explained in part with a closer look at the dataset. The safest dataset consists of only 1,534 full traces (5,000 cells), with an average 1,478 and mean 950 of cells per trace.

4 EVOLVED MACHINES

During the first half of 2020 we used genetic programming together with the circuit padding simulator to evolve machines. We evolved machines for several months of wall-time using an AMD Ryzen 7 2700X and NVIDIA GeForce RTX 2070.

4.1 Method

We experimented early with a number of different fitness functions (including information-theoretic ones based on trace collisions), but landed on \(1 - \text{recall}\), where recall is computed using DF with threshold 0.0. That is, we aim to minimize the maximum recall of DF against the evolved machines. Recall is used because it captures when the client visits a monitored page, and it tells us how many out of all visits by the client the classifier accurately detects. More importantly, as a metric, it ignores how the classifier performs against unmonitored testing traces. DF does not use time, so it is appropriate to use with the circuit padding simulator. It might seem overkill to use deep learning, but our execution time was dominated by simulating the evolved machines. In our implementation, to reach parity between simulating traces and computing the fitness function (deep learning) using a modest NVIDIA GeForce RTX 2070 we would need in the order of a 100 CPU cores.

We used a small population size of ten machines, where the initial population was randomly generated. This might seem small, but each machine has to be simulated against 20,000 traces, taking significant time. We experimented relatively briefly with different population sizes, but found no improvement in larger sizes. We used the full dataset of 20,000 traces at the safest security level (the smallest and easiest to protect, see Section 3.3) to make maximum recall as good as possible of a fitness function.

Given a population of machines and their fitness determined based on their max recall with DF, the next generation was evolved as follows. First, we selected an elitist fraction of the most fit machines and copied them over as-is. For most of our runs, this was only the single best machine. We briefly experimented with keeping a diversity fraction of randomly selected machines, but opted to disable this due to lack of initial results. For the remaining slots in the population (typically nine), we evolved new machines using crossover and mutation. For crossover, we performed single-point crossover between complete states of machines. For mutation, with some probability, we mutated each part of each state (the inter-arrival distribution, the length distribution, and the state transitions). Parents were selected at random from the previous generation, weighted by fitness. The client and relay parts of machines never interacted; each evolved independently.

Each machine actually consists of a pair of machines: one machine running on the client and one on the relay (we target the second hop, i.e., the middle relay). In particular, we do not evolve symmetric machines (as in, e.g., WTF-PAD), so the client and relay logic may be completely different. A single machine consists of four states (compared to three in WTF-PAD), but only uses distributions for length- and time-sampling (so no histograms) to limit the search space. It is also known from WTF-PAD that tailoring histograms is a significant challenge for deployment (or even evaluation across datasets). The circuit padding framework enables us to put both absolute and relative overhead limits for padding circuit and machine. We used generous limits, with the final machines allowing 1,000 cells in absolute terms, that are then followed by a 50% overhead as a percentage of total traffic. Note that for evaluating the fitness of machines we use the first 5,000 cells of each trace. Finally, all machines start as soon as streams are attached to the circuit. Due to how we collected our dataset, the first stream directly carries data to connect to the destination website.
4.2 Results

During each month—from February until June 2020—we looked at the most fit machines and made minor tweaks and/or fixes to our software for evolving machines. Table 1 gives a summary of the most fit machines each month and their bandwidth overheads in total and per direction (from the client’s perspective). For reference, on unprotected traces DF gets 0.88 max recall and 0.93 precision. From the table, we note that the June machine is basically useless, despite having the highest total bandwidth (242%). In comparison, from the evolved machines, the best machine is April with a max recall of 0.57, 0.52 precision, and only 206% overhead.

Table 1. The five best evolved machines from February to June with their maximum recall and corresponding precision against the safest dataset. Average bandwidth (BW) is shown in total (where 100% means no overhead) as well as per direction (fraction of total in parenthesis).

| Machine | Max Recall | Precision | Total BW | Sent BW (total) | Recv BW (total) |
|---------|------------|-----------|----------|----------------|-----------------|
| February | 0.79       | 0.79      | 173%     | 817% (48%)     | 100% (52%)      |
| March   | 0.86       | 0.79      | 173%     | 816% (48%)     | 100% (52%)      |
| April   | 0.57       | 0.52      | 206%     | 396% (19%)     | 185% (81%)      |
| May     | 0.71       | 0.64      | 182%     | 439% (24%)     | 153% (76%)      |
| June    | 0.89       | 0.84      | 242%     | 597% (25%)     | 202% (75%)      |

From the results in Table 1 and details above one might wonder how come we see such varying results between months. The answer is simple: bugs in our evaluation code together with the importance of overhead limits and time spent evolving. To help explain how the machines changed over time, Figure 5 visualizes the first 200 defended traces for each selected evolved machine, using colors to differentiate between sent nonpadding (white), sent padding (green), received nonpadding (black), and received padding (red) cells. The completely white connected parts to the top-right of each figure is empty traces (technically transparent but white due to medium).

Fig. 5. Color visualizations of a selection of the traces for selected evolved machines. Black represents received nonpadding and white sent nonpadding. Red shows received padding and green sent padding. Note the type of padding and the importance of padding limits.

Starting with February, we see our first results. From Figure 5a the evolved tactic of the machine is clear: send as much padding as possible up until the overhead limits kick in. At this early stage, the allowed padding was set to 2,000 cells, which is slightly less than half the length of the trace (max 5,000 cells). Also, the fitness function was set to the recall at threshold 0.5, making the fitness calculation less stable. Notably, the defense completely ignores any padding from the relay to the client (received padding, red). This was due to a bug in our use of the circpad simulator (padding to the guard instead of the middle relay, which is not supported).
The results from March builds upon February by changing the fitness to the minimal recall (threshold 1.0). While this resulted in worse fitness (higher max recall), we note from Figure 5b that the padding is now better distributed throughout the traces.

For April we see significant improvements in both Table 1 and Figure 5c. We fixed the bug that prevented any padding from the relay to the client (received padding, red), set the fitness function to consider the maximum recall (threshold to 0.0), and made the padding limits more strict (1,000 padding cells then at most 50% padding). Both sent and received padding are distributed throughout the traces, achieving 0.57 max recall. We will return to this machine in more detail later.

For the May machine we restarted evolving machines from a clean slate with the hope of finding other tactics for padding. Table 1 shows weaker protection than April, but still a notable improvement over no defense, and less overhead. As we can see in Figure 5d, the received overhead is significantly reduced (note the total as well as received bandwidth reduction), in particular towards the end of the traces.

The last evolved machine is from June, where we restarted from scratch and fixed yet another bug. The generated c-code for machines did not correctly set dist_added_shift_usec: a value added to the sampled delay distribution for deriving the final padding delay. While this does not invalidate our prior results, it makes our search space significantly bigger due to being such a central parameter (up to eight states have this parameter and large, randomly generated values significantly change the final padding delay). Figure 5e is in a sense similar to Figure 5a; we never get past the initial phase of being dominated by our padding limits.

5 MANUALLY TUNED MACHINES

Using the evolved machines as a starting point, we set out to create manually tuned machines. The source code of the evolved machines are available online\textsuperscript{11}, omitted here for sake of brevity.

We used April as a starting point for the Spring machine, name from the fact that April was the most effective evolved machine from spring. The following changes were made:

- upped padding limit to 1500
- removed transitions and states that never could do anything
- removed useless IAT dists (CIRCPAD_DIST_NONE)
- removed each max_length, hardly ever hit

The main change in behavior of the machine was the upped padding limit, reducing max recall from 0.57 to 0.47. The full source code of Spring is in Appendix A.

The cleaned up Spring machine in turn was the basis for our final machine: Interspace. The name comes from the song Interspace by Starcadian, that our Spotify radio played at the time of creation. Thank you randomness (or rather, deep learning based recommendation engine trained with over ten years of personal listening history). For Interspace we introduce the concept of probabilistically defined machines. As part of little-t tor startup, circpad_machines_init() initializes all padding machines. Here, we make the actual definition of Interspace randomized. This is similar to how ScrambleSuit (and later obfs4) picks a “polymorphic shape” per server instance.

We spent a modest amount of time (about a week) exploring different randomization tactics. The full source code of Interspace is in Appendix B, and has the following main changes from Spring:

- The client machine is changed to include—with 50% probability each—transitions between the two main states that act on received padding or non-padding, respectively.
- With 50% probability, the relay machine consists of either the Spring relay machine or another, completely hand-crafted, machine. The hand-crafted machine, in turn, uniformly selects one of two tactics: either attempt to extend real bursts of cells or inject completely fake bursts.

\textsuperscript{11}https://github.com/pylls/padding-machines-for-tor/tree/master/machines/phase2
of modest size. For iat and length distributions, we randomize the parameters to the used log-logistic (waiting time before injecting a fake burst) and pareto (for length, i.e., number of padding cells to send at most, and short iat between cells of a burst) distributions.

Figure 6 shows the effectiveness of our our manually tuned machines for two security levels. We also include a comparison with one configuration of WTF-PAD using the most effective default configuration. To make the WTF-PAD configuration to produce approximately the same amount of padding as reported by Juarez et al. (177%), we scaled the timestamps of all cells in the dataset until we reached nearly the same overhead on the standard dataset (178%), as measured by their tool. In gist, WTF-PAD offers some protection, Spring is notably more effective, and Interspace even more so. The differences between the defenses are bigger than the differences between Tor Browser security levels. Table 2 shows the overhead for the defenses and security levels. In a sense, the results are a reverse of Figure 6: the more effective the defense, the less efficient it is in comparison.

![Fig. 6. Precision-recall curve of our manually tuned machines, compared to the WTF-PAD defense (the norm-rcv config, the best config on our datasets), for two security levels from Goodenough February.](image)

Table 2. Overheads for the two tuned machines as well as WTF-PAD (as measured by their own tool) on the February Goodenough dataset for two security levels of Tor Browser.

| Machine      | Level   | Total BW | Sent BW (total) | Recv BW (total) |
|--------------|---------|----------|-----------------|-----------------|
| Spring       | standard| 210%     | 408% (19%)      | 189% (81%)      |
| Spring       | safest  | 285%     | 731% (25%)      | 236% (75%)      |
| Interspace   | standard| 230%     | 604% (27%)      | 188% (73%)      |
| Interspace   | safest  | 305%     | 909% (30%)      | 238% (70%)      |
| WTF-PAD      | standard| 178%     | —               | —               |
| WTF-PAD      | safest  | 248%     | —               | —               |

The overhead of each machine is capped by allowed_padding_count and max_padding_percent, set for both the relay and client machines. Keeping max_padding_percent fixed at 50%, Figure 7 shows the max-recall and overhead trade-off of Interspace when alternating allowed_padding_count from 1 to 1,500 (symmetrically, for both the client and relay) for the standard and safest security levels. For reference, WTF-PAD had a max call at about 0.7 (average over all folds) at 178% overhead for the standard level and a max recall around 0.65 at 248% overhead for the safest level. Interspace can reach the same defense effectiveness at 150% overhead, significantly more efficiently.
6 DISCUSSION

We consider the good, the bad, and the ugly of our evolved and manually tuned machines.

6.1 The Good

In April, we evolved a machine that is a more effective defense than WTF-PAD, within the constraints of the circuit padding framework of Tor against the state-of-the-art DF attack. We also showed that WTF-PAD may offer some protection against DF in our more realistic setting—represented by our dataset and evaluation method—assuming the way we manually tweaked the dataset to make WTF-PAD’s default configuration work was not too drastic. This is an indication that we need to further consider how we evaluate WF attacks and defenses.

Our manually tuned machines offer further improvements. Interspace provides an effective defense for both the standard and safest security levels in our dataset. The overhead is larger than WTF-PAD, so Interspace is less efficient. That said, the notion of overhead is worth to consider. With allowed_padding_count set to 1500, this is a minimum of 1500 cells: about 750 KiB. This is not overwhelming. We know from Figure 4 that the early parts of traces are the most important. Accepting, say, a 1 MiB overhead for web circuits (with added logic on the client to only negotiate the machine when a stream is attached using port 80 or 443) would likely go a long way in making attacks harder, yet, not adding significant overheads over typical website sessions that likely contain media such as images or even videos of relatively large sizes.

Thanks to the circuit padding framework, Interspace is also tweakable, offering efficiency–effectiveness trade-offs. We see a clear relationship between overhead and maximum recall in Figure 7 for both security levels. In part, by probabilistically defining the machine, its effectiveness was improved. This appears to be a promising tactic to further explore.

6.2 The Bad

In gist, by using genetic programming to evolve machines, our results are generated by trial-and-error. There is probably a significant room for improvement. In a sense, we do not really understand why the machines work other than more general observations such as the relative importance of padding early rather than later.

While our dataset was captured on the live network from clients, the relay portions were simulated. Further, we simulated all our defenses on those traces and used DF that ignores time. Validating the machines on the live network is a natural next step. An attenuating circumstance is that each trace in our dataset was collected on its own unique circuit with no fixed relays. Hopefully,
this means that we have not overfitted our parameters to any particular network circumstance. Future work will tell.

6.3 The Ugly

If the goal was a paper, we are pretty much done now. However, towards the goal of effective and efficient padding machines for Tor, and not only for publication, we look deeper. What has hopefully been clear so far is that our machines reduce the effectiveness of the DF attack. The question of what exactly an “effective” defense against WF attacks looks like though has been debated in the community. Issues such as dataset freshness, different attacker goals (e.g., inline classification for censorship or ex-post for detection), website vs website fingerprinting, and victim as well as website base rates are all good examples. In part, these issues relate to the proper experiment design as part of the method of evaluation of WF attacks and defenses. We provided some improvements by taking into account webpage-to-website fingerprinting and different security levels of Tor Browser.

In our experiments we simulate the machines by using circpad-sim. We, as well as an attacker, can of course simulate each trace multiple times instead of just once. This should be about the same as visiting webpages of target websites more times for the sake of training, with the caveat that we also give repeated samples of the unmonitored websites. By multiplying the number of times we simulate our machines per trace, we get increasingly more training data. Given that Interspace is probabilistically defined, simulating the same trace several times may also be particularly useful. Figure 8 shows the max recall of DF (only one fold) as we simulate each trace by a factor from 1–20 (from 20,000 to 400,000 samples in the dataset, split 8:1:1). We see that this decreases the effectiveness of Interspace, improving max recall up to a bit over 0.6 until the gain stalls around a factor 15 or so.

![Figure 8. The maximum recall for Interspace as we grow the dataset by a variable factor through repeated simulation, for two security levels from Goodenough February.](image)

7 CONCLUSIONS

The WF setting is challenging. We improved the method of evaluation by considering webpage-to-website fingerprinting and the security level of Tor Browser, collecting extensive datasets, and identifying the general parts of traces most useful for distinguishing between websites. For attacks we used Deep Fingerprinting (DF), a state-of-the-art deep-learning model.

Using genetic programming and months of wall-time computing with a GPU, we evolved defenses against DF. The defenses, in the form of padding machines in Tor’s circuit padding framework,

---

12This is not strictly in line with how unmonitored websites are represented in WF datasets, but because of the large number of websites labeled as unmonitored (10,000), we believe that this is negligible.
were evaluated against DF withing the circuit padding simulator. Using the most promising evolved machines, we manually tuned and built new machines, landing in our best candidate: Interspace.

We have created several padding machines for Tor that are more effective defenses than WTF-PAD, the defense that inspired the design of Tor’s circuit padding framework. Some of our machines are less efficient. Interspace provides a tweakable trade-off between efficiency and effectiveness, using the global machine parameters of Tor’s framework.

Finally, we showed that the effectiveness of Interspace could be reduced by significantly increasing the training data available to DF through repeated simulation of its defense on our collected traces. While it is promising that this peaked around a factor 15 or so, a max recall of above 0.6 may or may not be effective enough of a defense. It is also frustrating that central to our approach is treating DF as a black box. We do not really understand why defenses work to the extent they do or why, in this particular instance, DF could be improved to such an extent by adding more training data. Clearly, it is a challenge to perform genetic programming on such large datasets.

One particularly important lesson is that we observed significantly reduced attack effectiveness when training on one type of dataset and classifying on another. We saw this between the standard and safest security levels of TB. Interspace is based on similar ideas by probabilistically defining its machines. Table 3 shows cross-classification across different trained models, security levels, and datasets. Here we see again that the DF attack suffers on not being able to train on the correct dataset. This might appear obvious at first, but it is a largely unexplored area for WF defenses.

| trained model | Interspace | Spring | WTF-PAD |
|---------------|------------|--------|---------|
|               | standard   | safest | standard | safest | standard | safest |
| Interspace    | 0.35       | 0.06   | 0.30     | 0.05   | 0.03     | 0.01   |
| safest        | 0.06       | 0.31   | 0.05     | 0.26   | 0.01     | 0.02   |
| standard      | 0.16       | 0.04   | 0.46     | 0.07   | 0.01     | 0.01   |
| safest        | 0.04       | 0.14   | 0.09     | 0.42   | 0.02     | 0.02   |
| standard      | 0.05       | 0.03   | 0.07     | 0.03   | 0.72     | 0.14   |
| safest        | 0.03       | 0.05   | 0.04     | 0.06   | 0.17     | 0.69   |

The above begs the question: what is the proper way of evaluating WF defenses? This has been discussed for a long time in the research community, and while we hope that Interspace and the lessons learned here move us forward towards the ultimate goal of effective and efficient padding machines for Tor, we are far from done.

Code and datasets available at https://github.com/pylls/padding-machines-for-tor.

Acknowledgements

This research was funded by generous grants from NGI Zero PET and the Swedish Internet Foundation. Thank you Mahdi Akil for the review.
REFERENCES

[1] S. Bhat, D. Lu, A. Kwon, and S. Devadas. Var-cnn: A data-efficient website fingerprinting attack based on deep learning. Proc. Priv Enhancing Technol., 2019(4):292–310, 2019.

[2] X. Cai, X. C. Zhang, B. Joshi, and R. Johnson. Touching from a distance: website fingerprinting attacks and defenses. In CCS, 2012.

[3] H. Cheng and R. Avnur. Traffic analysis of SSL encrypted web browsing. Project paper. University of Berkeley, 1998.

[4] R. Dingledine, N. Mathewson, and P. F. Syverson. Tor: The second-generation onion router. In USENIX Security, 2004.

[5] D. Herrmann, R. Wendolsky, and H. Federrath. Website fingerprinting: attacking popular privacy enhancing technologies with the multinomial naive-bayes classifier. In CCSW, 2009.

[6] A. Hintz. Fingerprinting websites using traffic analysis. In PET, 2002.

[7] M. Juárez, M. Imani, M. Ferry, C. Diaz, and M. Wright. Toward an efficient website fingerprinting defense. In I. G. Askozyakakis, S. Ioannidis, S. K. Katsikas, and C. A. Meadows, editors, Computer Security - ESORICS 2016 - 21st European Symposium on Research in Computer Security, Heraklion, Greece, September 26-30, 2016, Proceedings, Part I, volume 9878 of Lecture Notes in Computer Science, pages 27–46. Springer, 2016.

[8] M. Liberatore and B. N. Levine. Inferring the source of encrypted HTTP connections. In CCS, 2006.

[9] N. Mathews, P. Sirinam, and M. Wright. Understanding feature discovery in website fingerprinting attacks. In IEEE Western New York Image and Signal Processing Workshop (WNYISPW), 2018.

[10] S. E. Oh, S. Sunkam, and N. Hopper. p1-fp: Extraction, classification, and prediction of website fingerprints with deep learning. Proc. Priv. Enhancing Technol., 2019(3):191–209, 2019.

[11] A. Panchenko, F. Lanze, J. Pennekamp, T. Engel, A. Zinnen, M. Henze, and K. Wehrle. Website fingerprinting at internet scale. In NDSS, 2016.

[12] A. Panchenko, L. Niessen, A. Zinnen, and T. Engel. Website fingerprinting in onion routing based anonymization networks. In WPES, 2011.

[13] T. Pulls and R. Dahilberg. Website fingerprinting with website oracles. PETs, 2020.

[14] P. Sirinam, M. Imani, M. Juárez, and M. Wright. Deep fingerprinting: Undermining website fingerprinting defenses with deep learning. In CCS, 2018.

[15] Q. Sun, D. R. Simon, Y. Wang, W. Russell, V. N. Padmanabhan, and L. Qiu. Statistical identification of encrypted web browsing traffic. In IEEE S&P, 2002.

[16] P. Winter, T. Pulls, and J. Fuß. Scramblesuit: a polymorphic network protocol to circumvent censorship. In A. Sadeghi and S. Foresti, editors, Proceedings of the 12th annual ACM Workshop on Privacy in the Electronic Society, WPES 2013, Berlin, Germany, November 4, 2013, pages 213–224. ACM, 2013.

A SPRING

A.1 Client

```c
1  circpad_machine_spec_t *client = tor_malloc_zero(sizeof(circpad_machine_spec_t));
2  client->conditions.state_mask = CIRCPAD_CIRC_STREAMS;
3  client->conditions.purpose_mask = CIRCPAD_PURPOSE_ALL;
4  client->conditions.reduced_padding_ok = 1;
5
6  client->name = "spring_client";
7  client->machine_index = 0;
8  client->target_hopnum = 2;
9  client->is_origin_side = 1;
10  client->allowed_padding_count = 1500;
11  client->max_padding_percent = 50;
12  circpad_machine_states_init(client, 3);
13
14  client->states[0].next_state[CIRCPAD_EVENT_PADDING_RECV] = 1;
15
16  client->states[1].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 2;
17
18  client->states[2].length_dist.type = CIRCPAD_DIST_PARETO;
19  client->states[2].length_dist.param1 = 4.776842508009852;
```
client->states[2].length_dist.param2 = 4.807709366988267;
client->states[2].start_length = 1;
client->states[2].iat_dist.type = CIRCPAD_DIST_PARETO;
client->states[2].iat_dist.param1 = 3.3391870088596;
client->states[2].iat_dist.param2 = 7.179045336148708;
client->states[2].dist_max_sample_usec = 9445;
client->states[2].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 1;
client->states[2].next_state[CIRCPAD_EVENT_PADDING_SENT] = 2;
client->machine_num = smartlist_len(origin_padding_machines);
circpad_register_padding_machine(client, origin_padding_machines);

A.2 Relay

circpad_machine_spec_t *relay = tor_malloc_zero(sizeof(circpad_machine_spec_t));
relay->name = "spring_relay";
relay->machine_index = 0;
relay->target_hopnum = 2;
relay->is_origin_side = 0;
relay->allowed_padding_count = 1500;
relay->max_padding_percent = 50;
circpad_machine_states_init(relay, 4);
relay->states[0].iat_dist.type = CIRCPAD_DIST_PARETO;
relay->states[0].iat_dist.param1 = 5.460653840184872;
relay->states[0].iat_dist.param2 = 7.080387541173288;
relay->states[0].dist_max_sample_usec = 94722;
relay->states[0].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 1;
relay->states[0].next_state[CIRCPAD_EVENT_PADDING_RECV] = 1;
relay->states[1].iat_dist.type = CIRCPAD_DIST_LOGISTIC;
relay->states[1].iat_dist.param1 = 1.2767765551835941;
relay->states[1].iat_dist.param2 = 0.11492671368700358;
relay->states[1].dist_max_sample_usec = 31443;
relay->states[1].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 2;
relay->states[2].length_dist.type = CIRCPAD_DIST_LOGISTIC;
relay->states[2].length_dist.param1 = 4.11964473793041;
relay->states[2].length_dist.param2 = 2.7250362139341764;
relay->states[2].start_length = 5;
relay->states[2].iat_dist.type = CIRCPAD_DIST_LOGISTIC;
relay->states[2].iat_dist.param1 = 5.232180204916029;
relay->states[2].iat_dist.param2 = 5.469677647300559;
relay->states[2].dist_max_sample_usec = 94733;
relay->states[2].next_state[CIRCPAD_EVENT_PADDING_SENT] = 2;
relay->states[2].next_state[CIRCPAD_EVENT_PADDING_RECV] = 3;
relay->states[3].length_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[3].length_dist.param1 = 1.6167675237934875;
relay->states[3].length_dist.param2 = 6.128003159320049;
relay->states[3].start_length = 5;
relay->states[3].iat_dist.type = CIRCPAD_DIST_UNIFORM;
relay->states[3].iat_dist.param1 = 4.270468437086448;
Towards Effective and Efficient Padding Machines for Tor

relay->states[3].iat_dist.param2 = 7.926284402139126;
relay->states[3].dist_max_sample_usec = 55878;
relay->states[3].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 3;
relay->states[3].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 0;
relay->states[3].next_state[CIRCPAD_EVENT_PADDING_RECV] = 2;
relay->machine_num = smartlist_len(relay_padding_machines);
circpad_register_padding_machine(relay, relay_padding_machines);

B INTERSPACE

B.1 Client

const struct uniform_t my_uniform = {
    .base = UNIFORM(my_uniform),
    .a = 0.0,
    .b = 1.0,
};
circpad_machine_spec_t *client = tor_malloc_zero(sizeof(circpad_machine_spec_t));
client->conditions.state_mask = CIRCPAD_CIRC_STREAMS;
client->conditions.purpose_mask = CIRCPAD_PURPOSE_ALL;
client->conditions.reduced_padding_ok = 1;
client->name = "interspace_client";
client->machine_index = 0;
client->target_hopnum = 2;
client->is_origin_side = 1;
client->allowed_padding_count = 1500;
client->max_padding_percent = 50;
circpad_machine_states_init(client, 3);

// wait until the relay is active
client->states[0].next_state[CIRCPAD_EVENT_PADDING_RECV] = 1;

// wait for something to either mask the length of or inject a fake request
if (dist_sample(&my_uniform.base) < 0.5) {
    client->states[1].next_state[CIRCPAD_EVENT_PADDING_RECV] = 2;
}

client->states[2].length_dist.type = CIRCPAD_DIST_PARETO;
client->states[2].length_dist.param1 = 4.7;
client->states[2].length_dist.param2 = 4.8;
client->states[2].start_length = 1;
client->states[2].iat_dist.type = CIRCPAD_DIST_PARETO; // tweak for log-logistic?
client->states[2].iat_dist.param1 = 3.3;
client->states[2].iat_dist.param2 = 7.2;
client->states[2].dist_max_sample_usec = 9445;
client->states[2].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 1;
client->states[2].next_state[CIRCPAD_EVENT_PADDING_SENT] = 2;
if (dist_sample(&my_uniform.base) < 0.5) {
    client->states[2].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 1;
client->machine_num = smartlist_len(origin_padding_machines);
circpad_register_padding_machine(client, origin_padding_machines);

B.2 Relay

circpad_machine_spec_t *relay = tor_malloc_zero(sizeof(circpad_machine_spec_t));

// short define for sampling uniformly random [0,1.0]
const struct uniform_t my_uniform = {
    .base = UNIFORM(my_uniform),
    .a = 0.0,
    .b = 1.0,
};
#define CIRCPAD_UNI_RAND (dist_sample(&my_uniform.base))

// uniformly random select a distribution parameters between [0,10]
#define CIRCPAD_RAND_DIST_PARAM1 (CIRCPAD_UNI_RAND*10)
#define CIRCPAD_RAND_DIST_PARAM2 (CIRCPAD_UNI_RAND*10)

relay->name = "interspace_relay";
relay->machine_index = 0;
relay->target_hopnum = 2;
relay->is_origin_side = 0;
relay->allowed_padding_count = 1500;
relay->max_padding_percent = 50;
circpad_machine_states_init(relay, 4);

if (CIRCPAD_UNI_RAND < 0.5) {
    /*
     * machine has following states:
     * 0. init: don't waste time early
     * 1. wait: either extend or fake
     * 2. extend: obfuscate length of existing bursts
     * 3. fake: inject fake bursts
     */
    // wait for client to send something, no point in doing stuff too early
    relay->states[0].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 1;

    if (CIRCPAD_UNI_RAND < 0.5) {
        // wait: extend real burst
        relay->states[1].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 2;
    } else {
        // wait: inject a fake burst after a while (FIXME: too long below)
        relay->states[1].iat_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
        relay->states[1].iat_dist.param1 = CIRCPAD_UNI_RAND*1000; // alpha, scale
        relay->states[1].iat_dist.param2 = CIRCPAD_UNI_RAND*10000; // shape, when
        relay->states[1].dist_max_sample_usec = 100000;
        relay->states[1].next_state[CIRCPAD_EVENT_PADDING_SENT] = 3;
// extend: add fake padding for real bursts
relay->states[2].length_dist.type = CIRCPAD_DIST_PARETO;
relay->states[2].length_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[2].length_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[2].start_length = 1;
relay->states[2].iat_dist.type = CIRCPAD_DIST_PARETO;
relay->states[2].iat_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[2].iat_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[2].dist_max_sample_usec = 10000;
relay->states[2].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 1;
relay->states[2].next_state[CIRCPAD_EVENT_PADDING_SENT] = 2;

// fake: inject completely fake bursts
relay->states[3].length_dist.type = CIRCPAD_DIST_PARETO;
relay->states[3].length_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[3].length_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[3].start_length = 4;
relay->states[3].iat_dist.type = CIRCPAD_DIST_PARETO;
relay->states[3].iat_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[3].iat_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[3].dist_max_sample_usec = 10000;
relay->states[3].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 1;
relay->states[3].next_state[CIRCPAD_EVENT_PADDING_SENT] = 3;
}
else {
    // spring-mr
relay->states[0].iat_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[0].iat_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[0].iat_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[0].dist_max_sample_usec = 10000;
relay->states[0].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 1;
relay->states[0].next_state[CIRCPAD_EVENT_PADDING_RECV] = 1;
relay->states[1].iat_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[1].iat_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[1].iat_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[1].dist_max_sample_usec = 31443;
relay->states[1].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 2;
relay->states[2].length_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[2].length_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[2].length_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[2].start_length = 5;
relay->states[2].iat_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[2].iat_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[2].iat_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[2].dist_max_sample_usec = 100000;
relay->states[2].next_state[CIRCPAD_EVENT_PADDING_SENT] = 2;
relay->states[2].next_state[CIRCPAD_EVENT_PADDING_RECV] = 3;
relay->states[3].length_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[3].length_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[3].length_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[3].start_length = 5;
relay->states[3].iat_dist.type = CIRCPAD_DIST_LOG_LOGISTIC;
relay->states[3].iat_dist.param1 = CIRCPAD_RAND_DIST_PARAM1;
relay->states[3].iat_dist.param2 = CIRCPAD_RAND_DIST_PARAM2;
relay->states[3].dist_max_sample_usec = 55878;
relay->states[3].next_state[CIRCPAD_EVENT_NONPADDING_RECV] = 3;
relay->states[3].next_state[CIRCPAD_EVENT_NONPADDING_SENT] = 0;
relay->states[3].next_state[CIRCPAD_EVENT_PADDING_RECV] = 2;
relay->machine_num = smartlist_len(relay_padding_machines);
circpad_register_padding_machine(relay, relay_padding_machines);