Leaked-Web: Accurate and Efficient Machine Learning-Based Website Fingerprinting Attack through Hardware Performance Counters

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Abstract—Users’ website browsing history contains sensitive information, like health conditions, political interests, financial situations, etc. In order to cope with the potential website behavior leakage and enhance the browsing security, some defense mechanisms such as SSH tunnels and anonymity networks (e.g., Tor) have been proposed. Nevertheless, some recent studies have demonstrated the possibility of inferring website fingerprints based on important usage information such as traffic, cache usage, memory usage, CPU activity, power consumption, and hardware performance counters information. However, existing website fingerprinting attacks demand high sampling rate which causes high performance overheads and large network traffic, and/or they require launching an additional malicious website by the user which is not guaranteed. As a result, such drawbacks make the existing attacks more noticeable to users and corresponding fingerprinting detection mechanisms. In response, we propose Leaked-Web, a novel accurate and efficient machine learning-based website fingerprinting attack through processor’s Hardware Performance Counters (HPCs). Leaked-Web efficiently collects hardware performance counters in users’ computer system at a significantly low granularity monitoring rate and sends the samples to the remote attack’s server for further classification. Leaked-Web examines the web browsers’ microarchitectural features using various advanced machine learning algorithms ranging from classical, boosting, deep learning, and time-series models. Our experimental results indicate that Leaked-Web based on a LogitBoost ML classifier using only the top 4 HPC features achieves 91% classification accuracy outperforming the state-of-the-art attacks by nearly 5%. Moreover, our proposed attack obtains a negligible performance overhead (only <1%) which is around 12% lower than the existing hardware-assisted website fingerprinting attacks.

Index Terms—Website Fingerprinting, Hardware Performance Counters, Machine Learning, Computer Security, Privacy Breach

I. INTRODUCTION

Over the last decades, the Internet has become an essential element of people’s social lives to obtain new knowledge, information, and conduct businesses and daily tasks. However, new concerns about users’ privacy have aroused from the transformation to the virtual world such that the users’ browsing history could disclose some sensitive information about their background and motives, such as financial status, sexual orientation, health conditions, or political views. Therefore, through stealing users’ online behaviors and access patterns, attackers could further induce personal and sensitive information of the users. This has introduced web browser fingerprinting attacks to violate the privacy of the users by extracting and stealing the browsing history of the Internet users. To achieve this, a number of recent works [26], [29] developed attacks that observe device-specific information and website access patterns such as packet sizes, packet timings, and direction of communication to infer the websites that the user is visiting with the aid of Machine Learning (ML) algorithms.

To protect the online privacy of users, a number of researches have also proposed to hide the network traffic of users [4], [23], [34]. Tor network [34] constructs an overlay network of collaborating servers, called relays. It encrypts the Internet traffic between users and web servers by transmitting the traffic between relays in a way that prevents external observers from identifying the traffic of specific users. The Tor Browser based on the Firefox web browser further protects users by disabling features that may be used for tracking users. Despite considerable progress on developing users’ privacy protections mechanisms, there are still a number of recent privacy violation attacks that rely on the application of Machine Learning (ML) algorithms that are trained with computer systems’ side-channel information collected when a website is open. These attacks stem from existing side-channel vulnerabilities like systems power analysis [20], CPU activity [4], on-chip cache memories [31], memory footprints [13], storage [17], and hardware events [9]. In this work, we comprehensively reviewed the existing studies on web browser fingerprinting attacks and identified some important challenges associated with these methods that could potentially result in underestimation of the security threats.

Challenge 1 High Sampling Rate and Performance Overheads: Existing web privacy violation attacks obtain the data access pattern of the users at 1000-250000 per second sampling rate and employ machine learning classification techniques to identify the website’s characteristics visited by the users with 80%-90% accuracy. Though relatively effective in terms of detection accuracy, such attacks require significant data sampling rate which results in large data network traffic and high performance overhead. Therefore, these attacks are
### Challenge 2: Limitation in Monitoring of Websites’ Information
Recent website fingerprinting attacks [13], [17] adopt side-channel information such as CPU activity, memory usage, and storage to learn the browsing history of the user. Accurate collection of such information demands high level of isolation in which only a single website should be open on the system. Nevertheless, in real-world scenarios a browser could open multiple websites at the same time which has been ignored in existing attack models.

### Challenge 3: The Need to Malicious Website Trigger
Majority of privacy violation attacks [17], [31], [35] adopt a malicious website to launch the data monitoring process (e.g., the command-line version of Wireshark in [29]). However, visiting the malicious website by the user could lower the threat of the attacks. Moreover, new research studies such as [12] has shown that such attacks could be mitigated by combining static and dynamic JavaScript analysis that could successfully detect JavaScript-based attacks.

### Challenge 4: Lack of Analysis on Monitoring and Number of Features
Our study indicates that prior website fingerprinting attacks have ignored to conduct a comprehensive analysis on the impact of different monitoring duration and number of features collected from website to infer accurate results. Nonetheless, such analysis is critical to thoroughly evaluate the effectiveness of the deployed attack threats and highlight the importance of adapting better protection mechanisms against such privacy violation attacks.

To address the above-discussed challenges, in this paper we thoroughly investigate the security threats brought by exploiting hardware-related features collected from processor’s Hardware Performance Counters (HPCs) and machine learning classification techniques. The HPCs are special-purpose registers implemented into modern microprocessors to capture the trace of hardware-related events [7]. To this aim, we propose Leaked-Web a novel accurate and efficient machine learning-based website fingerprint attack model that exploits the information from performance counters with significantly low number of samples and performance overheads. Unlike prior works, the proposed Leaked-Web attack offers the lowest sampling rate which incurs the least performance overhead to the system. Leaked-Web adopts advanced machine learning algorithms to further acquire website browsing history violating the privacy of the user. Since the HPC events in Leaked-Web could be collected from user space with no privileged access and no hardware overhead/modification, which makes the proposed fingerprinting more practical and efficient. To thoroughly analyze the effectiveness of Leaked-Web, we also investigate the impact of monitoring granularity and the number of required samples on systems’ performance overhead and attack success rate.

In Table 1, we have comprehensively analyzed the characteristics of the proposed HPC-based Leaked-Web attack as compared with state-of-the-art website fingerprinting attacks across various metrics such as target browser, attack model, performance overhead, the number of samples, deployed ML models, success rate, etc. It can be found that hardware-based, native code-based, and JavaScript-based are three main methods to exploit side-channel information and infer browsing history. However, JavaScript-based attacks [31], [35] can only be launched when the malicious website is visited, greatly undermining the capability of the attacks. Some other works [17] also adopt native code attack model, while the memory or storage information can only be measured per browser instead of per website. Another drawback of previous works is the high sampling rate which can cause high performance overhead. For example, our analysis shows that monitoring hardware performance counters with 10,000 sampling rate could incur around 12% performance overhead (will be discussed in detail in Section 3). Compared to previous work, this work achieves a high accuracy with lowest sampling rate and performance overhead. Furthermore, it does not require visiting malicious website to launch the attack, which offers higher flexibility and less restriction for Leaked-Web. In particular, the main contributions of our work are summarized below:

- We examine the impact of various HPC features for the hardware-based website fingerprinting attack and identify the most prominent low-level features that are crucial to be protected from user space.
- The influence of the number of application traces (sampling rate) and samples per traces are investigated to evaluate the effectiveness and stealing capability of the attack when fewer traces and samples are available.
II. BACKGROUND AND RELATED WORKS

A. Website Fingerprinting Attacks

Since website browsing history contains much sensitive information like medical status, political interest, etc., it is critical to prevent leakage, protect users’ privacy, and enhance the system’s security against potential cyber-attacks. However, prior research has demonstrated that fingerprinting attacks can be independent of operating systems and browsers and rely on side-channel information collected passively. Such attacks can be launched both remotely and locally, or via a peripheral device. The side-channel information exists across different computing abstracts, including hardware, system, and network. Once the side-channel information is collected, ML-based classification is leveraged to infer users’ visited website information. There are three popular threat models targeting stealing users’ browsing history, including native attack model [9], malicious website attack model [31], and hardware attack model [5].

1) Native Attack Model: In this attack model, the assumption is that the malicious code is resided in the host machine already, which can be done by inserting it into benign applications or downloading accidentally. With this model, attacks can be activated as long as the malicious codes are installed already and do not need users to open certain websites.

2) Malicious Website Attack Model: By comparison, this attack model assumes that users click on a malicious website link; thereby, malicious JavaScript codes are executed in local computers. Compared to the native model, this model is more flexible to update the attack and can be less visible since local malware scan cannot detect malicious codes. For both models, the malicious codes are only in charge of side-channel information monitoring without compromising systems.

3) Hardware Attack model: As shown in Figure 1c, this model collects hardware properties, mainly power consumption, when various websites are opened. Some of them infer the side-channel information based on hardware monitoring components such as USB and power meter. Though physical access is needed under this mode, [5] measures the power consumption and achieves 98% website classification accuracy, posing a significant security threat to computer systems and privacy.

B. Hardware Performance Counters (HPCs)

Hardware performance counters are a set of special-purpose registers built-in modern microprocessors to capture the count of hardware-related events. HPCs have been extensively used to predict the power, performance tuning [24], [36], [38], attacks detection [30], [33], [37], [39]–[46], debugging, and energy efficiency of computing systems. It also enhances systems’ security by providing microarchitectural information of malware, side-channel attacks, and building detectors based on the events’ information [7], [16], [50]. However, recent studies have shown the suitability of such HPCs-based classification for spying on users’ behaviors and violating users’ privacy [9], [25]. Such privacy breach attacks gain access to HPCs via Perf tool which is a Linux-based low-level performance monitoring tool and provides considerable functionality and abstraction in the kernel, making the interface straightforward for ordinary users [1], [6]. Though Perf is equipped with access control setting, i.e. perf_event_paradigm, attacks are still able to access HPCs of applications initiated outside kernel space unless perf_event_paradigm equals 4. Hence, the HPCs-based fingerprinting attacks still pose significant threats to system security and users’ privacy.

C. Machine Learning based Classification

1) Boosting: Boosting aims to enhance the performance of machine learning algorithms, where the incorrectly classified data from the previous model is employed to implement an ensemble of models. Compared to Adaboost using exponential loss function, the Logitboost [14] algorithm uses a binomial log-likelihood that changes the loss function linearily. This attribute makes the target model less sensitive to outliers and noise. To the best of our knowledge, no research to date has investigated the performance of the Logitboost algorithm in the field of website fingerprinting attacks. In this work, we applied LogitBoost, as a boosting learning technique on classical machine learning algorithm RandomForest (RandomF) where the boosted model is abbreviated as Logit-RandomF.

2) Deep Learning: Fully Convolutional Neural Network (FCN) A convolutional layer in a deep neural network learns patterns of local structure in the input signal and can learn feature representations over a sequence of input data [18]. FCN is based on the convolutional neural network (CNN) technique, where models employ continuous convolution layers to extract time-series features. Long Short-Term Memory (LSTM) For the LSTM [15], each temporal trace includes a time-ordered sequence of HPCs on which an LSTM network detects temporal patterns that are important for discriminating different websites. One and two layers of LSTM neurons with various numbers of neurons per layer were explored. Each node learns a different sequence pattern and the collection of sequence pattern detectors from all the nodes connected to the output layer are used to classify each HPC temporal sequence.

3) Time-series Classification: Time-series classification methods deal with such temporal datasets which is representing them in time-domain format and then calculate the distance as difference between time series [21]. In this work, three
prominent classification algorithms are chosen as representatives to compare with the proposed including the dynamic time warping (DTW) \[2\], Shaplet \[48\], Bag of Patterns (BOP) \[22\] are selected as representatives. DTW-KNN determines the best alignment that will produce the optimal distance and classifies data according to the calculated distance between time-series sub-sequences. BOP is a structure-based algorithm where a time-series sequence will be transformed into symbolic words while BOP records frequency of each symbol without order information. Shaplet \[48\] overcomes the time and space complexity and allows detection for phase-independent shape-based similarity of sub-sequences.

D. Related Work

Protecting browsing history has emerged recently as a crucial concept to ensure the preservation of users’ privacy. In response, \[28\], \[49\] are proposed to leverage SSH based protection methods; \[49\] encrypts and authenticates messages in one session, and \[28\] adds cover traffic conservatively while maintaining high levels of security. Similarly, Tor project \[34\] is one of the most popular traffic transmission approaches, where messages are not directly routed to the receiver but encrypted and forwarded according to ephemeral paths of an overlay network. Though great progress made by such works, there are still a number of attacks which could bypass such protection mechanisms and extract users’ browsing history.

Some recent website fingerprint attacks exploit the clients’ machine information when visiting different websites, like memory footprint \[13\], storage \[32\], etc. To obtain the information, some attacks prepare a malicious website for users to visit, or a local malware to be launched on the target host. For example, \[31\] launches a Prime+Probe attack to measure cache occupancy through a malicious website. Then, a deep learning method is leveraged to classify websites and recover users browsing history. Other works such as \[13\] samples the memory footprint of browsers through the perf tools file system in Linux. To defend against such attacks, \[12\] proposes ML-based syntactic-semantic approach that detects browser fingerprinting attacks’ behaviors by incorporating both static and dynamic JavaScript analysis. \[8\] proposes to monitor the running Web objects on user’s browser and collect fingerprinting related data. Then, it analyzes them and searches for patterns of fingerprinting attempts. Though effective, they only work for attacks deployed through malicious websites. Furthermore, advanced attacks \[27\] can be deployed in native code and bypass such detection systems. \[27\] randomizes properties, like offsetHeight and plugins, to the JavaScript environment, which generates different fingerprints even for the same website and increases non-determinism for attackers. However, the randomization is complex and can change the visual appearance of websites.

III. OVERVIEW OF LEAKED-WEB ATTACK MODEL

This section presents the details of the proposed Leaked-Web attack model. Leaked-Web is an accurate and efficient HPC-based attack which fingerprints websites with one local HPCs monitoring unit and a remote machine learning-based trace analyzer as shown in Figure 2. During the offline attack implementation phase, HPCs data are collected for each website and the importance (ranking) of HPC features are evaluated. Next, various machine learning algorithms are implemented to find the most effective model using a percentage split training-testing method where 70% of data (50 traces per website) is assigned to training set and 30% of data (20 traces per website) is dedicated to testing set. Then, the trained ML model is launched and deployed for online attacking process. For the attacking phase, there are three steps considered in Leaked-Web: 1) the browser-related process is scanned every second; 2) HPCs monitoring will be initiated once new browser process is found; and 3) the ML classification model is deployed to predict the website’s information based on the newly collected HPCs trace.

A. Threat Model

As shown in Figure 14 for our threat model we consider that the malicious codes reside in the host machine, initiate HPCs collection, and send them to a remote attacker. The malicious codes can be launched by inserting it into benign applications or downloading accidentally. With this model, the website fingerprinting attacks can be activated as long as the malicious codes are installed already and do not need users to open certain malicious websites. Furthermore, perf\_event\_paranoid is set less than 4, giving access to reading HPCs from registers. The attacker is able to obtain the potential websites users might open at Alex top site [2].

B. Experimental Setup

In this work, all experiments are conducted on an Intel i5-3470 desktop with 4 cores and 8GB DRAM, three-level cache system. In this on-chip cache memory subsystem, while L1 and L2 caches are exclusively separated, the L3 cache memory is inclusive and shared among all cores. In addition,
the operating system is Ubuntu 20.04 LST with Linux kernel 5.8.0. The proposed HPC-based attack is implemented on a widely used web browsers, Firefox.

C. Hardware Performance Events Monitoring

In this work, we use Perf [1] to measure the hardware-related features, and memory and processor’s low-level behavior. Perf is a profiling and performance analysis tool that can help to track the hardware performance counters. As introduced in Section II, any value less than 4 for /proc/sys/kernel/perf_event_paranoid gives users access to the HPC-based profiling of website process. Additionally, we examine the performance overhead and sample size caused by HPCs monitoring in Figure 3. As depicted, the x-axis represents applied the sampling rate ranging from 1^6 to 1^0, the primary y-axis denotes the execution time of victim applications, and the second y-axis represents performance overhead under different sampling rate. Moreover, execution time under no HPCs monitoring is used to obtain the performance overhead percentage. It is observed that generally, the smaller the sampling rate is, the larger the performance overhead is. For instance, when the monitoring scale is 1^0, the performance overhead is at its highest value reaching to 30%. Hence, to make the influence of sampling rate on system performance and the proposed attack less noticeable, we choose 1^0 for the HPCs monitoring in Leaked-Web.

D. Database Description

We select the top 30 websites from Alexa Top Sites [2]. Similar to previous works no traffic modeling is applied in our database implementation. For the purpose of thorough analysis, this work considers both Closed World and Open World datasets as described below:

1) Closed World Dataset: The closed world dataset means that each website is sensitive and exists in training dataset. The proposed attack model considers distinguishing a relatively small list of websites (30) and each websites has 50 traces for training a classification model and 20 traces for testing.

2) Open World Dataset: Besides the sensitive websites mentioned in the closed world dataset, open world dataset also contains a large set of non-sensitive web pages, all of which the attacker is expected to generally label as “non-sensitive” [31]. For the open world dataset, we add additional 500 traces in which each of them represents the behavior of a single unique website.

E. HPC Events Importance Evaluation

Figure 4 compares the accuracy of Logit-RandomF-based classifier for websites classification using different HPC events (due to space limitations only 5 events are reported). As can be seen in this figure, changing the HPC could result in over 10% accuracy loss when the same ML classifier is applied. Furthermore, given that there exists a limited number of HPC registers physically available on modern microprocessors’ chips that can be accessed simultaneously [11], it is necessary to identify the most important HPCs for classifying the websites. To select the most prominent HPC features we employ Correlation Attribute Evaluation

| Rank | HPC                        | Rank | HPC                        |
|------|---------------------------|------|---------------------------|
| 1    | cache-misses              | 9    | branch-instructions       |
| 2    | node-loads                | 10   | dTLB-load                  |
| 3    | branch-misses             | 11   | iTLB-load-misses          |
| 4    | branch-load-misses        | 12   | dTLB-load-misses          |
| 5    | LLC-store-misses          | 13   | dTLB-load-misses          |
| 6    | branch-loads              | 14   | dTLB-stores               |
| 7    | L1-dcache-stores         | 15   | node-stores               |
| 8    | L1-icache-load-misses    | 16   | L1-dcache-load-misses    |
Fig. 4: The average classification accuracy under Firefox for each HPC

(CorrelationAttributeEval in Weka [10]) with its default settings to calculate the Pearson correlation between attributes (HPC features) and classes (websites). Correlation attribute evaluation algorithm calculates the Pearson correlation coefficient between each attribute and class, as given below:

\[ \rho(i) = \frac{\text{cov}(Z_i, C)}{\sqrt{\text{var}(Z_i) \text{var}(C)}} \]  

where \( \rho \) is the Pearson correlation coefficient, \( Z_i \) is the input dataset of event \( i \) (\( i = 1, \ldots, 16 \)), \( C \) is the output dataset containing labels, i.e., websites, like "google.com", "youtube.com" and etc. in our case. The \( \text{cov}(Z_i, C) \) measures the covariance between input data and output data. The \( \text{var}(Z_i) \) and \( \text{var}(C) \) measure variance of both input and output datasets, respectively. Next, the HPCs will be ranked according as shown in Table II and this work chooses the top 4 HPCs for classification.

F. Machine Learning Classifiers

In the proposed Leaked-Web attack, supervised learning is used to model the website fingerprinting attack. The ML implementation stage consists of a building step (training) and attack step (testing). In the building step, multiple traces (50) from each website are collected and labeled. The labeled dataset is used to train various types of ML classifier including classical machine learning, classical machine learning with boosting, time-series, or deep learning models. The rationale for choosing these machine learning models is that they are from different branches of ML including classical model (RandomForest, LogitBoost RandomForest), deep learning models (FCN, LSTM), time-series models (DTW, BOP, Shapelet) techniques covering a diverse range of learning algorithms that support our comprehensive analysis and experiments. For the attacking phase, the proposed attack model receives unlabeled traces in which each of the trace is corresponding to a user’s website visit and the trained classifier outputs the prediction results. Each website has 20 traces for testing and the accuracy is calculated by comparing correctly classified labels and actual samples.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we comprehensively evaluate the effectiveness of the proposed Leaked-Web attack model in terms of classification accuracy and F-measure (F-score) analysis with different ML models, number of HPCs features, monitoring duration. Such analysis gives insight into the cost of HPCs-based fingerprinting attacks and further indicate the requirements of protection approaches.

A. ML Classification Models Comparison

As introduced in Section III-D, 30 websites selected from the Alexa ranking are executed on our target system and each website has 50 traces for training and 20 traces for testing. Various ML classification models from classic, boosting, time-series and deep learning methods are investigated. As shown in Figure 5 and Figure 6, X-axis represents the number of traces for training in selected classification models from four ML types (classic, boosting, time-series, and deep learning methods) and Y-axis represents the classification accuracy and F-measure respectively for closed world. F-measure is interpreted as a weighted average of the precision (p) and recall (r) which is formulated as \( \frac{2 \times (p \times r)}{p + r} \). The precision is the proportion of the sum of true positives versus the sum of positive instances and the recall is the proportion of instances that are predicted positive of all the instances that are positive. F-measure is a comprehensive evaluation metric since it takes both the precision and the recall into consideration. More importantly, F-measure is also resilient to class imbalance in the dataset which is the case in our experiments.
As observed from the results, generally, reducing number of traces in training phase reduces both classification accuracy and F-measure values. This observation becomes more noticeable as we reduce the traces to lower than 20 where the accuracy becomes below 80% for all the applied ML classification models. Another interesting observation is that Logit-RandomF classifier outperforms the previous work Perf-Web [9] for most of the training sizes (except when the number of traces for training drops to 5). When training traces is 50, Logit-RandomF classifier achieves the highest classification accuracy and F-measure, 91% and 0.901 respectively. As seen, the accuracy is improved in Leaked-Web by around 5% from 86% of previous work [9]. Another observation is that Shaplet-based classification model has shown to be more effective than the rest of two time-series classification models.

V. CONCLUSION

Website fingerprinting attacks have emerged recently through stealing users’ online behaviors and access patterns, to induce users’ personal and sensitive information. In hardware-assisted website fingerprinting attacks, when users open a website in a web browser, they leave a distinct pattern on the underlying hardware that is reflected in the microarchitectural state of the processor running the browser. While Hardware Performance Counters (HPCs) are widely used for performance tuning, application profiling, malware detection, etc., this work presents Leaked-Web, a fast and unified HPC-based attack model that collects microarchitectural HPC samples by using Perf tool under Linux and trains accurate and efficient machine learning classifiers with the HPCs’ traces. Compared to prior works, Leaked-Web demands significantly lower network traffic per website visit and achieves up to 91% classification accuracy outperforming the state-of-the-art attack by nearly 5%. We also explored that the accuracy under different number of HPCs features is around 90% even with 2 HPC features, indicating that the proposed HPCs-based attack is effective to be adopted in other modern processor architectures (e.g., ARM) with less available resources (only 2 HPC registers).
overhead (less than 1%) which is more than 12% lower than the existing HPC-based attacks.

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