Mind the Portability: A Warriors Guide through Realistic Profiled Side-channel Analysis

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***Abstract*—Profiled side-channel attacks represent a practical threat to digital devices, thereby having the potential to disrupt the foundation of e-commerce, Internet-of-Things (IoT), and smart cities. In the profiled side-channel attack, adversary gains knowledge about the target device by getting access to a cloned device. Though these two devices are different in real-world scenarios, yet, unfortunately, a large part of research works simplifies the setting by using only a single device for both profiling and attacking. There, the portability issue is conveniently ignored in order to ease the experimental procedure. In parallel to the above developments, machine learning techniques are used in recent literature demonstrating excellent performance in profiled side-channel attacks. Again, unfortunately, the portability is neglected.**

In this paper, we consider realistic side-channel scenarios and commonly used machine learning techniques to evaluate the influence of portability on the efficacy of an attack. Our experimental results show that portability plays an important role and should not be disregarded as it contributes to a significant overestimate of the attack efficiency, which can easily be an order of magnitude size. After establishing the importance of portability, we propose a new model called the Multiple Device Model (MDM) that formally incorporates the device to device variation during a profiled side-channel attack. We show through experimental studies, how machine learning and MDM significantly enhances the capacity for practical side-channel attacks. More precisely, we demonstrate how MDM is able to improve the results by $> 10\times$, completely negating the influence of portability.

***Index Terms*—Side-channel attacks, Machine learning, Portability, Overfitting, Multiple Device Model**

I. Introduction

Modern digital systems, ranging from high-performance servers to ultra-lightweight microcontrollers, are universally equipped with cryptographic primitives, which act as the foundation of security, trust, and privacy protocols. Though these primitives are proven to be mathematically secure, poor implementation choices can make them vulnerable to even an unsophisticated attacker. A range of such vulnerabilities are commonly known as side-channel leakage [1], which exploits various sources of information leakage in the device. Such leakages could be in the form of timing [2], power [3], electromagnetic emanation [4], speculative executions [5], remote on-chip monitoring [6] etc. To exploit these physical leakages, different side-channel attacks (SCAs) have been proposed over the last two decades. In this work, we focus on power side-channel attacks targeting secret key recovery from cryptographic algorithms.

In side-channel attacks, profiling based attacks are considered as one of the strongest possible attacks [7]. The strength of profiling based attacks arises from their capability to fully characterize the device. There, the attacker has full control over a clone device, which can be used to build its complete profile. This profile is then used by the attacker to target other similar devices to recover the secret information. An illustration of profiled SCA is shown in Figure 1. The most common profiled SCA is template attack [7], which profiles model with mean and standard deviation.

In an ideal setting, the device for profiling and testing must be different. However, most of the works in existing literature, do not consider multiple devices but profile and test the same device [8] (see Figure 1 and the difference between reality and expected cases). Consequently, despite the common perception about the practicality of SCA, a large body of results come from unrealistic experimental settings. Indeed, the presence of process variation or different acquisition methods [9], [10] may cause a successful "single-device-model" attack to completely fail. In [11], authors perform a template attack on AES encryption in a wireless keyboard. They report 28% success on a different keyboard as compared to 100% when profiled and tested on the same keyboard. While solutions to make templates work on different devices were proposed [12], [11], the method stays empirical and requires case specific processing. This issue is popularly known as portability, where we consider all effects due to different devices and keys between profiling device and device under attack.

Definition 1: Portability denotes all settings where an attacker has no access to traces from the device under attack to conduct a training but only to traces from a similar or clone device, with uncontrolled variations.

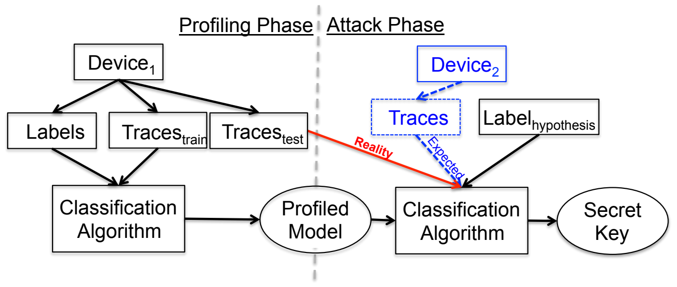


Fig. 1: Illustration of profiling side-channel attacks highlighting the actual case and the usual practice in the literature. While template attacks were used as a classification algorithm in the past, adoption of machine learning has been the recent trend. Note how the measurements to attack are commonly obtained from the same device as the measurements to build the model while disregarding the requirement to use a different device to attack.

A. *Machine Learning-based SCA*

Recently, machine learning techniques have soared in popularity in the side-channel community [13], [14]. There, the supervised learning paradigm can be considered similar to profiling based methods used in side-channel attacks. Considering Figure 1, a machine learning algorithm replaces template attacks as a classification algorithm.

It has been shown that machine learning techniques could perform better than classical profiling side-channel attacks [14]. In those classical approaches, side-channel leakages (traces) need to be manually pre-processed and analyzed before starting the profiling phase. This is because the targeted traces are often measured from different settings, setups, etc., and hence, additional pre-processing and analysis has to be done before running the attack. The researchers first started with simpler machine learning techniques like Random Forest and support vector machines and targets without countermeasures [15], [16], [17], [18], [19]. Already these results suggested machine learning to be very powerful, especially in settings where the training phase was limited, i.e., the attacker had a relatively small number of measurements to profile. More recently, researchers also started using deep learning, most notably multilayer perceptron and convolutional neural networks. Such obtained results surpassed simpler machine learning techniques but also showed remarkable performance on targets protected with countermeasures [13], [14], [20], [21], [22], [23]. As an example, Kim et al. used deep learning (convolutional neural networks) to break a target protected with the random delay countermeasure with only 3 traces in the attack phase [24].

B. *Related Work on Portability*

Exploring portability in the context of profiling side-channel attacks received only limited attention up to now. Elaabid and Guilley highlighted certain issues with template attacks, such as when the setups changed, for example, due to desynchronization or amplitude change [25]. They proposed two pre-processing methods to handle the templates mismatches: waveform realignment and acquisition campaigns normalization. Choudary and Kuhn analyzed profiled attacks on 4 different Atmel XMEGA 256 A3U 8-bit devices [12]. They showed that even on similar devices, the differences could be observed which makes the attack harder and carefully tailored Template Attacks (TA) could help to mitigate the portability issue. Device variability was also a consideration in hardware Trojan detection [9]. There, the authors show that the results are highly biased by the process variation. The experiments were conducted on a set of 10 Virtex-5 FPGAs. Kim et al. demonstrated the portability in the case of wireless keyboard, by building the template based on the recovered AES key to attack another keyboard [11]. They highlighted that some correction has to be performed before directly using the built template. In 2018, the CHES conference announced side-channel CTF event for "Deep learning vs. classic profiling', which also considers the case of portability. One of the contest categories was protected AES implementation. The winning attack was a combination of linear classifier (decision tree and perceptron) in a combination with SAT solver. The attack needed 5 traces and 44 hours of SAT solver time to achieve 100% success for different devices, but only one trace was enough for attacking the same device [26]. In a nutshell, all previous work applied a target specific pre-processing or post-processing to fight portability.

From this vantage point, it would appear that machine learning-enabled SCA can provide a generic solution to tackle the portability issue in profiled side-channel attacks. However, this aspect of machine learning-based SCA is not properly explored. In this paper, we conduct a detailed analysis of portability issues arising in profiled side-channel attacks. We start by first establishing a baseline case, which represents the scenario mostly used in related works where both profiling and attacking is done on the same device and using the same secret key. Later, we explore different settings which would turn up in a realistic profiled SCA, considering scenarios of separate keys and devices. We are able to show that this case can be orders of magnitude more difficult than the scenario where one device is used and thus undermining the security of the target due to poor assumptions. *As shown later with experimental data, the best attack in the hardest setting with different devices and keys needs* $> 20\times$ *more samples for a successful attack, when compared to a similar attack in the easiest setting of the same device and key, clearly highlighting the issue of portability.* We identify that one of the problems lies in the validation procedure and overfitting phenomenon. To remedy that, we propose a new model that we call the Multiple Device Model. We are able to experimentally show that this model can help assess and improve the realistic attack efficiency in practical settings. The proposed MDM applies to both profiled SCA with and without the usage of machine learning.

C. Contributions

The main contributions of this work are:

1) We conduct a detailed analysis of portability issues considering 4 different scenarios and state-of-the-art machine learning techniques. We show that the realistic setting with different devices and keys in profiling and attacking phases is significantly more difficult than the commonly explored setting where a single device and key is used for both profiling and attack. To the best of our knowledge, such analysis has not been done before.
2) We are able to show that a large part of the difficulty when considering portability scenario comes from the fact that machine learning algorithms overfit due to a sub-optimal validation phase.
3) We propose a new model for profiled SCAs called the Multiple Device Model (MDM). We show this model to be able to cope with validation problems better and consequently, achieve significantly better attack performance.

Firstly, we use the Normalized Inter-Class Variance (NICV [27]) metric to characterize the difference in measurements between different devices/keys. There, we see that while those differences can be very small, the resulting effect on the attack performance can be substantial. Furthermore, our results show that longer tuning phases for machine learning or even having more measurements in the training phase does not guarantee better performance due to overfitting. At the same time, having more features seems to be beneficial as it results in more complex models that require longer executions and more measurements to trigger overfitting.

The rest of this paper is organized as follows. In Section II, we briefly discuss the profiled side-channel analysis. Afterward, we introduce machine learning techniques we use in this paper and provide a short discussion on validation and cross-validation techniques. Section III discusses the threat model, hyper-parameter tuning, experimental setup, and 4 scenarios we investigate. In Section IV, we give results for our experiments and provide some general observations. In Section V, we discuss the validation phase and over fitting. Afterward, we introduce the new model for profiling side-channel attacks. Finally, in Section VI, we conclude the paper and provide several possible future research directions.

II. Background

In this section, we start by providing information about profiled side-channel analysis. Then, we discuss 4 machine learning algorithms we use in our experiments and differences between validation and cross-validation procedures.

A. Profiled Side-channel Analysis

Side-channel attacks use implementation related leakages to mount an attack [3]. In the context of cryptography, attacks target physical leakage from the insecure implementation of otherwise theoretically secure cryptographic algorithms. These physical leakages can come from a variety of sources like power consumption, timing, cache misses, branch prediction, etc. In this work, we focus on the most basic but still strong leakage source, i.e., power consumption.

Profiled side-channel attacks are the strongest type of side-channel attacks as they assume an adversary with access to a clone device. In the present context, the adversary can control all the inputs to the clone device and observe corresponding power consumption. This means that the adversary would observe various power traces corresponding to random plaintext and a key to allow detailed characterization. The adversary collects only a few power traces from the attack device where the secret key is not known. By comparing the attack traces with the characterized model, the secret key is revealed. Due to the divide and conquer approach, where small parts of the secret key can be recovered independently, the attack becomes more practical. Ideally, only one trace from the target device should be enough if the characterization is perfect. However, in real scenarios, the traces are affected by noise (environmental or intentionally introduced by countermeasures). Thus, several traces might be needed to determine the secret key.

Template attack [7] was the first profiled side-channel attack. It uses mean and standard deviation of the power measurements for building characterized models (or templates). The attack traces are then compared using the maximum likelihood principle. Later, machine (or deep) learning (ML or DL) approaches were proposed as a natural alternative to templates. In fact, advanced machine learning algorithms like convolution neural networks (CNN) were also shown to naturally break few side-channel countermeasures like random jitter [14]. Template attack is known to be optimal from an information theoretic perspective if ample profiling traces are available. However, in realistic scenarios where only limited measurements with noise are available, ML or DL approaches outperform templates [20]. In this paper, we focus only on machine learning algorithms as 1) they proved to be more powerful than template attack in many realistic settings, and 2) there are no results for portability with machine learning.

Guessing Entropy: To assess the performance of the attacks, a common option is to use Guessing entropy (GE) [28]. The guessing entropy metric is the average number of successive guesses required with an optimal strategy to determine the true value of a secret key. Here, the optimal strategy is to rank all possible key values from the least likely one to the most likely one. More formally, given T_a traces in the attacking phase, an attack outputs a key guessing vector $\mathbf{g} = [g_1, g_2, \dots, g_{|\mathcal{K}|}]$ in decreasing order of probability where $|\mathcal{K}|$ denotes the size of the keyspace. Then, guessing entropy is the average position of k_a^* in $\mathbf{g}$ over a number of experiments (we use 100 experiments).

B. Machine Learning

This subsection recalls some of the commonly used ML algorithms in the context of side-channel analysis and supervised learning.

1) Supervised Learning: When discussing profiling side-channel attacks and machine learning, we are usually interested in the classification task as given with the supervised machine learning paradigm. There, a computer program is asked to specify which of c categories (classes) a certain input belongs to.

More formally, let calligraphic letters ($\mathcal{X}$) denote distributions over some sets, capital letters (X) denote sets drawn from distributions, i.e., $X \in \mathcal{X}$, and the corresponding lowercase letters (x) denote their realizations. We denote the set of N examples as $X = x_1, \ldots, x_N$, where $x_i \in \mathcal{X}$. For each example x, there is a corresponding labels y, where $y \in \mathcal{Y}$. Typically, we assume that examples are drawn independently and identically distributed from a common distribution on $\mathcal{X} \times \mathcal{Y}$. We denote the measured example as $x \in X$ and consider a vector of D data points (features) for each example such that $x = x_1, \ldots, x_D$.

The goal for supervised learning is to learn a mapping $f : \mathbb{R}^n \rightarrow \{1, \ldots, c\}$. When $y = f(x)$, the model assigns an input described by x to a category identied by y. The function f is an element of the space of all possible functions $\mathcal{F}$.

Supervised learning works in two phases, commonly known as the training and testing phases. In the training phase, there are N available pairs (x_i, y_i) with $i = 1, \ldots, N$ which are used to build the function f. Then, the testing phase uses additional M examples from X, i.e., $x_1, \ldots, \vec{x}_M$ and function f to estimate the corresponding classes $Y = y_1, \ldots, y_M$. In order to build a strong model f, we need to avoid overfitting and underfitting. Overfitting happens when our model learned the training data too well and it cannot generalize to previously unseen data. Underfitting happens when our model cannot model the training data or generalize to new data.

C. Validation vs. Cross-validation

When using the validation approach, the data is divided into 3 parts: training, validation, and test data. One trains a number of models with different hyper-parameters on the training set and then test the model with on the validation set. The hyper-parameters giving the best performance on the validation set are selected. Then, the model with such selected hyper-parameters is used to predict on test data.

In cross-validation, the data is divided into 2 parts: a training set and testing set. The training data is then randomly partitioned into complementary subsets. Then, machine learning models with different hyper-parameters are trained against different combinations of those subsets and validated on the remaining subsets. The hyper-parameters giving the best results are then used with the whole train data in order to obtain the model which is then used on test data. The most common cross-validation setting is the k-fold cross-validation. There, the training set is randomly divided into k subsets and different $(k-1)$ subsets are used for training models with different hyper-parameters and the remaining one is used for validation.

Both validation and cross-validation are aimed at preventing overfitting. The main advantage of cross-validation is that one does not need to divide the data into 3 parts. On the other hand, validation is computationally simpler and usually used with deep learning as there, training can last a long time. We discuss in the next sections the advantages and drawbacks with these two techniques when considering portability issues.

D. Classification Algorithms

First, we discuss classical machine learning techniques where we must conduct a pre-processing phase to select the most important features. Afterward, we use deep learning techniques with all the features.

1) Naive Bayes: The Naive Bayes (NB) classifier is a method based on the Bayesian rule that works under a simplifying assumption that the predictor features (measurements) are mutually independent among the D features, given the class value Y. Existence of highly-correlated features in a dataset can influence the learning process and reduce the number of successful predictions. Additionally, Naive Bayes assumes s normal distribution for predictor features. The Naive Bayes classifier outputs posterior probabilities as a result of the classification procedure [29].

2) Random Forest: Random Forest (RF) is a well-known ensemble decision tree learner [30]. Decision trees choose their splitting attributes from a random subset of k attributes at each internal node. The best split is taken among these randomly chosen attributes and the trees are built without pruning. RF is a stochastic algorithm because of its two sources of randomness: bootstrap sampling and attribute selection at node splitting.

3) Multilayer Perceptron: The multilayer perceptron (MLP) is a feed-forward neural network that maps sets of inputs onto sets of appropriate outputs. MLP consists of multiple layers (at least three) of nodes in a directed graph, where each layer is fully connected to the next one and training of the network is done with the backpropagation algorithm.

4) Convolutional Neural Network: Convolutional neural networks (CNNs) are a type of neural networks first designed for 2-dimensional convolutions as inspired by the biological processes of animals' visual cortex [31]. They are primarily used for image classification but in recent years, they have proven to be a powerful tool in security applications [32], [33]. From the operational perspective, CNNs are similar to ordinary neural networks (e.g., multilayer perceptron): they consist of a number of layers where each layer is made up of neurons. CNNs use three main types of layers: convolutional layers, pooling layers, and fully-connected layers. A convolutional neural network is a sequence of layers, and every layer of a network transforms one volume of activation functions to another through a differentiable function. When considering the CNN architecture, input holds the raw features. Convolution layer computes the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. Pooling performs a down-sampling operation along the spatial dimensions. The fully-connected layer computes either the hidden activations or the class scores. Batch normalization is used to normalize the input layer by adjusting and scaling the activations after applying standard scaling using running mean and standard deviation.

III. Experimental Setup

In this section, we start by discussing 4 scenarios we investigate in our experiments. Next, we provide details about hyper-parameter tuning. Finally, we give details about our measurement setup.

A. Threat Model

The threat model is a typical profiled side-channel setting. The adversary has access to a clone device running target cryptographic algorithm (AES-128 in this case). The clone device can be queried with a known key and then the plaintext and corresponding power consumption measurement trace is stored. Ideally, the adversary can have infinite queries and corresponding database of side-channel power measurements to characterize a precise model. Next, the adversary queries the attack device with known plaintext in order to obtain the unknown key. The corresponding side-channel power measurement is compared to the characterized model to recover the key. We consider this to be a standard model as a number of certification laboratories are evaluating hundreds of security critical products under it on a daily basis.

B. Setup

While profiled side-channel analysis is known since 2002 [7], very few studies are done in realistic settings. By realistic we mean that the adversary profiles a clone device and finally mounts the attack on a separate target device. Most studies, if not all, profile and attack the same device. Further, some studies draw profiling and testing sets from the same measurement pool, which generally is least affected by environmental variations. Such biases in the adversary model can lead to highly inaccurate conclusions on the power of the attack.

To perform a realistic study about profiled side-channel analysis, which is actually performed on separate devices, we needed multiple copies of the same device. The target device is an 8-bit AVR microcontroller mounted on a custom designed PCB. The PCB is adapted for side-channel measurement. Precisely, a low-noise resistor (39 Ω) is inserted between the V_{CC} (voltage input) of the microcontroller and the actual V_{CC} from the power supply. Measuring the voltage drop across the resistor allows side-channel measurement in terms of power consumption. The PCB is designed to have special measurement points for accessing this voltage drop easily.

The choice of microcontroller, i.e., AVR Atmega328p 8-bit microcontroller is motivated by the underlying technology node. Since the chip is manufactured in $350nm$ technology, the impact of process variation is low. Therefore the obtained results will reflect the best case scenario. Also, side-channel countermeasures are considered out of scope to reflect the best case scenario. A choice of a newer manufacturing node or countermeasures would make it difficult to carefully quantify the impact of portability alone, independent of process variation or impact of protections. Moreover, this device is often used for benchmarking side-channel attacks allowing fair comparison in different research works.

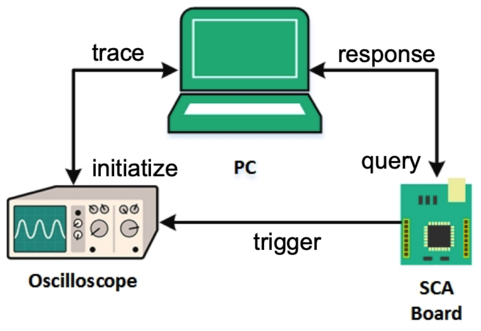


Fig. 2: Illustration of the measurement setup.

The overall measurement setup is depicted in Figure 2. The microcontroller is clocked at $16MHz$ and runs AES-128 algorithm in software. The board is connected to a two-channel Tektronix TDS2012 oscilloscope with a sampling rate of $2GS/s$ (Giga-samples per second). The power traces are captured corresponding to AES-128 execution, synchronized with a board generated trigger. A computer is used to pilot the whole setup. It generates random 128-bit plaintext and, via UART, transmits it to the board and awaits acknowledgment of the ciphertext. Upon receiving ciphertext, the software then retrieves the waveform samples from an oscilloscope and saves it to hard-drive indexed with corresponding plaintext and ciphertext. To minimize the storage overhead, the trace comprised of 600 sample points captures only the execution of the first SubBytes call, i.e., the target of the following attacks (the output of the first AES S-box in the SubBytes layer). AES S-box is an 8-bit input to an 8-bit output, which computes multiplicative inverse followed by an affine transformation on polynomials over GF(2). For performance reasons, it is implemented as a precomputed look-up table. The table is indexed with $p[0] \oplus k[0]$, where $(p[0], k[0])$ are the first bytes of plaintext and key, respectively. The output of the S-box is stored in the internal registers or memory of the microcontroller and is the main side-channel leakage that we target. The labeling of data is done on the output byte of the S-box. Due to the nonlinearity of the S-box, it is much easier to statistically distinguish correct key from wrong keys at the output of the S-box, which is why we choose to attack here.

Figure 3 shows an example measurement trace for the full amount of 600 features on the top. Below is the correlation between the measurement set and the activity corresponding to S-box look-up with the first byte of plaintext. We highlight the 50 features with the highest absolute Pearson correlation in red. One can see that these 50 features cover nearly all leaking points.

Finally, in order to investigate the influence of the number of training examples, we consider settings with 10 000 and 40 000 measurements in the training phase. In total, we conducted more than 150 experiments in order to provide a detailed analysis of the subject.

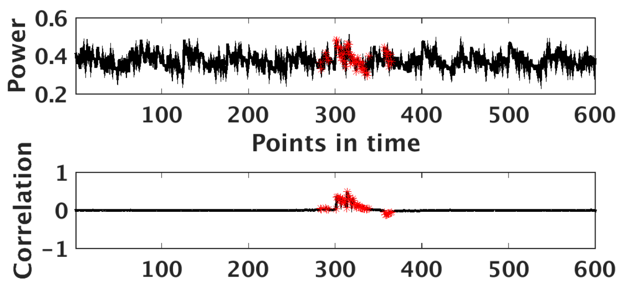


Fig. 3: Measurement trace and corresponding correlation (selected 50 features in red).

C. Parallel Measurement

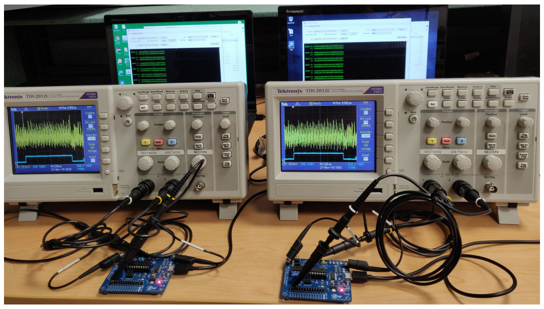
We use 4 copies of the target device to conduct our study. Four experiments were set up in parallel (two parallel setups shown in Figure 4a). Parallel setups allowed us to collect the experimental data faster as well as to minimize the effect of change in environmental conditions. To be able to test different scenarios, we measured 50 000 side-channel corresponding for 50 000 random plaintext on different boards (B1, B2, B3, B4) with three randomly chosen secret keys. In the following, each dataset is denoted in the format Bx_Ky, where x denoted board ID and y denotes the key ID. For example, $B1\_K1$, denotes the dataset corresponding to $K1$ measured on board $B1$. The four boards and keys used for collecting various datasets are shown in Figure 4b. In this case, $B4\_K1$ is repeated. This is to provide a benchmark comparison in the scenario where both the device and the keys are the same, although not measured at the same time.

Although the measurement setups are identical, executing exactly the same code and measuring exactly the same operations, there will be still some difference due to process and environmental factors. To highlight the difference of the leakages from different devices, we calculate Normalized Inter-Class Variance (NICV [27]). NICV can be used to detect relevant leakage points in side-channel traces as well as compare the quality of side-channel measurements. It is computed as:

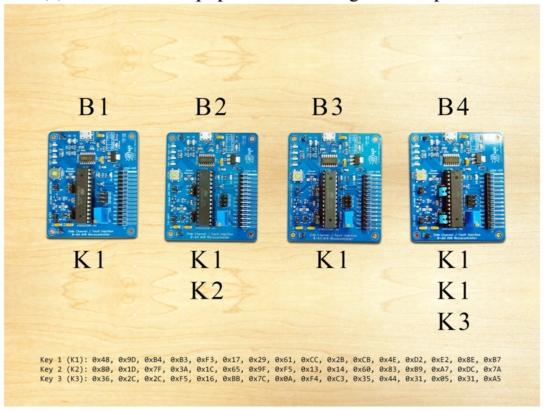
$$NICV = \frac{\mathbb{V}\{\mathbb{E}\{T|X\}\}}{\mathbb{V}\{T\}} \quad , \tag{1}$$

where T denotes a side-channel trace and X is the public parameter (plaintext/ciphertext), used to partition the traces. $\mathbb{E}\{\cdot\}$ and $\mathbb{V}\{\cdot\}$ are statistical expectation and variance. NICV is bounded in the range $[0, 1]$.

From Figure 5a, it is clear that even for similar implementations, the leakage differs and each setting has its own leakage characteristics. The impact of these difference will be evaluated in the following sections using ML-based profiled side-channel attacks. As a comparison, for the same device and key scenario ($B4\_K1$), as given in Figure 5b, the NICV pattern is almost completely the same.



(a) Two sets of equipment recording data in parallel.



Key 1 (K1): 0x48, 0x9D, 0xB4, 0xB3, 0xF3, 0x17, 0x29, 0x61, 0xCC, 0x2B, 0xCB, 0x4E, 0xD2, 0xE2, 0x8E, 0xB7
Key 2 (K2): 0x80, 0x1D, 0x7F, 0x3A, 0x1C, 0x65, 0x9F, 0xF5, 0x13, 0x14, 0x60, 0x83, 0xB9, 0xA7, 0xDC, 0x7A
Key 3 (K3): 0x36, 0x2C, 0x2C, 0xF5, 0x16, 0xBB, 0x7C, 0x0A, 0xF4, 0xC3, 0x35, 0x44, 0x31, 0x05, 0x31, 0xA5

(b) SCA Boards labelled with different keys.

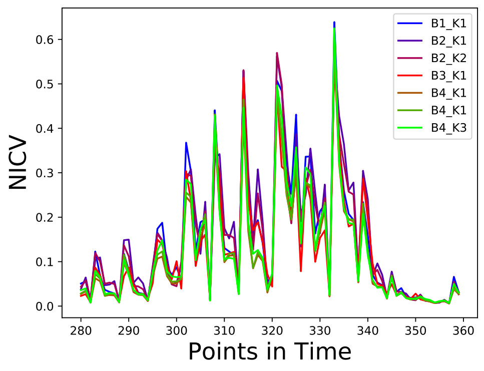
Fig. 4: Parallel Equipment Setup

D. Scenarios under Consideration

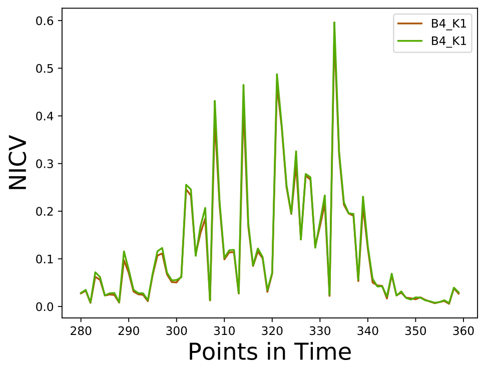
In our experiments, we consider several scenarios with respect to the targets:

- **Same device and same key**. In this setting, we use the same device and only a single key to conduct both profiling/validation and attack. Despite the fact that this scenario is far from the realistic setting, it is usually explored in the SCA community. Consequently, most of the works consider this scenario and report results for it. We emphasize that this is also the simplest scenario for the attacker.
- **Same device and different key**. In this scenario, we assume there is only one device to conduct both profiling and attack, but the key is different in those 2 phases. This scenario can sound unrealistic since there is only one device, we still consider it as an interesting stepping stone toward more realistic (but also more difficult) scenarios.
- **Different device and same key**. Here, we assume there are two devices (one for profiling and the second one for the attack) that use the same key. While this scenario can again sound unrealistic, we note that it emulates the setting where one key would be hardcoded on a number of devices.
- **Different device and different key**. This represents the realistic setting since it assumes one device to train and a second device to attack. Additionally, the keys are different on those devices.

To the best of our knowledge, such a variety of considered



(a) All devices



(b) $B4\_K1$

Fig. 5: NICV comparison

scenarios have never been tested before.

E. Hyper-parameter Tuning

In our experiments, we consider 4 machine learning techniques: Naive Bayes, Random Forest, multilayer perceptron, and convolutional neural networks. We also distinguish between two settings for these techniques:

- In the first setting, we select 50 most important features to run the experiments. To select those features, we use the Pearson correlation. The Pearson correlation coefficient measures linear dependence between two variables, x and y, in the range $[-1, 1]$, where 1 is the total positive linear correlation, 0 is no linear correlation, and -1 is the total negative linear correlation. Pearson correlation for a sample of the entire population is defined by [34]:

$$Pearson(x, y) = \frac{\sum_{i=1}^{N}((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}}. \quad (2)$$

  In this setting, we use Naive Bayes, Random Forest, and multilayer perceptron.
- In the second setting, we consider the full amount of features (i.e., all 600 features) and we conduct experiments with multilayer perceptron and convolutional neural networks. Note that MLP is used in both scenarios since it can work with a large number of features but also does not need the features in the raw form (like CNN).

For the experiments with 50 features, we use scikit-learn [35] while for the experiments with all features, we use Keras [36]. For Naive Bayes, Random Forest, and multilayer perceptron when using 50 features, we use k-fold cross-validation with $k = 5$. For experiments when using all features, we use 3 datasets: train, validate, and test. Training set sizes are 10 000 and 40 000, validation set size equals 3 000, and test set size is 10 000. Since there is in total 50 000 measurements with 10 000 measurements used for testing, when using the validation set, then the largest training set size is not 40 000 but 37 000.

a) Naive Bayes: Naive Bayes has no parameters to tune.

b) Random Forest: For Random Forest, we experimented with the number of trees in the range $[10, 100, 200, 300, 400]$. On the basis of the results, we use 400 trees with no limit to the tree depth.

c) Multilayer Perceptron: When considering scenarios with 50 features, we investigate $[relu, tanh]$ activation functions and the following number of hidden layers $[1, 2, 3, 4, 5]$ and number of neurons $[10, 20, 25, 30, 40, 50]$.

On the basis of our tuning phase, we selected $(50, 25, 50)$ architecture with $relu$ activation function (recall, ReLU is of the form $max(0, x)$). We use the $adam$ optimizer, the initial learning rate of 0.001, $log - loss$ function, and a batch size of 200.

When considering all features and MLP, we investigate the following number of hidden layers $[1, 2, 3, 4]$ and number of neurons $[100, 200, 300, 400, 500, 600, 700, 800, 900, 1\,000]$. Based on the results, we select to use 4 hidden layers where each layer has 500 neurons. We set the batch size to 256, the number of epochs to 50, the loss function is categorical cross-entropy, and optimizer is $RMSprop$ with a learning rate of 0.001.

d) Convolutional Neural Network: For CNN, we consider architectures of up to 5 convolutional blocks and 2 fully-connected layers. Each block consists of a convolutional layer with $relu$ activation function and average pooling layer. The first convolutional layer has a filter size of 64 and then each next layer increases the filter size by a factor of 2. The maximal filter size is 512. Kernel size is 11. For the average pooling layer, pooling size is 2 and stride is 2. Fully-connected layers have $relu$ activation function and we experiment with $[128, 256, 512]$ number of neurons. After a tuning phase, we select to use a single convolutional block and 2 fully-connected layers with 128 neurons each. Batch size equals 256, the number of epochs is 125, the loss function is categorical cross-entropy, the learning rate is 0.0001, and optimizer is $RMSprop$.

IV. Results

In this section, we present results for all 4 scenarios we investigate. Afterward, we discuss the issues with the validation procedure and present our Multiple Device Model. As mentioned earlier, we use guessing entropy as the metric

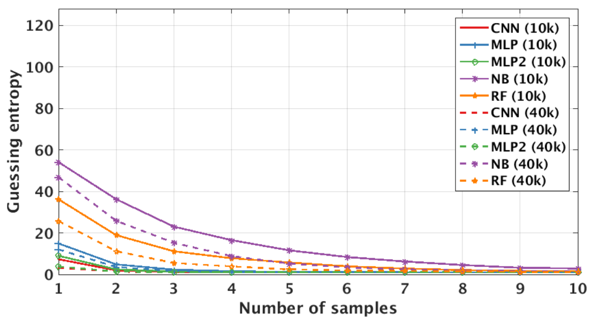


Fig. 6: Same device and key scenario.

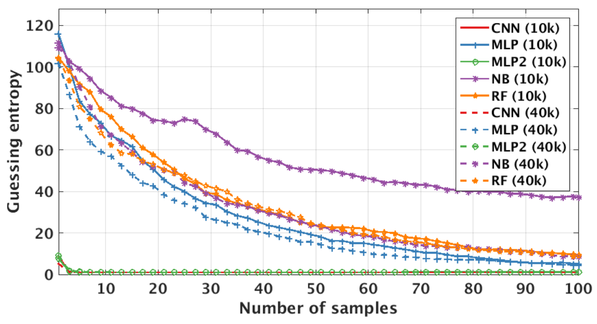


Fig. 7: Same device and different key scenario.

for comparison. In other words, we observe the average rank of the key against the number of traces or measurement samples. *An attack is effective if the guessing entropy goes to 0 with minimum required samples.* If at the end of attack if the guessing entropy stays at x, the attacker must brute force 2^x different keys for key recovery. Note that we give averaged results for a certain machine learning technique and number of measurements. We denote the scenario where we use multilayer perceptron with all 600 features as MLP2, while the scenario where multilayer perceptron uses 50 features we denote as MLP.

A. *Same Key and Same Device*

The first scenario we consider uses the same devices and keys for both training and testing phases. Consequently, this scenario is not a realistic one but is a common scenario examined in the related works. This scenario does not consider any portability aspect and is the simplest one for machine learning techniques so we consider it as the baseline case. The results for all considered machine learning techniques are given in Figure 6. We give averaged results over the following settings: $(B1\_K1)-(B1\_K1), (B2\_K2)-B2\_K2), (B3\_K1)-(B3\_K1), (B4\_K3)-(B4\_K3)$. As can be seen, all results are very good, and even the worst performing algorithm reaches guessing entropy of 0 in less than 10 measurements. Thus, an attack would need only 10 side-channel traces from the target device in order to perform the full key-recovery. Additionally, we see that adding more measurements can improve the performance of attacks. The worst performing algorithm is Naive Bayes, followed by Random Forest. The differences among other algorithms are very small and we see that guessing entropy reaches 0 for 3 measurements. Note that despite somewhat smaller training sets (37 000) for algorithms using all 600 features (CNN and MLP2), those results do not show any performance deterioration. In fact, the algorithms are able to reach guessing entropy of 0 with up to 3 traces. Since we are using the same device and key to train and attack, and we are using validation or cross-validation to prevent overfitting, accuracy in the training phase is only somewhat better than accuracy in the test phase (depending on the algorithm, $\approx 10-40\%$).

B. *Same Device and Different Key*

Next, we consider the scenario where we use the same device in the training phase and testing phase but we change keys between those phases. When different user compute on shared resources and standard cryptographic libraries (like SSL), this scenario becomes relevant. The malicious user profiles the library on own application with all access rights and attacks when the target user application is running. We present the results for this scenario in Figure 7. Here, we give averaged results over scenarios $(B2\_K1)-(B2\_K2)$ and $(B2\_K2)-(B2\_K1)$. The first observation is that this setting is more difficult for machine learning algorithms. Indeed, Naive Bayes, Random Forest, and multilayer perceptron with 50 features require more than 100 measurements to reach guessing entropy less than 10 (note that Naive Bayes with 10 000 measurements reaches only guessing entropy of around 40). Interestingly, for these 3 techniques, adding more measurements (i.e., going from 10 000 to 40 000) does not bring a significant improvement in performance. At the same time, both techniques working with all features (MLP2 and CNN) do not seem to experience performance degradation when compared to the first scenario. Regardless of the number of measurements in the training phase, they reach guessing entropy of 0 after 3 measurements. For this scenario, we observed that accuracy in the training phase can be up to an order of magnitude better than accuracy in the test phase, which indicates that our algorithms overfit.

C. *Same Key and Different Device*

The third scenario we consider uses two different devices but the key stays the same. Note, since we consider different devices we can talk about the real-world case but the same key makes it still a highly unlikely scenario. The results are averaged over settings $(B1\_K1)-(B2\_K1)$ and $(B2\_K1)-(B1\_K1)$. When considering performance, we see in Figure 8 that this scenario is more difficult than the previous two as different targets introduce their own noise patterns. Similarly as in the previous scenario, all techniques using 50 features require more than 100 measurements to reach guessing entropy less than 10. Additionally, adding more measurements does not improve results significantly. When considering techniques using all 600 features, we see this scenario to be more

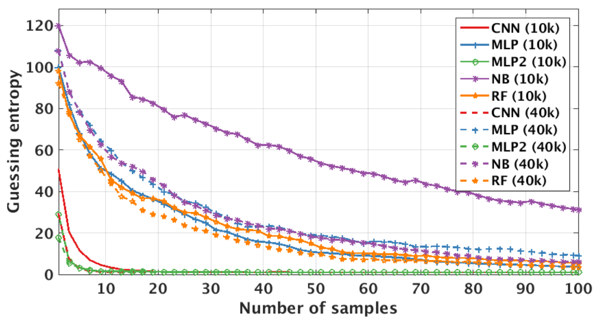


Fig. 8: Same key and different device scenario.

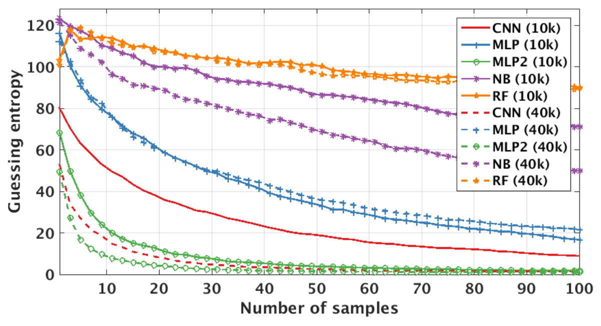


Fig. 9: Different key and device scenario.

difficult than the previous ones as we need 7 or more traces to reach guessing entropy of 0. Additionally, CNN using 10 000 measurements is clearly performing worse than when using 40 000 measurements, which is a clear indicator that we require more measurements to avoid underfitting on the training data. Finally, we remark that in these experiments, accuracy in the training set was up to an order of magnitude higher than for the test set. Consequently, we see that while we require more measurements in the training phase to reach the full model capacity, those models already overfit as the differences between devices are too significant.

D. Different Key and Device

Finally, we investigate the setting where training and testing are done on different devices where those devices use different secret keys. Consequently, this is the full portability scenario one would encounter in practice. As expected, this is by far the most difficult scenario for all techniques as seen in Figure 9. In this scenario, the results are averaged over 8 different settings: $(B1\_K1) - (B4\_K3), (B4\_K3) - (B1\_K1)$, $(B2\_K2) - (B4\_K3), (B4\_K3) - (B2\_K2)$, $(B3\_K1) - (B4\_K3), (B4\_K3) - (B3\_K1)$, $(B1\_K1) - (B2\_K2)$, and $(B2\_K2) - (B1\_K1)$.

Interestingly, here Random Forest is the worst performing algorithm and with 100 measurements it barely manages to reach guessing entropy less than 90. Naive Bayes and multilayer perceptron with 50 features perform better but still with 100 measurements, they are not able to reach guessing entropy less than 15. At the same time, we see a clear benefit of added measurements only for Naive Bayes. When considering CNN and multilayer perceptron with all features, we observe we require somewhat more than 60 measurements to reach guessing entropy of 0. There is a significant difference in performance for CNN when comparing settings with 10 000 and 40 000 measurements. For MLP2 that difference is much smaller and when having a smaller number of measurements, MLP2 outperforms CNN. When CNN uses 40 000 measurements in the training phase, it outperforms multilayer perceptron with 10 000 measurements and both techniques reach guessing entropy of 0 with the approximately same number of measurements in the testing phase. As in the previous scenario, we see that CNN needs more measurements to build a strong

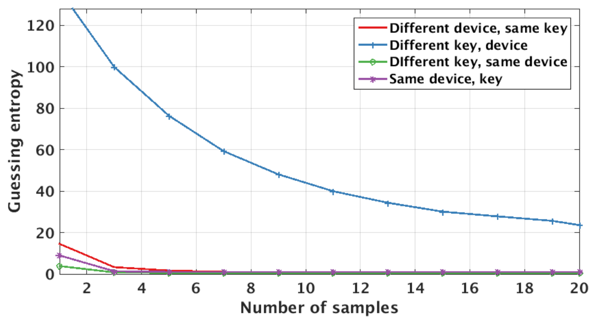


Fig. 10: Multilayer perceptron with 600 features over all scenarios, 10 000 measurements.

model. This is in accordance with the intuitive difficulty of the problem as more difficult problems need more data to avoid underfitting and to reach good model complexity. Interestingly, in this scenario, accuracy for the training set is easily two orders of magnitude higher than for the test set, which shows that all techniques overfit significantly. Indeed, while we see that we can build even stronger models if we use more measurements in the training phase, such obtained models are too specialized for the training data and do not generalize well for the test data obtained from different devices.

E. General Observations

When considering machine learning techniques we used and investigated scenarios, we see that multilayer perceptron using all features performs the best (the difference with CNN is small, especially if considering 40 000 measurements in the training phase). In order to better understand the difficulties stemming from specific scenarios, we depict the result for MLP2 and all 4 scenarios in Figure 10.

Clearly, the first two scenarios (having the same device and key as well as changing the key but keeping the same device) are the easiest. Here, we see that the results for the scenario when changing the key indicate it is even slightly easier than the scenario with the same device and key. While other machine learning techniques point that using the same key and device is the easiest scenario, they all show these two scenarios to be easy. Next, a somewhat more difficult case is the scenario where we change the device and use the same key.

Again, the exact level of increased difficulty depends on the specific machine learning algorithm. Finally, the most difficult scenario is when we use different devices and keys. Here, we can see that the effect of portability is much larger than the sum of previously considered effects (changing only key or device).

While all scenarios must be considered as relatively easy when looking the number of traces needed to reach guessing entropy of 0, the increase in the number of required measurements is highly indicative how difficult problem portability represents. Indeed, it is easy to see that we require more than an order of magnitude more measurements for the same performance if we consider scenarios 3 and 4. At the same time, already for scenario 3, we require double the measurements than for scenarios 1 or 2.

While we use only a limited number of experimental settings, there are several general observations we can make:

1) Any portability setting adds to the difficulty of the problem for machine learning.
2) Attacking different devices is more difficult than attacking different keys.
3) The combined effect of different key and different device is much larger than their sum.
4) Adding more measurements does not necessarily help but on average also does not deteriorate the performance.
5) CNN requires more measurements in portability settings to build strong models.
6) While our results indicate that additional measurements in the training phase would be beneficial to reach the full model capacity, we observe that in portability settings, there is a significant amount of overfitting. This represents an interesting situation where we simultaneously underfit on training data and overfit on testing data.
7) The overfitting occurs due to the fact that we do not train on the same data distribution as we test.

V. Multiple Device Model

In this section, we first discuss the overfitting issue we encounter in portability. Next, we propose a new model for portability called the Multiple Device Model where we experimentally show its superiority when compared to the usual setting.

A. *Overfitting*

Recall from Section II-B1 that we are interested in supervised learning where on the basis of training examples (data X and corresponding labels Y) a function f is obtained. That function is later used on testing data to predict the corresponding labels. Here, the function f is estimated from the observed data. That observed data is drawn independently and identically distributed from a common distribution. To avoid overfitting, we use validation (e.g., k-fold cross-validation or a separate dataset for validation).

As it can be observed from the results in the previous section, when training and testing data come from the same device, the machine learning techniques do not have problems

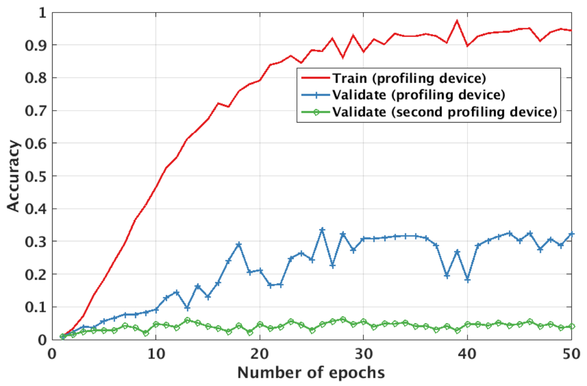


Fig. 11: Training and validation on the same device vs. validation done on different device.

in building good models as the model is fitted to the same distribution of data as will be used in the attack phase. There, validation on the same data distribution helps to prevent overfitting.

However, when there are two devices, one for training and the second one to attack, the problem of overfitting is much more pronounced and having validation done on a training device does not help significantly. Naturally, the problem is that our model is fitted to the training data but we aim to predict on testing data, which may not have the same distributions. We depict this in Figure 11 where we show results for training and validation on the device $B1\_K1$ versus training on the device $B1\_K1$ and validation on the device $B4\_K3$. In this scenario, we experiment with multilayer perceptron and we use all features (MLP2). We can clearly observe that when conducting validation on the same device as training, the accuracy increases with the number of epochs. At the same time, when we run validation with measurements from a different device, there is almost no improvement coming from a longer training process.

On the basis of these results, we identify overfitting as one of the main problems in the portability scenarios. There, overfitting occurs much sooner than indicated by validation if done on the same device as training. Additionally, our experiments indicate that k-fold cross-validation suffers more from portability than having a separate validation dataset. This is because it allows a more fine-grained tuning, which further eases overfitting.

To prevent overfitting, there are several intuitive options:

1) Adding more measurements. While this sounds like a good option, it can bring some issues as we cannot know how much data needs to be added (and in general in SCA, we will use already from the start all available data). Also, in SCA a longer measurement setup may introduce additional artifacts in the data distribution [37]. Additionally, simply increasing the amount of training data does not guarantee to prevent overfitting as we do not know what amount of data one needs to prevent underfitting.

2) Restricting model complexity. If we use a model that has too much capacity, we can reduce it by changing the network parameters or structure. Our experiments also show the benefits of using shallower networks or shorter tuning phases, but it is difficult to estimate a proper setting without observing the data coming from the other distribution.
3) Regularization. There are multiple options here: dropout, adding noise to the training data, activation regularization, etc. While these options would certainly reduce overfitting in general case, they are unable to assess when overfitting actually starts for data coming from a different device, which makes them less appropriate for the portability scenarios. We note that some of these techniques have been also used in profiling SCA but not in portability settings, see, e.g., [14], [24].

B. New Model

Validation on the same device as training can seriously affect the performance of machine learning algorithms if attacking a different device. Consequently, we propose a new model that uses multiple devices for training and validation. We emphasize that since portability is more pronounced when considering different devices than different keys (and their combined effect is much larger than their sum), it is not sufficient to build the training set by just using multiple keys and one device. Indeed, this is a usual procedure done for template attack but it is insufficient for full portability considerations.

In its simplest form, our new model, called the "Multiple Device Model" (abbreviated MDM) consists of 3 devices: 2 for training and validation and one for testing. Since we use more than one device for training and validation, the question is which device to use for train and which one for validation. The simplest setting is to use one device for training and the second one for validation. In that way, we are able to prevent overfitting as the model will not be able to learn the training data too well. Still, there are some issues with this approach: while we said we use one device for training and the second one for validation, it is still not clear how to select which device to use for what. Indeed, our results clearly show that training on device x and validating on device y in order to attack device z will produce different results when compared to training on device y and validating on device x to attack device z. This happens because we cannot know whether device x or y is more similar to device z, which will influence the final results.

Instead of deciding on how to divide devices among phases, we propose the Multiple Device Model where a number of devices participate in training and validation. More formally, let the attacker has on his disposal t devices with N data pairs x_i, y_i from each device. The attacker then takes the same number of measurements k from each device to create a new train set and the same number of measurements j from each device to create a validation set. Naturally, the measurements in the training and validation set need to be different. The training set then has the size $t \cdot k$ and the validation set has size $t \cdot j$. With those measurements, the attacker builds a model f, which is then used to predict labels for measurements obtained from a device under attack. We emphasize that in training and validation, it is necessary to maintain a balanced composition of measurements from all available devices in order not to build a model skewed toward a certain device. We depict the MDM setting in Figure 12.

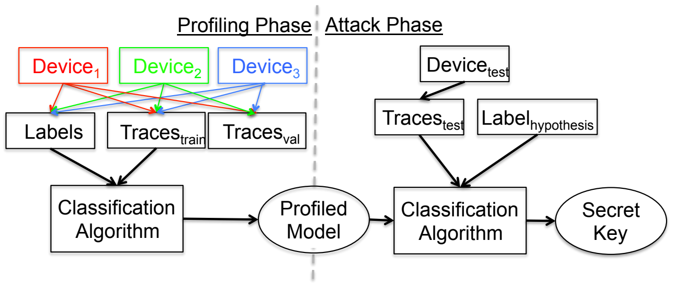


Fig. 12: Illustration of the proposed MDM model. Note a clear separation between training/validation devices and a device under attack, cf. Figure 1.

Definition 2: The Multiple Device Mode denotes all settings where an attacker has no access to traces from the device under attack to conduct a training but only to traces from a number of similar devices (at least 2), with uncontrolled variations.

While MDM requires a strong assumption on the attacker's capability (i.e., to have multiple devices of the same type as the device under attack) we consider it to be well within realistic scenarios. If a third device is not available, one could simulate it by adding a certain level of noise to the measurements from the training device. This solution is far from optimal since we cannot know a proper level of noise, but it could still force machine learning algorithms to generalize better as the trained model would overfit less.

We present results for MDM and multilayer perceptron that uses all features (MLP2) and 10 000 measurements as it provided the best results in the previous section. The results are for specific scenarios so they slightly differ from previous results where we depict averaged results over all device combinations. Finally, we consider here only the scenario where training and attacking are done on different devices and use different keys. Consequently, the investigated settings are selected so as not to allow the same key or device to be used in the training/validation/attack phases.

In Figure 13a, we depict several experiments when using different devices for training and validation. First, let us consider the cases $(B1\_K1) - (B4\_K3) - (B2\_K2)$ and $(B1\_K1) - (B2\_K2)$. There, having separate devices for training and validation improves over the case where validation is done on the same device as training. On the other hand, cases $(B4\_K3) - (B2\_K2) - (B1\_K1)$ and $(B4\_K3) - (B1\_K1)$ as well as $(B4\_K3) - (B1\_K1) - (B2\_K2)$ and $(B4\_K3) - (B2\_K2)$ show that adding an additional device for validation actually significantly degrades the performance. This happens because the difference between the training and validation device is larger than the difference between the training and testing device. Next, the cases $(B2\_K2)-(B4\_K3)-(B1\_K1)$ and $(B2\_K2)-(B1\_K1)$ show very similar behavior, which means that validation and testing datasets have similar distributions. Finally, for three devices, e.g., cases $(B1\_K1)-(B4\_K3)-(B2\_K2)$ and $(B4\_K3)-(B1\_K1)-(B2\_K2)$, the only difference is the choice of training and validation device/key. Yet, the performance difference is tremendous, which clearly shows the limitations one could expect if having separate devices for training and validation.

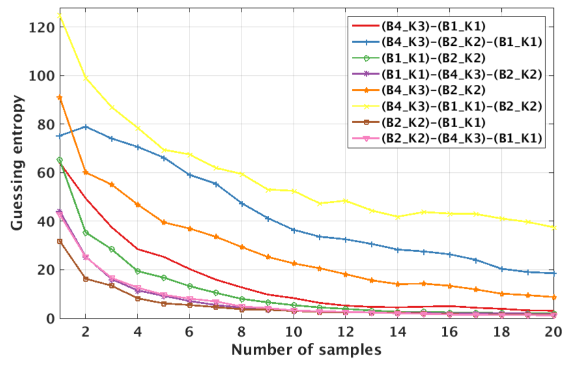
Next, in Figure 13b, we depict the results for our new MDM model where training and validation measurements come from two devices (denoted with "multiple" in the legend). As it can be clearly seen, our model is able to improve the performance significantly for two out of three experiments. There, we are able to reach the level of performance as for the same key and device scenario. For the third experiment, $(B1\_K1)-(B2\_K2)-(B4\_K3)$, we see that the improvement is smaller but still noticeable, especially for certain ranges of the number of measurements. We see that MDM can result in an order of magnitude better performance than using two devices. At the same time, with MDM we did not observe any case where it would results in performance degradation when compared to the usual setting.

MDM may not be always necessary: if both training and attacking devices contain small levels of noise and are sufficiently similar, then using only those two devices could suffice. Still, as realistic settings tend to be much more difficult to attack, having multiple devices for training and validation would benefit attack performance significantly.

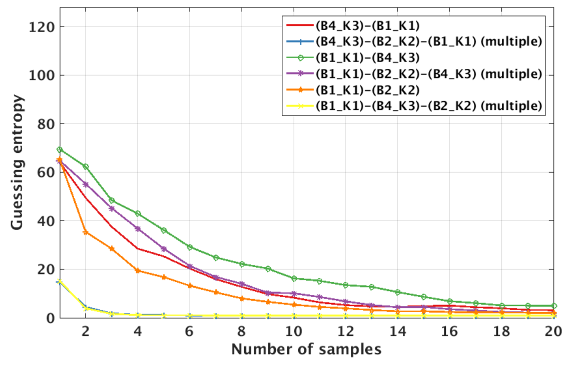
VI. Conclusions and Future Work

In this paper, we tackle the portability issue in machine learning-based side-channel attacks. We show how even small differences between devices can cause attacks to perform significantly different. As expected, our results clearly show that the scenario where we use different keys and devices in the profiling and attacking phase is the most difficult one. This is important because it means that most of the attacks conducted in related works greatly overestimate their power as they use the same device and key for both training and attack. We identify the validation procedure as one of the pitfalls for portability and machine learning. Consequently, we propose a new attack model called the Multiple Device Model that assumes separate devices for profiling/validation and attack. With this model, we are able to improve attack performance by $> 10\times$.

In our experiments, we considered AVR targets that have no countermeasures. The choice was motivated by finding the best case measurements to focus on the portability problems. In future work, we plan to use different platforms and investigate what is the influence of various countermeasures (both hiding and masking) to the performance of machine learning classifiers when considering portability. Additionally, we plan to experiment with a larger number of devices in order to improve the generalization capabilities of machine learning algorithms. A natural extension of this work would be when the different devices are not measured on non-identical setups. Finally, our experiments indicate that smaller datasets could be less prone to overfitting. It would be interesting to see whether we can obtain good performance with small training set sizes, which would conform to setting as described in [38].



(a) Results for separate devices for training and validation.



(b) Results for MDM.

Fig. 13: Results for different settings with multiple devices for training and validation.

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