Adaptive Traffic Fingerprinting: Large-scale Inference under Realistic Assumptions

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Abstract—The widespread adoption of encrypted communications (e.g., the TLS protocol, the Tor anonymity network) fixed several critical security flaws and shielded the end-users from adversaries intercepting their transmitted data. While these protocols are very effective in protecting the confidentiality of the users’ data (e.g., credit card numbers), it has been shown that they are prone (to different degrees) to adversaries aiming to breach the users’ privacy. Traffic fingerprinting attacks allow an adversary to infer the webpage or the website loaded by a user based only on patterns in the user’s encrypted traffic. In fact, many recent works managed to achieve a very high classification accuracy under optimal conditions for the adversary.

This paper revisits the “optimality” assumptions made by those works and discusses various additional parameters that should be considered when evaluating a fingerprinting model. We propose three realistic scenarios simulating non-optimal fingerprinting conditions where various factors could affect the adversary’s performance or operation. We then introduce a novel adaptive fingerprinting adversary and experimentally evaluate its accuracy and operation. Our experiments show that adaptive adversaries can reliably uncover the webpage visited by a user among several thousand potential pages, even under considerable distributional shift (e.g., the webpage contents change significantly over time). Such adversaries could infer the products a user browses on shopping websites or log the browsing habits of state dissidents on online forums andencyclopedias. Our technique achieves ~90% accuracy in a top-15 setting where the model distinguishes the article visited out of 6,000 Wikipedia webpages, while the same model achieves ~80% accuracy in a dataset of 13,000 classes that were not included in the training set.

I. INTRODUCTION

Several works on webpage fingerprinting have demonstrated that eavesdropping adversaries can distinguish the websites visited by a user even when the traffic is routed through the Tor anonymity network [1], [2], [3], [4], [5], [6], [7], [8]. Most of these attacks operate by extracting features from the encrypted data exchanged between a targeted user and the entry node of the anonymity network used (e.g., Tor). For example, neural networks have been shown to be able to fingerprint websites based on the sequence of bytes transmitted by each party and their respective direction [6], [7], [8].

Similarly, a smaller body of work has focused on manifestations of such attacks on the Transport Layer Security (TLS) protocol [10], [11], [12], [13], [14]. The TLS protocol is the most widely used encrypted-communications protocol on the Internet and aims to protect the confidentiality and the integrity of the data transmitted from both eavesdropping and malicious adversaries [13], [15]. By design, TLS 1.2 and 1.3 reveal the IP address of the website visited by the user but conceal the requested webpage (and its contents) by encrypting all transmitted data as well as the URL’s path. Thus, fingerprinting attacks against the TLS protocol aim to uncover the specific webpage loaded by the user and not the website.

Despite the fact that TLS is used by several millions of users, the literature on webpage fingerprinting is sparse and aged compared to that on website fingerprinting. Nonetheless, both lines of research share a common methodology when evaluating fingerprinting techniques. In particular, they adopt scenarios that study the performance of the proposed fingerprinting model under optimal for the adversary conditions (i.e., worse-case scenario for the user). This is a common practice in the security literature as the accuracy of the model serves as a privacy upper-bound that the user can reliably assume under all possible circumstances. However, optimal fingerprinting scenarios are not reliable indicators of a model’s practicality. For example, a fingerprinting model that has very high classification accuracy under some very specific optimal conditions is not guaranteed to remain performant in other more realistic settings.

This leaves a gap in the literature on fingerprinting attacks and raises doubts about the degree of threat they pose [14], [16]. For example, despite the fact that webpage fingerprinting attacks are a known problem, generic claims about “privacy” on TLS appear in several specifications and industry documents [17], [18], [19], [20], [21], [22], [13]. The TLS 1.2 Request for Comments (RFC) explicitly includes “privacy” in the primary goals of the protocol [12] but does not define it.

"The primary goal of the TLS protocol is to provide privacy and data integrity between two communicating applications."

Similarly, privacy is also mentioned in a variety of articles
and technical reports [17], [18], [19], [20], [21], [22]. While TLS provides some “privacy” compared to plaintext communications, it cannot be assumed to reliably protect the user’s browsing habits from sophisticated eavesdropping adversaries. On the other hand, the constrained scenarios considered in the literature ([11], [12], [1], [13], [14]) are not strong evidence that those attacks are practical and scale to larger websites, and potentially provided a false sense of privacy to Internet users.

This work revisits those assumptions and argues that fingerprinting models should be also evaluated under non-ideal conditions. We compile a list of important factors that can directly affect the performance of a model and, consequently, its practicality. These factors correspond to some of the main difficulties faced by passive adversaries in modern deployments (e.g., large number of webpages, fast-changing contents). We then outline the basic properties that a fingerprinting adversary should have in order to be practical and argue that most of the existing fingerprinting techniques fail to meet one or more of them. This is because those models were designed to operate optimally under static, non-changing conditions (e.g., constant webpage/website contents) and provide no adaptation mechanisms. Thus, an adversary has to constantly retrain the model in order to keep up with any form of distributional shift.

To evaluate if a realistic and performant adversary is possible, we introduce adaptive fingerprinting and study it under various adverse scenarios. The novelty of our technique is that it allows for rapid and inexpensive adaptation to distributional shift without the need for retraining. Our results show that it performs very well on static settings and that it retains similar levels of accuracy in scenarios where the fingerprinting targets evolve over time. Moreover, we find that neither TLS 1.2 and TLS 1.3 can reliably provide privacy in the presence of webpage fingerprinting adversaries, even in the case of websites with thousands of pages. Thus, users can rely on the TLS protocol to protect their credit card numbers and other private information (e.g., medical results) but not their browsing habits (e.g., eBay product pages, frequently visited subreddit webpages, online lemmas).

Besides attacks, fingerprinting techniques have also found applications in malware detection in network settings [23], [16], [24], [25], [26]. Network administrators employ fingerprinting techniques to identify malware based on the TLS channels it establishes with its remote command & control servers (e.g., botnets using Twitter profiles to receive commands from their controllers [27], [28], [29], [30], [31]). In the rest of this work, we focus on surveillance scenarios due to the ramifications of such attacks to the privacy of individuals. However, we believe that our results could inform advancements in malware detection too.

Overall, this paper makes the following contributions:

- Introduces a novel adaptive fingerprinting model that can reliably classify thousands of webpages, has low overhead and is robust to various forms of distributional shift (e.g., content, website, and TLS protocol version changes). The model is trained only once and provides a rapid and inexpensive adaptation procedure that allows the adversary to fingerprint webpages/classes that were not included in the original training set.

- Shows that the TLS protocol cannot provide privacy with regard to the users’ browsing habits even in the case of large websites. For the first time, we demonstrate that fingerprinting attacks can be effective on websites with thousands of webpages, regardless of the website’s details and the protocol version used (TLS 1.2 or 1.3).

II. Preliminaries

This section introduces some fundamental concepts of web traffic encryption and machine learning.

A. The Transport Layer Security Protocol

The TLS protocol is a cryptographic protocol that is commonly used to establish secure two-party communication channels over untrusted networks (e.g., the Internet). It is utilized in a wide range of applications such as web browsing, email, instant messaging and voice over IP, and employs end-to-end encryption between the two parties to protect the integrity and the confidentiality of the transmitted data. The two participants first negotiate the ciphersuite details and then perform an one-time handshake to generate the cryptographic keys that will be used to protect the contents of their communication. Following a successful handshake, all the data exchanged is encrypted. To prevent man-in-the-middle attacks a client accessing a TLS-enabled server verifies the identity of the server through a public-key certificate issued by a trusted certification authority. For a detailed analysis of the TLS protocol please refer to [32], [33], [15], [34]. In this work, we focus on the latest two versions of TLS, 1.2 [13] and 1.3 [15].

B. Neural Networks

Neural networks and stochastic gradient descent (SGD) are the core work horses behind the “deep learning revolution” [35], [36]. Given access to data, X, with label set Y, the goal of supervised machine learning is to learn the conditional distribution p(Y|X). Neural networks define a parameterized function f_w : X → Y that when trained with SGD attempts to approximate the conditional p(Y|X). A neural network is a composition of one or more layers of artificial neurons (i.e., perceptrons) such that given an input x, to layer i, the input to layer i + 1 is given by

\[ \sigma(w_i^T \cdot x + b_i) \]

where \( w_i \) denotes the model weights that govern the strength of a connection between two neurons, \( b_i \) is a bias vector, and \( \sigma \) is a non-linear activation function. Popular choices of non-linear activation functions are ReLU(x) =
max(0, x) and the sigmoid function. One can interpret the final layer as a probability vector by applying the softmax function to outputs (sometimes referred to as logits). Given an input \( x \), logits \( f_w(x) \), where \( f_w(x)_k \) is the logit value of the \( k \)-th class, and true label \( y \), a loss function outputs a scalar based on how strongly an input would be assigned the true class label. The most common loss function to use in supervised neural network training is the log-loss defined as

\[
y \log(f_w(x)_y)
\]

Model weights are then updated based on \( \frac{\partial - y \log(f_w(x)_y)}{\partial w} \); averaging this loss over batches of inputs, computing the derivative with respect to model weights, and updating these weights in the opposite direction to this derivative is what is known as SGD and has produced state-of-the-art results on classification problems in a large number of fields [36], [37].

C. Low-dimensional Embeddings

Neural network embeddings are learned representations of discrete variables (e.g., words or sequences of words) as continuous vectors in a low-dimensional space [38], [39]. Such representations significantly reduce the dimensionality of the input data, while they retain most of its information content. Embedding techniques are commonly used in recommendation systems as the reduction in the feature space makes learning easier. Similar benefits have been also observed in the context of classification, where the accuracy of a classifier and the volume of the training data needed, depend heavily on the dimensionality of the input space [40], [41]. Besides these, dimensionality reduction can also provide additional application-specific advantages e.g., enhance the robustness of the classifier to perturbations [42], [43].

D. Webpage vs. Website Fingerprinting

As discussed in Section I, the majority of past works has focused on website fingerprinting against users that route their traffic through anonymity networks (e.g., the Tor anonymity network). Such works aim to uncover the website visited by the user from a pool of possible websites that are of interest to the eavesdropping adversary. Website fingerprinting is orthogonal to that goal as it aims to identify the specific webpage accessed by the user. Such attacks can be launched against both anonymity networks and standard end-to-end encryption protocols such as TLS. So far, webpage fingerprinting has not received much attention in the literature, despite the fact that the Tor user-base is only a fraction of the total number of TLS users.

From a technical perspective, both attacks rely on extracting data-transmission patterns (i.e., byte counts, sender and recipient) to uniquely identify a website or a webpage. However, webpage fingerprinting presents additional challenges, as websites tend to reuse the same template/theme in all their pages. Thus, webpages belonging to the same website exhibit only partially unique transmission patterns, with the only differentiating factor being the content of each page. This limits the amount of useful identifying information one can extract from the traffic stream. In contrast, in website fingerprinting, the whole stream can be uniquely identifying as websites usually use different themes/template.

We believe that webpage fingerprinting is a pressing issue and has received disproportionately low attention. Especially, when considering the number of users that are exposed to such attacks and the nature of the data that can be leaked (e.g., health info from users browsing condition-specific articles on medical websites). In comparison, website fingerprinting attacks affect mainly Tor users (perhaps a more sensitive group) and reveal only the website visited, which in cases of large websites (e.g., Wikipedia) may not leak much information about the user’s interests or habits.

III. Adversarial Model

We now introduce the threat model, the attack scenarios and the practicality constraints that we will consider in the rest of this work.

A. Threat Model

Due to the generic nature of our work, we consider two almost identical threat models: One for webpage fingerprinting adversaries and another for website fingerprinting. In both models, we assume a polynomially-bound passive adversary that can capture (but not tamper with) the packets exchanged between the client and the server. Such adversaries are used in the majority of the works on traffic fingerprinting [2], [3], [6], [8], [7], [1], [4], [5], [9].

In the case of webpage fingerprinting, we adopt the adversarial setup outlined in TLS 1.2 and 1.3 specifications [13], [15]: The client communicates with a server over an encrypted channel established through TLS while the adversary intercepts some or all of the packets exchanged. The goal of the adversary is to infer the specific webpage visited by the user (e.g., Wikipedia lemma, eBay product page). Neither TLS 1.2 nor 1.3 conceal the IP address of the webserver and thus we assume that the adversary is aware of the website that the user is visiting \(^1\).

Similarly, in the case of website fingerprinting the adversary intercepts the encrypted traffic exchanged between the user and the entry node of the anonymity network used. The adversary has the same capabilities as before but their goal is to uncover the website loaded by the user. This model is relevant to attacks against anonymity networks such as Tor that conceal the IP address of the website/server visited by the user.

B. Realistic Fingerprinting Scenarios

In this work, we focus on fingerprinting scenarios that provide a realistic representation of the conditions under which an adversary has to operate. While this may make it harder to design and implement effective attacks, it enables us to draw reliable conclusions about the the capabilities of the adversary in real settings. In particular, we focus on three aspects of such scenarios: 1) Number of classes (e.g., webpages, websites), 2) Distributional shift (e.g., content

\(^1\)Even though an IP address may correspond to many websites (i.e., multihosting), this is neither guaranteed (e.g., large websites have dedicated servers) nor provides a provably large/secure anonymity set.
updates), and 3) Shared resources (e.g., common HTML theme, shared images).

Number of classes
Past works on webpage fingerprinting considered scenarios where the user is assumed to visit a fixed set of known webpages while the adversary aims to infer which webpage was loaded [1], [10], [11], [12]. Unfortunately, their experiments were conducted on datasets of up to 500 webpages. Such datasets have been criticized as being unrealistically small [6] and led to doubts about the practicality of the proposed attacks, especially as many modern websites comprise of several hundred or even thousands of unique webpages. In comparison, recent works on website fingerprinting evaluated their proposed techniques under more realistic, practical conditions [6], [5]. Overall, we argue that fingerprinting techniques should be evaluated in at least one scenario with a moderate or large number of classes.

Distributional Shift
Another common assumption in past works on fingerprinting is static webpage/website contents. While assuming content invariability may look reasonable at first glance, it results in significant performance degradation in practice as pages change over time [8]. A model that is trained to classify a set of pages (e.g., Wikipedia articles, subreddits, eBay listings) will have to retain its accuracy as their contents get updated. This can be achieved either by retraining the classification model on the latest version of the webpages/websites or through other means. From an adversarial perspective, the cost of keeping up with the ever-changing contents is directly connected to the practicality of the technique. For example, a model that needs to be retrained each time one or more webpages get updated is likely to incur large operational costs thus making the technique inapplicable (even if it performs very well). Overall, the degree of tolerance to distributional shift and the cost of adapting to changes are also important factors that must be considered when evaluating a fingerprinting technique.

Shared Resources
While the previous two factors concerned both webpage and website fingerprinting, webpage fingerprinting scenarios should also account for an additional parameter. It is common for the pages of a website to share a HTML theme (e.g., the same stylesheet, Javascript scripts, background image files). This reduces the volume of unique information carried in each traffic trace, thus making it harder for the adversary to uniquely identify each webpage.

C. Practicality Considerations
We now outline the requirements for a fingerprinting technique to be considered realistic.

Accuracy & Scalability. An effective fingerprinting technique needs to provide high inference accuracy for at least medium-sized and preferably large-sized websites (with regards to their number of webpages). For example, a technique that achieves 80% accuracy on a set of 100 websites is not necessarily equally accurate when used on larger sets.

Adaptability. As discussed in Section III-B, websites periodically add and remove webpages, as well as update their contents. Practical fingerprinting techniques must be resilient to such distributional shift and retain their accuracy over time [8]. Moreover, while adversaries may be able to cope with small page updates, it is not uncommon for webpages to have most of their content replaced over time (through small but frequent updates). This gradual process leads to a large distributional shift where the current version of a page has a very small overlap with the version the model was initially trained on. The practicality and the performance of a fingerprinting technique depend on its ability to adapt to such changes (e.g., frequent retraining, low generalization error) and the operational cost this entails.

Provisioning & Operational Costs. Making inferences from traffic traces should come at a reasonable operational cost (i.e., in time and computational resources), while provisioning the fingerprinting model may have a larger one-off cost. Minimizing these costs results in more practical and easily-applicable models

Protocol-agnostic. While past works have focused on a specific protocol version, it is advantageous for a practical adversary to be able to fingerprint webpages/websites regardless of the underlying protocol version used by the user. For example, a fingerprinting deployment that is tailored to only one protocol version of the TLS protocol could potentially be temporarily circumvented by switching to a different version (e.g., from TLS 1.2 to 1.3) or even to a different ciphersuite than the current one. This is not a strict requirement (protocol-specific attacks can be also very effective), but we consider this a desirable (albeit not necessary) feature for highly-transferable models

IV. ADAPTIVE FINGERPRINTING
We now introduce a methodology that allows adversaries to fingerprint webpages from non-static, temporally-changing websites. The core components of our system (Figure 2) are the embedding neural network and the classification algorithm used to attribute samples to classes (i.e., traffic traces to webpages). Its operation comprises of three processes: provisioning, fingerprinting, and adaptation. The provisioning process takes place only once, while the fingerprinting and the adaptation processes are executed iteratively throughout the lifecycle of the deployment. This proposal aims to address the limitations of existing models that were designed with the optimal fingerprinting conditions in mind and lack provisions for more complex settings.

A. Provisioning
Before the system is usable, the embedding neural network that reduces the dimensionality of the input traffic traces needs to be trained. Our training process is illustrated in
Fig. 2. The eavesdropping adversary maintains a dataset of labeled traces from the webpages they monitor. These traces are processed by the embedding neural network and form the set of reference points. The reference points are then used to classify the user’s traffic based on a proximity-based algorithm (e.g., k-nearest neighbours). Optionally, the adversary can keep populating the dataset with new reference points to stay up-to-date with the latest version of the webpages, without the need to retrain the embedding model.

Figure 4 and involves four steps.

Data Collection & Preprocessing.
Initially, the adversary compiles a list of webpages (preferably from the website they intend to fingerprint) and then proceeds to repeatedly load each webpage several times. For each visit, the network traffic between the client and the server is stored in a packet capture file (pcap file) and placed in a library of raw traces.

Following the collection of the raw traffic traces, the adversary processes them into sequences of integers (Figure 3). Each sequence corresponds to one of the IP addresses that transmitted data during the pageload and contains the byte-counts sent by that IP address over time.

In particular, each time an IP address sends out traffic, the byte-count is appended to the corresponding sequence while the rest of the sequences are appended with a zero-count element. This is done to preserve the relative order of the transmissions. If an IP address sends more than one consecutive packets (i.e., no traffic from other IP addresses is interleaved), the byte-counts of those packets are aggregated and only their sum is appended.

Works on website fingerprinting represent the data exchange as a single sequence where incoming packets are denoted by their byte-count and a negative sign, while outgoing packets are denoted by the byte-count with a positive sign. This is equivalent to using only two IP sequences, one for incoming and one for outgoing traffic. The reduction in the number of sequences is because anonymity networks (e.g., Tor) conceal the IP addresses involved in a pageload as all the traffic is routed through an entry node of the network. In contrast, TLS does not protect the IP addresses of the servers involved in a page load (e.g., user’s client, main Wikipedia server, servers for auxiliary JavaScript files and images).

Following this step, the sequences can be optionally quantized to eliminate noisy artifacts (e.g., small differences in the byte counts). At the end of this process, the adversary has a dataset of labeled traces (each trace is a set of IP sequences corresponding to a single page load) that can be used to train the neural network (leftmost block in Figure 4).

Pair Generation
Given the dataset of labeled traces, the adversary generates positive and negative pairs. Positive pairs comprise of two traces corresponding to the same webpage, while negative pairs to different ones. The most straightforward strategy to generate pairs is at random, while more advanced techniques have been proposed in the relevant ML literature (e.g., Hard-Negatives, Semi-Hard-Negatives). The pairs are labeled based on the similarity of the samples (1 for similar, 0 for different) and are then used to train the embedding model.

Training
In this step, we train the machine learning model to produce embeddings that are in close proximity when the input traces originate from the same webpage, and far-apart otherwise. Intuitively, the role of the embedding network is to extract robust features that are less sensitive to artifacts (e.g., packet re-transmissions, non-deterministic resource loading order) and map the samples in the embedding space (Figure 2). As outlined in Section II-C, classification algorithms (e.g., k-nearest neighbours) that rely on the distance between the samples (e.g., euclidean, cosine) perform significantly better in low-dimensional spaces compared to when they operate on the original high-dimensional feature space. The specific architecture of the neural network and its training details...
Fig. 4. To train the embedding model, we use a dataset of labeled traffic traces that originate from the same website (e.g., Wikipedia). Using that set, we generate pairs of traces from the same class and from different ones (i.e., positive and negative pairs). These pairs are then used to iteratively train the model until sufficient accuracy has been achieved.


depend on the needs of the adversary and the use case.

Following the methodology outlined in [47], [48], for every training pair, we embed the two input sequences and compute the similarity of the two embeddings. For positive pairs, the similarity must be approximately equal to 1, while for negative pairs approximately equal to 0. To estimate the correctness of our model and update the network parameters accordingly, we compute the contrastive loss [48] given by the formula:

\[ L(d, y) = yd^2 + (1 - y) \max(\text{margin} - d, 0)^2 \]  

where \( d \) is the (euclidean) distance between the two embeddings \( e_1 \) and \( e_2 \) \( (d = ||e_1 - e_2||_2) \), \( y \) is the known similarity label of the pair and the \text{margin} is a user defined parameter used to improve the separation between the different classes in the embedding space (i.e., dissimilar pairs should have a distance at least equal to the \text{margin}). The training process is completed once sufficient performance has been achieved.

Initialization

Following the training of the embedding model, the system is populated with data that serve as reference points when classifying unlabeled traffic traces captured by the adversary. The adversary compiles a list of the webpages they intend to fingerprint, crawls them and embeds the traffic sequences to generate a reference set of labeled embeddings (steps 1 and 2 in Figure 2). The reference set is then stored and used every time an unlabeled traffic trace is classified.

B. Fingerprinting

Given an initialized deployment with a populated reference set, the adversary can then proceed to fingerprint unlabeled samples captured from the user’s traffic.

Capturing and Mapping

Depending on the setup, the adversary may capture the user’s traffic at an Internet service provider (ISP) level or may reside in the same network and thus capture the traffic locally. Upon converting the packet capture into sequences, the adversary uses the embedding model to map the unlabeled sequence into the embedding space (step 3 in Figure 2).

Classifying

This is final step of the fingerprinting process and classifies the embedding that corresponds to the user’s traffic trace (step 4 in Figure 2). Intuitively, each captured sample is classified based on the labeled traces (reference points) that are in its proximity in the embedding space. The proximity between the embeddings and the specific algorithm can be freely chosen by the adversary. The algorithm outputs a list of the most probable labels for the examined sample and the frequency each one of them occurred (i.e., number of samples in proximity with that label).

C. Adaptation

Besides the initialization and the fingerprinting processes, our methodology involves an optional adaptation process. Its aim is to keep the deployment up to date with constantly changing webpages and prevent the performance degradation that occurs over time [8]. Initially, the adversary crawls and identifies the webpages/websites that have been updated. Given one such page, the adversary loads it, collects a traffic trace and fingerprints it as outlined in the previous section. If the accuracy of the classifier is not adequate, the adversary crawls the page several times and updates the labelled traces in the reference samples dataset. The decision to update the reference samples of a particular class (in case the contents of the page have changed) can be taken based on a user-defined accuracy threshold (e.g., maximum discrepancy from the accuracy of the freshly-initialized deployment).

The main advantage of this process is that it does not require any retraining of the model or of any other component of the system (unlike the majority of past works on fingerprinting [2], [3], [4], [5], [6], [11], [14], [1]). Retraining a machine learning model is a costly operation and would impede the scalability of the attack if it was to be executed every time one of the thousands of pages/websites is updated. Instead, adaptive fingerprinting enables the adversary to remain up to date with fast-changing pages through a short sequence of inexpensive and low-complexity operations.

While this extends beyond the scope of this paper, there is a body of work on efficiently monitoring and detecting changes in millions of webpages for web-archiving purposes [49], [50].
V. DATASETS

To better understand the performance of fingerprinting adversaries under non-ideal conditions, we evaluate our proposed fingerprinting technique on two datasets with TLS traffic traces: one with traces from Wikipedia and another with traces from Github. We focus on TLS as webpage fingerprinting attacks can affect many more users and have received little attention in the relevant literature. Moreover, webpage fingerprinting presents some additional practicality challenges (compared to website fingerprinting) that have not been studied thoroughly in the literature (e.g., the effect of shared HTML templates across all the pages of a website).

Each dataset contains (encrypted) traffic traces as they would be captured by the eavesdropping adversary introduced in Section III-A. We employed 100 Amazon EC2 instances distributed over five geographical regions (20 instances in each region). These instances crawled a given list of URLs, captured the generated traffic, stored it as a pcap file and processed it into sequences of bytes (Figure 3). To automate the crawling process, we used Python 3.7 with the Selenium automation framework3. Each instance ran only one crawling process that visited each URL on the list sequentia

Wikipedia. Our Wikipedia dataset consists of encrypted traffic traces from 19,000 distinct Wikipedia articles. To diversify our traces, each crawler shuffled the list and visited each article only once in a random order. Wikipedia uses TLS 1.2 and the page contents are usually loaded from two servers (one for text content and another one for media). In total, the resulting dataset contains 1,900,000 traffic traces (100 traces for each URL). We chose Wikipedia for our experiments as it contains a very large number of articles, the pages share the same template and permits crawling of its contents, albeit at a low rate (1 request per second).

Github. Github enables projects to display a README page with information on the project as well as with installation and usage instructions. The overlaying Github template is common for all the projects but the contents of each page are managed by the project’s contributors. Such pages include text, images and sometimes videos. Images and videos are stored either internally on Github or on external servers. Our dataset was generated by visiting the top 500 Github project pages, 1,000 times each. Each crawler instance shuffles the list of URLs and then visits each Github page 10 times over the span of several hours. Github uses TLS 1.3 and exhibits increased variability across various dimensions. It employs advanced load balancing techniques causing various discrepancies between subsequent pageloads of the same page, while the number of servers involved is heavily dependent on the contents of each project page (e.g., external images, scripts). Overall, the dataset contains 500,000 traffic traces (500 articles visited 10 times by 100 crawler instances). We chose Github as it was one of the few websites that had deployed TLS 1.3 at the time of the data collection and permits crawling of its pages. Moreover, it features a moderate number of webpages (i.e., projects) all sharing a common HTML theme.

VI. EXPERIMENTAL EVALUATION

In this Section, we evaluate our proposed methodology by deploying and testing its performance on real data. We use three scenarios that simulate real-world fingerprinting setups with non-optimal conditions for the adversary. We focus on scenarios of webpage fingerprinting as such attacks and have been overlooked in the literature (cf. website fingerprinting attacks). Webpage fingerprinting attacks are more severe as they affect many more users (i.e., the number of Tor users compared to that of Web users) and pose a more pressing threat to the privacy of individuals. For example, a website fingerprinting attack could infer that the user is visiting Wikipedia, while webpage fingerprinting attacks uncover the exact article loaded.

A. Implementation & Parameterization

For the implementation of our neural network, we use the Python deep learning library Keras as the front-end, and Tensorflow as the back-end. For the data preprocessing and classification algorithm, we use Numpy and Scipy, respectively. To allow for reproducibility of our results, we will publicly release both our source code and our datasets.

As outlined in Section V, we use contrastive loss to train our model on both positive and negative pairs. The margin of the loss function is set to be 10 and was determined through grid search among smaller and larger values. Moreover, we use the euclidean distance to measure the proximity of the embeddings and through grid search we determined the sizes of the hidden layers and the dimensionality of the produced embeddings (see Table I).

| Parameter                      | Value(s)                  |
|--------------------------------|---------------------------|
| Input layer                    | 30 LSTM units             |
| # hidden fully connected layers| 4 layers                  |
| Size of hidden fully connected layers | 100 to 2000 neurons |
| Activation for hidden layers   | ReLU [58]                 |
| Size of output layer           | 32 neurons                |
| Activation for output          | Leaky ReLU [59]           |
| Optimizer                      | Stochastic Gradient Descent [37] |
| Dropout                        | 0.1                       |
| Learning rate                  | 0.001                     |
| Batch Size                     | 512 pairs                 |
| Distance Metric                | Euclidean distance        |
| Contrastive Loss Margin        | 10                        |

TABLE I. THE HYPERPARAMETERS (TOP HALF) AND THE TRAINING PARAMETERS (BOTTOM HALF) OF OUR EMBEDDING NEURAL NETWORK.
For experiments 1 and 2, we use our Wikipedia dataset. The dataset is split into four smaller sets, both across its classes and its samples. Experiment 1 trains the embedding model on set A and then validates the accuracy of the produced embeddings on previously-unseen samples from the same classes (set B). In contrast, Experiment 2 reuses the trained model from Exp. 1 (trained on set A) to embed samples from set C as reference points. Experiment 2 uses set D as its test set. Note that the classes in sets C and D are not represented in sets A and B and vice versa.

For our classifier, we used the \textit{k-nearest neighbours} algorithm with \( k = 250 \). While we were able to achieve slightly better classification results by adjusting the \( k \) parameter depending on the size of the testing set, \( k = 250 \) produced consistently good results regardless of the number of classes. This allowed us to maintain the same configuration for all our experiments so as to more reliably compare our findings.

### B. Exp. 1: Static Webpage Classification

In this experiment, we assume an adversary that wants to fingerprint the pages of a small- or medium-sized website where all the pages share the same HTML template. This first experiment studies the performance of our proposed technique against a website with mostly-static webpages with a moderate percentage of shared content (the template and the graphics).

Using our methodology from Section IV we train the adversary’s embedding model on pairs of samples from our Wikipedia dataset. The training set of the model includes samples from 6,000 distinct webpages/classes (Set A in Figure 5). Upon completing the training phase, we deploy the model and use it to classify the samples in set B (Figure 5). The samples in set B originate from the same 6,000 classes but correspond to traffic traces that were not used during the training phase. During the classification phase, we use set A as the adversary’s labelled sequences corpus (~90 samples per class) and then use our trained model to classify the remaining ~10 samples per class from set B (60,000 samples in total).

To better study the performance of our model, we run our recognition task on different versions of Sets A and B containing 500, 1,000, 3,000 and 6,000 classes respectively.

As seen in Figure 5, out of a pool of 500 possible classes/articles, a top-3 adversary (i.e., the adversary is allowed to guess up to three classes) is able to correctly identify the Wikipedia article visited in more than \( >90\% \) of the cases. Moreover, top-1 adversaries have \( 58\% \) probability of correctly labelling the encrypted traffic trace, while top-10 adversaries are always able to correctly identify the page loaded. In comparison, [14] reported a top-15 adversary with accuracy up to \( 90\% \). This top-15 adversary has been the state-of-the-art so far, as the literature on webpage fingerprinting is sparse and dated. Moving on to larger sets, we evaluate the classification accuracy of our model in slices of Sets A and B with 1000, 3000 and 6000 classes (Figure 5). In the scenario of 1000 classes, a top-1 adversary is able to correctly classify previously unseen samples with \( 50\% \) accuracy, while in larger sets with 3000 and 6000 classes the same adversary achieves \( 35\% \) accuracy. In the 1000- and the 3000-classes scenarios, the top-10 adversaries are able to correctly classify more than \( 90\% \) of the samples. In the 6000-classes case, a top-20 adversary also achieved above-\( 90\% \) accuracy. In other words, an adversary who is allowed to choose 20 out of the 6000 labels (0.3% of the possible labels) has on average \( > 90\% \) likelihood of selecting the page visited by the user.

Overall, we demonstrated that adaptive fingerprinting adversaries are scalable and can classify with high accuracy samples originating from a large pool of potential webpages. This result extends past works [11], [14] on webpage fingerprinting that presented adversaries capable of classifying up to 500 pages but did not assume any content overlap (e.g., academic homepages). We conclude that attacks against webpages/websites that share part of their content are realistic and can be launched even by adversaries with limited resources.
C. Exp 2: Adaptability & Cross-class Transferability

One of the goals of our methodology is to retain its classification accuracy even in cases of distributional shift (e.g., temporal changes, addition of new classes) at a minimal cost for the adversary. Such a characteristic would significantly exacerbate the severity of fingerprinting attacks as it would make it practical for an adversary to fingerprint a dynamic set of webpages where classes are added, changed, removed periodically. For this purpose, our fingerprinting methodology decouples these two tasks and allows the “encoding” model to remain class-agnostic, thus avoiding the need for any costly retraining. Instead, the adversary can easily adapt to changes in the set of webpages/websites or the contents of the webpages by updating the reference samples in the corpus of labelled traces.

To simulate a scenario of extreme distributional shift, we design an experiment where the adversary is classifying a set of articles that is completely disjoint from the set that the model was trained on. This is the worst-case scenario for an adversary who classifies samples from a set of webpages that is completely disjoint to the set the training samples originated from. Such a difference between the training set and the testing set can occur in cases where the pages change drastically over time. For that purpose, we reuse the model trained in Experiment 1 (on Set A) to embed samples in Sets C and D. As shown in Figure 5, Set A does not overlap with Sets C (and D) as the former contains samples from 6,000 classes while the latter contains samples from 13,000 different classes. We consider our testing set to comprise Sets C and D, where Set C populates the adversary’s dataset of reference samples and Set D provides the samples that need to be classified. As in Experiment 1, we investigate the accuracy of the model for slices of Sets C and D with different numbers of classes i.e., 500, 1000, 3000, 6000, 13000.

As seen in Figure 4, the classification accuracy of the adversary remains almost identical to the accuracy achieved with sets of the same size in Experiment 1. A top-1 adversary achieves 58% accuracy in the 500-classes set and a top-3 adversary ~90% accuracy. Similarly, a top-1 adversary achieves almost 50% accuracy in the 1000-classes set and a top-4 adversary almost ~90% accuracy. This shows that the embedding model is learning equivalence rules of TLS streams rather than simply memorizing specific pairs of training samples or class-specific characteristics from the classes in the training set. For example, through manual inspection of the traffic traces collected, we observed that two samples of the same class differed significantly. In one of them, the images were downloaded in consecutive chunks of fixed length, while in the other they were fetched as a whole. Despite these differences, the model was correctly embedding the two samples in relative proximity. Moreover, the adversary performs considerably well in even larger sets of new classes. In particular, a top-10 adversary achieved an accuracy of 90%, 80% and 70% in set with 3000, 6000, and 13000 classes respectively. This shows that our fingerprinting methodology can be reliably used to embed and classify samples from classes that were never encountered during training.

We were not able to compare our results with past works as scenarios of completely disjoint training and testing sets have never been studied in the context of webpage fingerprinting. To our knowledge, [7] is the only work on website fingerprinting that considered a similar scenario. They trained on a dataset of 775 websites/classes and then tested on a small set of 100 websites. They report an accuracy of ~80% for a top-1 adversary and ~92% for a top-5. Due to the differences in the underlying encryption protocols (Tor vs TLS) and the considerably smaller set (100 websites vs 500-13,000 webpages), our results cannot be safely compared.

Furthermore, Figure 7 shows that the adversary needs to increase their number of guesses (i.e., parameter n of a top-n adversary) as the number of classes increases in order for them to maintain the same level of accuracy (e.g., 90%). This is due to the increasing number of collisions between cross-class samples in the embeddings space. As the number of classes increases, the number of samples who are erroneously mapped in proximity to another class increases as well. However, as seen in Table II, n increases slower than the number of classes. This implies that while the absolute number of collisions increases with the number of classes, the increase in collisions has a sublinear relationship with the increase of the number of classes. In other words, for any percent increase in the number of classes the adversary needs to increase their n by less than 1%.

D. Exp. 3: Sensitivity to Website themes and TLS versions

In this experiment, we examine the learning characteristics of our adaptive fingerprinting adversary. In particular, we evaluate 1) the effect of retaining multiple IP sequences, and 2) the degree that the model can sustain distributional shift across websites and TLS versions simultaneously.

As in Experiment 1, we train an embedding model on 6,000 Wikipedia articles (90 samples for each article) but we use...
TABLE II. AS THE NUMBER OF CLASSES INCREASES THE ACCURACY OF THE EMBEDDINGS DECREASES AS CROSS-CLASS COLLISIONS BECOME MORE LIKELY. THUS, ADVERSARIES NEED TO INCREASE PARAMETER $n$ TO MAINTAIN THE SAME LEVEL ACCURACY. HOWEVER, AS SEEN IN THE RIGHTMOST COLUMN $n$ HAS A SUBLINEAR RELATIONSHIP WITH THE NUMBER OF CLASSES.

| # Classes | Top-$n$ | Accuracy | $\frac{n}{\text{samples}}$ |
|-----------|--------|----------|-----------------------------|
| 500       | 3      | 89%      | 0.6%                        |
| 1000      | 4      | 89%      | 0.4%                        |
| 3000      | 10     | 90%      | 0.3%                        |
| 6000      | 20     | 92%      | 0.3%                        |
| 13000     | 30     | 89%      | 0.23%                       |

Fig. 8. We trained our embedding model on two-sequence traffic traces from Wikipedia (TLS 1.2) and used it to embed and classify traces collected from Github (TLS 1.3). The model performs considerably better when operating on traces from the same website and with the same protocol version it was trained on, however, it still retains some of its accuracy. This indicates that the distinguishable traffic characteristics are preserved even across very different setups.

As seen in Experiment 2, the adversary can use the adaptation process (Section IV-C) to swiftly swap the samples in the reference traces dataset with new ones so as to keep up with content updates or to include additional webpages in the set. This process does not require retraining as the embedding model can operate on any traffic trace even if it originates from a class not encountered during training. This simplifies the adaptation process to only a few low-complexity operations (i.e., collecting and embedding new samples) and enables the adversary to easily compensate for any distributional shift. Moreover, the deployment and the operation of the pipeline is inexpensive, as it requires only a small number of samples per class (~100) and only one training session for the embedding model. Nevertheless, the training of the model requires access to a computer with a capable Graphics Processing Unit card. However, this is an one-off cost (provisioning phase) that can be easily overcome with on-demand cloud computing resources.

In comparison, all past works on webpage fingerprinting assume a non-changing target set and would require some form of retraining to keep up with changes in the input distribution [11], [12], [1], [14]. While this cost may seem reasonable when considering small, fixed target sets (< 500 webpages), it quickly grows (due to the constant retraining required) when considering several hundreds or thousands of changing pages.

E. Operational & Adaptation Costs

The above experiments study several aspects of modern fingerprinting attacks and show that adaptive fingerprinting adversaries are scalable and accurate, even under non-ideal conditions. We now discuss the costs of operating such a fingerprinting deployment.

F. Defenses

We now look into the space of potential defences against adaptive fingerprinting adversaries and examine the applicability of solutions from the existing literature. While proposing a specific defence policy goes beyond the scope of this work, our findings allow us to rule out some approaches and draw attention on others that show potential in thwarting such attacks.

One important observation is that adaptive fingerprinting attacks can affect both the users of anonymity networks and the users of the TLS protocol (i.e., a very large portion of the Internet users). However, the scope of potential defenses for the TLS protocol is limited to only those countermeasures that have only a very light impact on the bandwidth used. Intuitively, a protocol-level countermeasure with a 10% bandwidth overhead, would result in an approximately equal increase in the web-traffic bandwidth worldwide. For this reason, the majority of the defenses proposed for Tor are not directly applicable to TLS.

...
In the rest of this section, we focus on defenses against webpage fingerprinting attacks. This is due to the widespread adoption of the protocol and the limited coverage that TLS fingerprinting countermeasures have received in the literature (cf. fingerprinting defences for Tor).

To overcome the strict bandwidth limitation, we move away from all-encompassing defenses. As specified in Section III-A, webpage fingerprinting aims to infer the specific page visited by a user from a set of pages all of which belong to the same website. This is a major difference to the website fingerprinting setup. In particular, each website can be treated as a separate entity and thus the defenses can be deployed and adjusted on a per-website basis. For example, a website with non-privacy-relevant pages (e.g., a list of hardware drivers) could decide to not deploy any countermeasure or optimize the deployment for low bandwidth impact (cf. for privacy). Alternatively, a website with sensitive content could use a more conservative configuration. In comparison, defenses for website fingerprinting attacks rely on a cross-website anonymity set and thus require the deployment of the specific countermeasure by several websites in order to be effective.

Furthermore, each website could configure the selected countermeasure so as to achieve an anonymity set size (i.e., number of webpages that are indistinguishable) that is appropriate for the sensitivity of its content. We expect that smaller websites (<500 webpages) could make all their pages indistinguishable at a relatively low bandwidth cost, while websites with more pages (e.g., Wikipedia) will have to split their content into anonymity sets and aim for indistinguishability within those sets.

For example, a straightforward approach could be to use padding so as to conceal the byte length of the webpages loaded. An advantage of this approach is that TLS already provides this capability and thus would not require any protocol changes [15], [60]. Moreover, given that padding is a well-studied technique, we could draw useful lessons from prior works (e.g., Pironti et al. [61] have shown that random-length padding is not sufficiently effective). Finding the optimal countermeasure, its policy and its configuration is an open problem that could be studied in future works.

Finally, while our experiments provide a good indication of the capabilities of passive adversaries, there are very few works on active fingerprinting attacks against Tor/websites [62], [63] and none (that we are aware of) against TLS/webpages. Such adversaries are potentially more capable as they have more actions at their disposal (e.g., trigger packet re-transmissions). It is thus necessary to also study the performance and characteristics of such adversaries so as to reliably inform the selection of defences.

VII. RELATED WORK

A. Fingerprinting attacks

The literature on fingerprinting attacks is very elaborate and covers several different manifestations of the problem. To begin with, several works attempt to identify the browser/app or infer characteristics of the setup (e.g., OS) used by the user [16], [24], [31], [64]. Such techniques are usually used to either identify malware initiating TLS connections or in general keep track of various traffic and application trends on the Internet. For example, one of the most recent works in the area is [65], uses an 8 billion unlabeled TLS sessions from several countries to identify popular enterprise TLS applications. This line of research is orthogonal to ours, as it does not aim to uncover the website/webpage loaded by the user. In fact, many of these works argue that their techniques do not pose a threat to the end-users’ privacy.

To the best of our knowledge, Cheng et al. [10] were the first to study the problem of webpage fingerprinting in 1998 on SSL 3.0. They introduce a fingerprinting methodology and run attack simulations on three small datasets, assuming static content. Mistry et al. [66] is another early work in the area which manages to fingerprint a small scale website (<100 pages) by observing the transfer sizes of SSL packets. Following up on these works, Sun et al. [67] proposed a Jaccard-coefficient-based similarity metric between observed and collected encrypted traffic traces. This technique achieved a low false positive rate, however, their results were based on traffic from different websites. Moreover, Danezis et al. [11] outlines a small-scale experiment on a static dataset (the exact size of the dataset is not reported), while Bissias et al. [12] and Cai et al. [1] propose improvements on the existing fingerprinting methodologies and verify their results on small (<100 webpages), static datasets too. Miller et al. [14] is one of the most recent works in the area. They use a dataset of webpages from various different websites and train and test their model on subsets of the whole set (up to 500 webpages each). They achieve a 90% accuracy on a top-15 adversary, while our model achieves superior performance (>90%) with a top-3 adversary. Moreover, they provide no experiments on larger websites or setups that would show how their technique could handle distributional shift. Finally, Dubin et al. [68] studies traces from video streaming services and proposes a technique that reaches 95% classification accuracy on a dataset of 100 Youtube videos.

Various insights used in webpage fingerprinting papers, where motivated by works on website fingerprinting attacks against the Tor anonymity network [69]. Such attacks focus on inferring the website that the user has visited but not the specific webpage loaded [2], [3], [6], [4], [5]. Previous works on Tor-based website fingerprinting has employed standard machine learning techniques for classification such as k-NN [2], Support Vector Machines [3], random forests [4], and more recently neural networks [6], [5]. Overall, the state of the art in website fingerprinting is considerably more advanced compared to that of webpage fingerprinting with some works being able to fingerprint up to 3,000 separate classes [5].

However, to our knowledge, [7] is the only work (both in website and webpage fingerprinting) that considers the problems of distributional shift and operational-cost and proposes a model that exhibits some adaptability. The main differences with our work are that they use the machine learning model for classification and they test their technique on sets of up to 100 classes. The former entails that some form of retraining is still needed every time a page/website changes considerably, while the latter does not provide a strong indication about the scalability of the technique to larger sets.
B. Machine Learning background

Traditional clustering algorithms such as k-means [70], Gaussian mixture models [71], and DBSCAN [72] operate on hand-crafted features designed to expose data structure and similarity. However, as the data dimensionality grows, uncovering the structure and designing reliable similarity metrics becomes a more difficult task. Transforming the data to a lower-dimension representation that preserves structure is therefore an appealing goal. Guo et al. [73] argue that the scope of shallow techniques for structure-preserving dimensionality reduction such as Principle Component Analysis (PCA) is limited. To counter this problem, a line of work [74], [75], [76] has focused on applying deep learning methods for dimensionality reduction upon which clustering can be applied. The most widely used deep learning approach in clustering algorithms are Stacked AutoEncoders (SAE) [76], [77], [78], [79], [74]. However, these often require layer-wise pre-training which can make the implementation costly as a large number of training samples is required. Broadly, deep learning based clustering algorithms fall into two categories: (1) learning a lower-dimensional representation of the data and then applying clustering, and (2) jointly accomplish feature learning and clustering by defining an objective in a self-learning manner. Our approach focuses on the former case. The most similar line of work within security research is that of anomaly and network-intrusion detection that use clustering based algorithms. For example, Alom and Taha [80] use a SAE to learn a lower-dimensional data embedding and then use k-means clustering for intrusion detection.

VIII. Conclusions

The widespread adoption of encrypted communications significantly reduced the scope of eavesdropping attacks against end-users and made adversaries seek alternatives. This gave rise to fingerprinting attacks that enable passive adversaries to infer information about the habits of a user, despite the fact that the encryption protocol’s cryptographic primitives remain sound. This work focuses on web-fingerprinting adversaries and studies the practicality of such attacks under realistic conditions and constraints. We introduce a novel adaptive fingerprinting model and, for the first time, show that such adversaries can be effective even under non-optimal conditions. Based on our findings, we argue that adaptive fingerprinting is practical and poses an immediate threat to the privacy of end-users unless appropriate defenses are deployed.

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