One trace is all it takes: Machine Learning-based Side-channel Attack on EdDSA

Léo Weissbart[1,2], Stjepan Picek[1], and Lejla Batina[2]

[1] Delft University of Technology, The Netherlands
[2] Digital Security Group, Radboud University, The Netherlands

Abstract. Profiling attacks, especially those based on machine learning proved as very successful techniques in recent years when considering side-channel analysis of block ciphers implementations. At the same time, the results for implementations public-key cryptosystems are very sparse. In this paper, we consider several machine learning techniques in order to mount a power analysis attack on EdDSA using the curve Curve25519 as implemented in WolfSSL. The results show all considered techniques to be viable and powerful options. The results with convolutional neural networks (CNNs) are especially impressive as we are able to break the implementation with only a single measurement in the attack phase while requiring less than 500 measurements in the training phase. Interestingly, that same convolutional neural network was recently shown to perform extremely well for attacking the AES cipher. Our results show that some common grounds can be established when using deep learning for profiling attacks on distinct cryptographic algorithms and their corresponding implementations.

1 Introduction

Side-channel attacks (SCAs) are techniques targeting the implementations of algorithms rather than the algorithms themselves. The first academic result was the attack using timing as side channel in 1996 [19], and it positioned the topic as the most powerful technique aiming at cryptographic implementations. In fact, SCAs have been successfully used to break a large number of cryptographic algorithms, regardless whether such algorithms belong to the symmetric key cryptography or public-key cryptography. In case that the side-channel attacker has access to a clone device previous to the attack, he can mount one especially powerful category of SCA: profiling attacks. There, the attacker has access to the clone device (i.e., he has full control of that device) and he profiles it offline. Afterward, in the attack phase, the attacker uses the knowledge from the profiling phase in order to break the implementation.

A well-known example of profiling attack is the template attack, which is the most powerful attack when considering "conventional" profiling SCA in the literature. In recent years, the researchers began using machine learning techniques in profiling attacks with significant success. Indeed, they identified a number of situations where machine learning techniques could outperform template attacks.

More recently, the SCA community started experimenting with deep learning and the results are also promising. In fact, not only that deep learning can outperform template attack and other machine learning techniques, but it can also break implementations protected with countermeasures. However, most of those results are obtained on block ciphers implementations (and more precisely on AES) and there are almost no results considering machine learning (deep learning) on public-key cryptography.

A natural question is whether attacking public-key cryptography (e.g., elliptic curve cryptography implementations) is easier or more difficult than the block ciphers. Additionally, what is the performance of various profiling techniques that proved powerful when considering block ciphers? Intuitively, there should not be anything specific in public-key cryptography implementations that would render them more difficult to break, but more research is necessary. In this paper, we consider the EdDSA implementation using curve Curve25519 as in WolfSSL and we consider profiling attacks in order to break it. To that end, we consider several machine learning techniques that proved to be strong profiling techniques in related work (albeit mostly on block ciphers) and template attack, which we consider the standard technique and a baseline setting. Our results show that all considered techniques should be seen as powerful attack options where convolutional neural networks are even able to break the implementation with only a single trace in the attack phase.

1.1 Related Work

As already mentioned, template attack is the most powerful attack in the information theoretic point of view and a standard tool for profiling SCA [9]. It could be sometimes computationally intensive and one option to make it more efficient is to use only a single covariance matrix, which is the so-called pooled template attack [11]. When considering machine learning in side-channel analysis of block ciphers, there is a plethora of works that use different machine learning techniques. A more in-depth analysis points out that the two standard choices are support vector machines (see, e.g., [29,24,17,21]) and random forest (see, e.g., [16,28,22]). In the last few years, besides the aforesaid machine learning techniques, neural networks have also proven to be a viable choice (actually, even more than viable since often neural networks exhibit the best performance among all tested algorithms). There, most of the research concentrated on either multilayer perceptron or convolutional neural networks [24,30,7,15]

There is a large portion of works considering profiling techniques for block ciphers but there is much less for public-key cryptography. Lerman et al. consider template attack and several machine learning techniques in order to attack RSA. However, the targeted implementation was not secure, which makes their finding inconclusive [21]. Poussier et al. use horizontal attacks and linear regression in order to conduct an attack on ECC implementations but their approach cannot be classified as deep learning [31]. Carbone et al. on the other hand, use deep learning to attack a secure implementation of RSA [8].

1.2 Contributions

There are two main contributions of this paper:

1. We present a comprehensive analysis of several profiling attacks with a different number of features in the measurements. This evaluation can be helpful when deciding on the optimal strategy for machine learning and in particular, deep learning attacks on implementations of public-key cryptography.
2. We consider elliptic curve cryptography (actually EdDSA using curve Curve25519) and profiling attacks where we show that such techniques, and especially the convolutional neural networks can be extremely powerful attacks.
3. We present a detailed analysis of several profiling attacks with a different number of features in the measurements.

Besides those contributions, we also present a publicly available dataset we developed for this work. With it, we aim to make our results more reproducible but also motivate other researchers to publish their datasets for public-key cryptography. Indeed, while the SCA community realizes the lack of publicly available datasets for block ciphers (and tries to improve it), the situation for public-key cryptography seems to attract less attention despite even worse availability of codes, testbeds, and datasets.

The rest of this paper is organized as follows. In Section 2, we discuss elliptic curve scalar multiplication, Ed25519 algorithm, and profiling attack techniques. In Section 3, we discuss how the dataset we use in our experiments is generated. Section4 gives the results of the hyper-parameter tuning phase, dimensionality reduction, and profiling results. Finally, in Section 5, we conclude the paper and give some possible future research directions.

2 Background

In this section, we start by introducing the elliptic curve scalar multiplication and EdDSA algorithm. Afterward, we discuss profiling attacks we use in our experiments.

2.1 Elliptic Curve Scalar Multiplication

In this attack, we aim to extract the ephemeral key r from its scalar multiplication with the Elliptic Curve base point B (see step 5 in Algorithm 2). To understand how this attack works, we decompose this computation as implemented in the case of WolfSSL Ed25519.

The implementation of Ed25519 in WolfSSL is based on Bernstein et al. work [3]. The implementation of elliptic curve scalar multiplication is a window-based method with radix-16, making use of a precomputed table containing results of the scalar multiplication of $16^i|r_i| \cdot B$, where $r_i \in [-8, 7] \cap \mathbb{Z}$ and B the base point of Curve25519. This methods is popular because of its trade-off between memory usage and computation speed, but also because the implementation is time-constant and does not rely on any branch condition nor array

Algorithm 1 Elliptic curve scalar multiplication with base point [4]

Input: R, a with $a = a[0] + 256 * a[1] + ... + 256^{31}a[31]$
Output: $H(a, s, m)$

for $i = 0; i < 32; ++i$ **do**
    $e[2i + 0] = (a[i] >> 0\&15)$
    $e[2i + 1] = (a[i] >> 4)\&15$
end for
$carry = 0$
for $i = 0; i < 63; ++i$ **do**
    $e[i]+ = carry$
    $carry = (e[i] + 8)$
    $carry >>= 4$
    $e[i]- = carry << 4$
end for
$e[63]+ = carry$ ▷ $\forall i < 64,\ -8 \leq e[i] \leq 8$
$ge\_p3\_0(h)$
for $i = 1; i < 64; i+ = 2$ **do**
    $ge\_select(\&t, i/2, e[i])$ ▷ load from precomputed table $(e[i] \cdot 16^i) \cdot B$ in E.
    $ge\_madd(\&r, R, \&t)$ $ge\_p1p1\_to\_p3(R, \&r)$
end for
$ge\_p3\_dbl(\&r, R)$ $ge\_p1p1\_to\_p2(\&s, \&r)$
$ge\_p2\_dbl(\&r, \&s)$ $ge\_p1p1\_to\_p2(\&s, \&r)$
$ge\_p2\_dbl(\&r, \&s)$ $ge\_p1p1\_to\_p2(\&s, \&r)$
$ge\_p2\_dbl(\&r, \&s)$ $ge\_p1p1\_to\_p3(R, \&r)$
for $i = 0; i < 64; i+ = 2$ **do**
    $ge\_select(\&t, i/2, e[i])$ ▷ load from precomputed table $(e[i] \cdot 16^i) \cdot B$ in E.
    $ge\_madd(\&r, R, \&t)$ $ge\_p1p1\_to\_p3(R, \&r)$
end for

indices and hence it is secure against timing attack. Leaking information from the corresponding value load from memory with a function *ge_select* is used here to recover q and hence can be used to easily connect to the ephemeral key r.

2.2 EdDSA

EdDSA [3] is a variant of the Schnorr digital signature scheme [33] using Twisted Edward Curves. The security of this algorithm is based on the generation of an ephemeral key that is created in a deterministic way and thus does not rely on a potentially weak random number generator.

EdDSA in case of curve Curve25519 [2] is referred to as Ed25519 and this implies the following domain parameters for EdDSA:

- Finite field F_q, where $q = 2^{255} - 19$ is the prime.
- Elliptic curve $E(F_q)$, Curve25519
- Base point B
- Order of the point B, l
- Hash function H, SHA-512 [14]
- Key length $u = 256$ (also length of the prime)

For more details on other parameters of Curve25519 and the corresponding curve equations we refer to Bernstein [2].

The ephemeral key is made of the hash value of the message and the auxiliary key, generating a unique ephemeral key for every message. EdDSA scheme for signature generation and verification is described in Algorithm 2. The first four steps are used once by the signer the first time that the private key is used. The notation $(x, \ldots, y)$ denotes the concatenation of the elements. The ephemeral key r is generated deterministically during Step 5 and used to generate the ephemeral public key in Step 6.

To verify a signature (R, S) on a message M with public key P a verifier follows the procedure described in Algorithm 2 from Step 11.

Table 1: Notation for EdDSA

Name	Symbol
Private key	k
Private scalar	a (first part of H(k)).
Auxiliary key	b (last part of H(k)).
Ephemeral key	r
Message	M

2.3 Profiling Attacks

In this paper, we consider several machine learning techniques that showed very good performance when considering side-channel attacks on block ciphers. Besides it, we briefly introduce the template attack, which serves us as a baseline to compare the performance of algorithms.

Algorithm 2 EdDSA Signature generating and verification

Keypair Generation (k,P):

1: Hash k such that $H(k) = (h_0, h_1, \ldots, h_{2u-1}) = (a, b)$
2: $a = (h_0, \ldots, h_{u-1})$, interpret as integer in little-endian notation
3: $b = (h_u, \ldots, h_{2u-1})$
4: Compute public key: $P = aB$.

Signature Generation:

5: Compute ephemeral private key $r = H(b, M)$.
6: Compute ephemeral public key $R = rB$.
7: Compute $h = H(R, P, M) \mod l$.
8: Compute: $S = (r + ha) \mod l$.
9: Signature pair (R, S)
10:

Signature Verification:

11: Compute $h = H(R, P, M)$
12: Verify if $8SB = 8R + 8hP$ holds in E

Random Forest Random Forest (RF) is a decision tree learner [6]. 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 parametric algorithm with respect to the number of trees in the forest. RF is a stochastic algorithm because of its two sources of randomness: bootstrap sampling and attribute selection at node splitting. The most important hyper-parameter to tune is the number of trees I (we do not limit the tree size.)

Support Vector Machines Support Vector Machines (denoted SVM) is a kernel based machine learning family of methods that are used to accurately classify both linearly separable and linearly inseparable data. The idea for linearly inseparable data is to transform them into a higher dimensional space using a kernel function, wherein the data can usually be classified with higher accuracy. The scikit-learn implementation we use considers libsvm's C-SVC classifier that implements SMO-type algorithm [13]. The multi-class support is handled according to a one-vs-one scheme. We investigate two variations of SVM: with a linear kernel and with a radial kernel. Linear kernel based SVM has the penalty hyper-parameter C of the error term. Radial kernel based SVM has two significant tuning hyper-parameters: the cost of the margin C and the kernel γ.

Convolutional Neural Networks Convolutional Neural Network (CNN) is a type of neural network initially designed to mimic the biological process of animal's cortex to interpret visual data [20]. CNNs show excellent results for classifying images for various applications and have also proved to be a powerful tool to classify time series data such as music or speech [26]. The *VGG-16* architecture introduced in [34] for image recognition was also recently applied to the problem of side-channel analysis with very good results [18]. 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. In CNN, every layer of a network transforms one volume of activation functions to another through a differentiable function. First, the 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. `ReLU` layer will apply an element-wise activation function, such as the $max(0, x)$ thresholding at zero. Max 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. To convert the output of a convolution part of CNN (which is 2-dimensional) into a 1-dimensional feature vector that is used in the fully-connected layer, we use the flatten operation. Dropout is a regularization technique for reducing overfitting by preventing complex co-adaptations on training data. The term refers to dropping out units (both hidden and visible) in a neural network. Note, the architecture of a CNN is dependent on a large number of hyper-parameters.

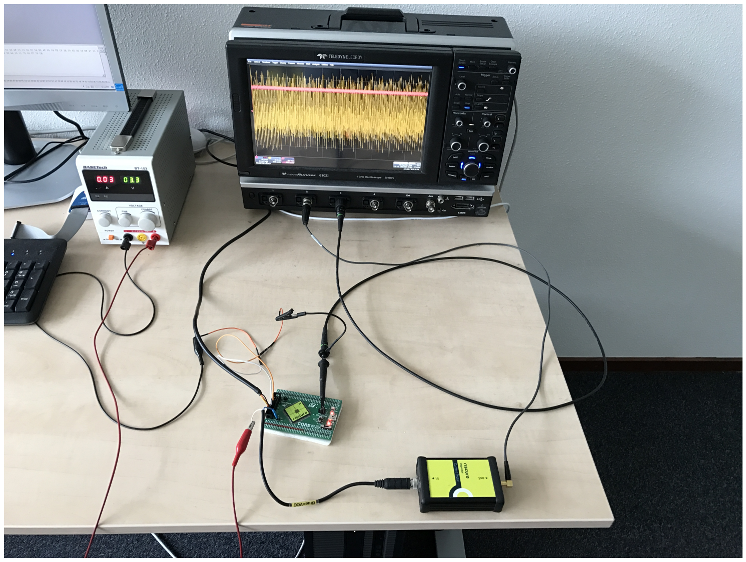
One of the advantages of using deep learning for power consumption analysis is that it can handle analyzing data with a large number of features. In the case of CNN, the data is analyzed through several layers that focuses on different dimensionalities. In the architecture described in [18], convolutional blocks can be viewed as analyzing information from the data and making emphasis on the most important part of the information. Then, the pooling layer makes a type of dimensionality reduction by selecting the highlighted information to create a refined dataset to be analyzed in the following convolutional block.

Template Attack The template attack (TA) relies on the Bayes theorem and considers the features as dependent. In the state-of-the-art, template attack relies mostly on a normal distribution [10]. Accordingly, template attack assumes that each $P(\boldsymbol{X} = \boldsymbol{x}|Y = y)$ follows a (multivariate) Gaussian distribution that is parameterized by its mean and covariance matrix for each class Y. The authors of [12] propose to use only one pooled covariance matrix averaged over all classes Y to cope with statistical difficulties and thus a lower efficiency. In our experiments, we use the version of the attack that uses only one pooled covariance matrix.

3 Dataset Generation

In this section, we present the measurement setup and explain the methodology for creating a dataset from the power traces obtained with our setup (see Figure 1).

Fig. 1: The measurement setup



3.1 Measurement Setup

The device under attack is a Piñata development board by Riscure [1]. The CPU of this board is a Cortex-M4, a 32-bit Harvard architecture running at the clock frequency of 138MHz. The board is modified to perform SCA through power consumption. The target is Ed25519 implementation of WolfSSL 3.10.2. As WolfSSL is an open-source library written in C, we have a fully transparent and controllable implementation for the profiling phase.

For this attack, we focus on the power consumption, measured with respect to the current used by the microcontroller when processing the data for signature generation. The current is measured with a current probe [2] placed between the power source and the board's power supply source. Power traces are obtained with an oscilloscope Lecroy Waverunner z610i. The measure is performed with a sampling frequency of 1.025GHz and is triggered up with an I/O pin of the board at the beginning of *ge_select* function (see Algorithm 1) for a part of the key **e** and triggered off when the function is terminated. We can recover the ephemeral key by collecting all the information about **e**.

[1] Pinata Board, (Accessed: April 3, 2019) URL:`https://www.riscure.com/product/pinata-training-target/`

[2] Current Probe, (Accessed: April 3, 2019) URL:`https://www.riscure.com/product/current-probe/`

3.2 Datasets

To the best of our knowledge, there are no publicly available datasets for SCA on public-key cryptography on elliptic curves. In order to evaluate the attack proposed in this paper and to facilitate reproducible experiments, we present the dataset we built for this purpose [1]. We follow the same format for the dataset as in recently presented ASCAD database [32].

Table 2: Organization of the database

DATABASE			
ATTACK_TRACES		PROFILING_TRACES	
TRACES	trace_1[1 000]	TRACES	trace_1[1 000]
	...		...
	trace_n_a[1 000]		trace_n_p[1 000]
LABELS	label_1[1]	LABELS	label_1[1]
	...		...
	label_n_a[1]		label_n_p[1]

Each trace in the database is represented by a tuple composed of a power trace and its corresponding label. The database is composed of two groups: first one is the PROFILING_TRACES which contains n_p tuples and the second is the ATTACKING_TRACES that contains n_a tuples (see Table 2). In total, there are 6 400 labeled traces. We chose to divide traces in 80/20 for profiling/attacking groups, and consequently, have $n_p = 5\,120$ and $n_a = 1\,280$.

A group contains two datasets: TRACES and LABELS. The dataset TRACES contains the raw traces recorded from different nibbles during the encryption. Each trace contains 1 000 samples and represents relevant information of one nibble encryption. The dataset LABELS contains the correct subkey candidate for the corresponding trace. In total, there are 16 classes since we consider all possible nibble values.

4 Experimental Setting and Results

To examine the feasibility and performance of our attack, we present different settings for power analysis. To compare methods we choose different metrics. We first present their performance with accuracy since it is a standard metric in ML and the second metric is success rate that is an SCA metric and gives a concrete idea on the power the attacker should have in order to be considered dangerous [35]. Note, we consider that the attacker can collect as many power traces as he wants and that the profiling phase is nearly-perfect as described by Lerman et al. [23].

4.1 Hyper-parameters Choice

TA: Classical Template Attack is applied with pooled covariance[11]. Profiling phase is repeated for a different choice of points-of-interest (POI).

RF: Hyper-parameter optimization is applied to tune the number of decision trees used in Random Forest. We consider the following number of trees 50, 100, 500. The best number of decision trees is 100 with no PCA and 500 when PCA is applied for 10 and 656 POI.

SVM: We apply hyper-parameter optimization for SVM and compare two types of kernel. For the linear kernel, the hyper-parameter to optimize is the penalty parameter C. We search for the best C among a range of $[1, 10^5]$ in logarithmic space. In the case of the radial basis function (RBF) kernel, we have two hyper-parameters to tune: the penalty C and the kernel coefficient γ. The search for best hyper-parameters is done among $C = [1, 10^5]$ and $\gamma = [-5, 2]$ in logarithmic spaces. We consider only the hyper-parameters that give the best scores for each choice of POI (see Table 3).

Table 3: Chosen hyper-parameters for SVM

Number of features	Kernel	C	γ
1 000	linear	1 000	–
	rbf	1 000	1
656	linear	1 000	–
	rbf	1 000	1
10	linear	1 333	–
	rbf	1 000	1.23

Table 4: Architecture of the CNN

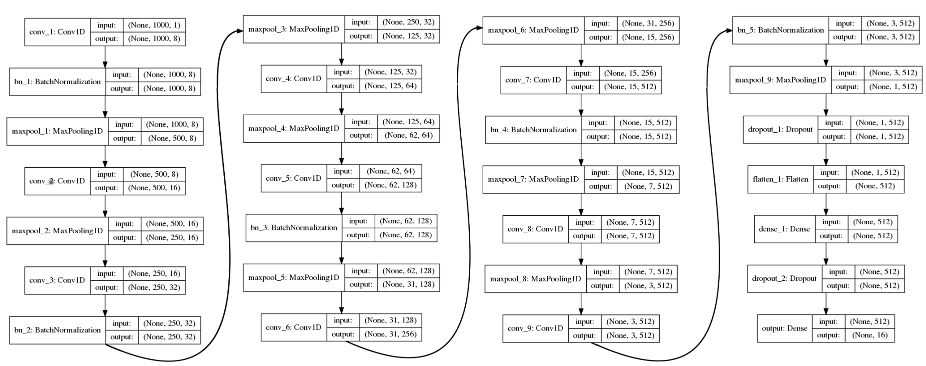
Hyper-parameter	Value
Input shape	$(1\,000, 1)$
Convolution layers	$(8, 16, 32, 64, 128, 256, 512, 512, 512)$
Pooling type	Max
Fully-connected layers	512
Dropout rate	0.5

CNN: The chosen hyper-parameters for *VGG-16* follows a number of rules that have been adapted for SCA in [18] or [32] and that we describe here:

1. The model is composed of several convolution blocks and ends with a dropout layer followed by a fully connected layer and an output layer with the Softmax activation function.
2. Convolutional and fully-connected layers use the ReLu activation function.
3. A convolution block is composed of one convolution layer followed by a pooling layer.
4. An additional batch normalization layer is applied for every odd-numbered convolution block and is preceding the pooling layer.
5. The chosen filter size for convolution layers is fixed of size 3.
6. The number of filters $n_{filters,i}$ in a convolution block i keeps increasing according to the following rule: $n_{filters,i} = max(2^i \cdot n_{filters,1}, 512)$ for every layer $i \geq 0$ and we choose $n_{filters,1} = 8$
7. The stride of the pooling layers is of size 2 and halve the input data for each block.
8. Convolution blocks follow each other until the size of the input data is reduce to 1.

The resulting architecture is represented in Table 4 and Figure 2.

Fig. 2: CNN architecture as implemented in Keras



4.2 Dimensionality Reduction

For computational reasons, one may want to select points-of-interest (POI) and consequently, we explore several different setting where we either use all features in trace or we conduct dimensionality reduction. In this paper, for dimensionality reduction, we use Principal Component Analysis (PCA) [5]. Principal component analysis (PCA) is a well-known linear dimensionality reduction method that may use Singular Value Decomposition (SVD) of the data matrix to project it to a lower dimensional space. PCA creates a new set of features (called principal components) that are linearly uncorrelated, orthogonal, and form a new coordinate system. The number of components equals the number of original features. The components are arranged in a way that the first component covers the largest variance by a projection of the original data and the subsequent components cover less and less of the remaining data variance. The projection contains (weighted) contributions from all the original features. Not all the principal components need to be kept in the transformed dataset. Since the components are sorted by the variance covered, the number of kept components, designated with L, maximizes the variance in the original data and minimizes the reconstruction error of the data transformation.

Note, while PCA is meant to select the principal information from a data, there is no guarantee that the reduced data form will give better results for profiling attacks than its complete form. In this paper, we apply PCA to have the least possible number of points-of-interest that maximize the score from TA (10 POI) and the number of POI using a Bayesian model selection that estimates the dimensionality of the data on the basis of a heuristics (see [25]). After an automatic selection of the number of components to use, we have 656 points-of-interest.

4.3 Results

In Table 5, we give results for all profiling methods when considering a single nibble of the key. As it can be observed, all profiling techniques reach very good performance, more precisely, all accuracy scores are above 95%. Still, some differences can be noted. When considering all features (1 000), CNN performs the best and has the accuracy of 100%. Both linear and rbf SVM and RF have exactly the same accuracy. The performance of SVM is interesting since the same value for linear and rbf kernel tells us there is no advantage of going into higher dimensional space, which indicates that the classes are linearly separable. Finally, TA performs the worst of all considered techniques.

Next, when considering the results with PCA that uses an optimal number of components (656), we see that the results for TA slightly improve while the results for RF and CNN decrease. While the drop in the performance for RF is small, CNN has a significant drop and now becomes the worst performing technique. SVM with both kernels retains the same accuracy level as for the full number of features. Finally, when considering the scenario where we take only the 10 most important components from PCA, all the results deteriorate when compared with the results with 1 000 features. Interestingly, CNN performs better with only 10 most important components than with 656 components but is still the worst performing technique from all the considered ones.

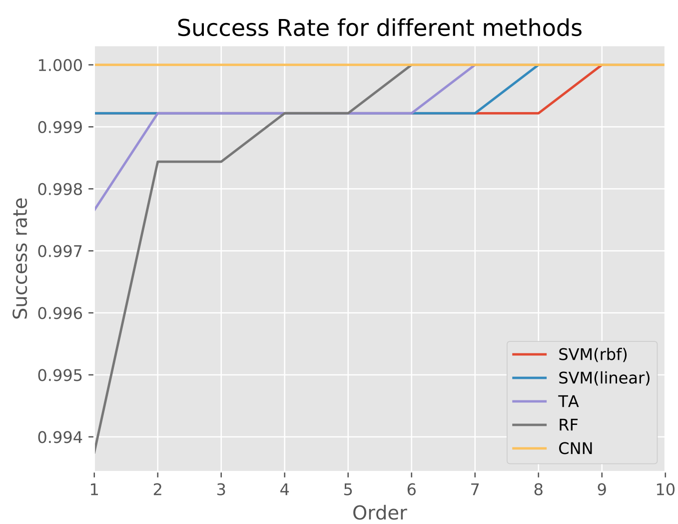
To conclude, all techniques exhibit very good performance but CNN is the best if no dimensionality reduction is done. There, the maximum accuracy is obtained after only a few epochs (see Figures 4 and 5). If there is dimensionality reduction, CNN shows a quick deterioration of the performance. This behavior should not come as a surprise since CNNs are usually used with the raw features (i.e., no dimensionality reduction). In fact, applying such techniques could reduce the performance due to a loss of information and changes in the spatial representation of features. Interestingly, template attack is never the best technique. SVM and RF show good and stable behavior for all feature set sizes.

In Figure 3, we give the success rate with orders up to 10 for all profiling methods on the dataset without applying PCA. A success rate of order o is the probability that the correct subkey is ranked among the o candidates of the guessing vector. While CNN has a hundred percent success rate of order 1, other methods achieve the perfect score only for orders greater than 6.

Table 5: Accuracy for the different methods obtained on the attacking dataset.

Algorithm	1 000 features	656 PCA components	10 PCA components
TA	0.9977	0.9984	0.9830
RF	0.9992	0.9914	0.9937
SVM (linear)	0.9992	0.9992	0.995
SVM (rbf)	0.9992	0.9992	0.995
CNN	1.00	0.95	0.96

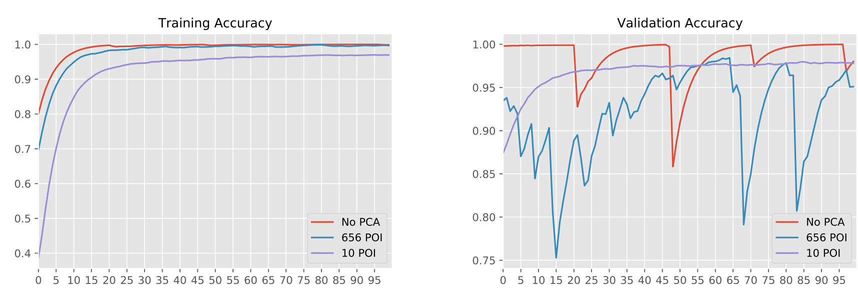
Fig. 3: Success rate



The results of all methods give similar results on the recovery of a single nibble from the key. If we want to have an idea of how good these methods are for the recovery of a full 256-bits key, we must apply the classification of the successive 64 nibbles. We can have a intuitive glimpse of the resulted accuracy P_c with cumulative probability of the probability of one nibble $P_s : P_c = \Pi_{64} P_s$ (see Table 6). The cumulative accuracy obtained in such a way can be interpreted as the predictive first-order success rate of a full key for the different methods in terms of security metric. From these results, we can observe that the best result is obtained with CNN when there is no dimensionality reduction. ML methods and TA are nonetheless powerful profiling attacks with up to 95 and 90 percent to recover the full key on the first guess with the best choice of hyper-parameters and dimensionality reduction. Note the low accuracy value for CNN when using 656 PCA components: this result is actually obtained as the accuracy of CNN for a single nibble raised to the power of 64 (since now we consider 64 nibbles). If considering results after dimensionality reduction, we see that SVM is the best performing technique, which is especially apparent when using only 10 PCA components. Finally, again we see that TA is never the best performing technique.

Table 6: Cumulative probabilities of the profiling methods.

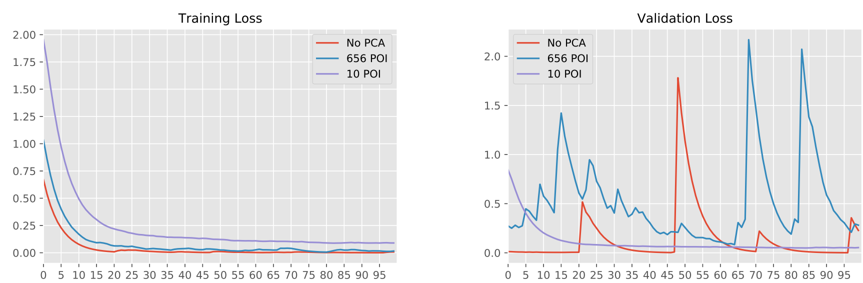
Algorithm	1 000 features	656 PCA components	10 PCA components
TA	0.86	0.90	0.33
RF	0.95	0.57	0.66
SVM (linear)	0.95	0.95	0.72
SVM (rbf)	0.95	0.95	0.72
CNN	1.00	0.03	0.07



(a) Training Accuracy (b) Validation Accuracy

Fig. 4: Accuracy of the CNN method over 100 epochs

As it can be observed from Figures 4 and 5, both scenarios without dimensionality reduction and dimensionality reduction to 656 components, reach the maximal performance very fast. On the other hand, the scenario with 10 PCA components does not seem to reach the maximal performance within 100 epochs since we see that the validation accuracy does not start to decrease. Still, even longer experiments do not show further increase in the behavior, which ultimately means that the network simply learned all that is possible and that there is no more information that can be used to further increase the performance.



(a) Training Loss (b) Validation Loss

Fig. 5: Loss of the CNN method over 100 epochs

Choosing the Minimum Number of Traces for Training on CNN As it is possible to obtain a perfect profiling phase on our dataset using CNN, we focus here on finding the smallest training set that gives a success rate of 1. More precisely, we evaluate the attacker in a more restricted setting in an effort to properly assess his capabilities [27]. To do so, we first reduce the size of the training set to k number of traces per class (in order to always have a balanced distribution of the traces), and then we gradually increase it to find out when the success rate reaches 1. We show in Table 7, the results obtained after one hundred epochs.

Table 7: Validation and test accuracy of CNN with an increasing number of training traces

Number of traces per class k	10	20	30	50	100	320
Validation accuracy	0.937	1.0	1.0	1.0	1.0	1.0
Testing accuracy	0.992	0.992	1.0	1.0	1.0	1.0

It turns out that 30 traces per class for training the CNN is enough to reach the perfect profiling of this dataset. Additional experiments did not show good enough behavior when having a lower number of traces per class. Consequently, while deep learning is usually considered in scenarios with a large training set size, we see that even in very restricted settings it can reach top performance.

5 Conclusions and Future Work

In this paper, we consider a number of profiling techniques in order to attack the Ed25519 implementation in the WolfSSL. The results show that although a number of techniques perform well, convolutional neural networks are the best if no dimensionality reduction is done. In fact, in such a scenario, we are able to obtain the accuracy of 100%, which means that the attack is perfect in the sense that we obtain the full information with only a single trace. What is especially interesting is the fact that the CNN used here is taken from related work (more precisely, that CNN is used for profiling SCA on AES) and is not adapted to the scenario here. This indicates that CNNs are able to perform well over various scenarios in SCA. Finally, to obtain such results, we require only 30 measurements per class, which results in less than 500 measurements to reach success rate of 1 with CNN.

The implementation of Ed25519 we attack here does the trade-off of security and speed and thus does not include real countermeasure for SCA (that is, beyond constant-time implementation). In future works, we will evaluate CNN for SCA on Ed25519 with different countermeasures to test the limits of CNN in side-channel analysis.

References

1. Database for EdDSA. URL: `https://anonymous.4open.science/repository/fee4f79a-5fec-480e-b09c-82c606497490/`
2. Bernstein, D.J.: Curve25519: new diffie-hellman speed records (2006). URL: `http://cr.yp.to/papers.html#curve25519`. Citations in this document **1**(5) (2016)
3. Bernstein, D.J., Duif, N., Lange, T., Schwabe, P., Yang, B.Y.: High-speed high-security signatures. Journal of Cryptographic Engineering **2**(2), 77–89 (2012)
4. Blake, I., Seroussi, G., Smart, N.: Elliptic curves in cryptography, vol. 265. Cambridge university press (1999)
5. Bohy, L., Neve, M., Samyde, D., Quisquater, J.J.: Principal and independent component analysis for crypto-systems with hardware unmasked units. In: Proceedings of e-Smart 2003 (January 2003), cannes, France
6. Breiman, L.: Random Forests. Machine Learning **45**(1), 5–32 (2001)
7. Cagli, E., Dumas, C., Prouff, E.: Convolutional Neural Networks with Data Augmentation Against Jitter-Based Countermeasures - Profiling Attacks Without Preprocessing. In: Cryptographic Hardware and Embedded Systems - CHES 2017 - 19th International Conference, Taipei, Taiwan, September 25-28, 2017, Proceedings. pp. 45–68 (2017)
8. Carbone, M., Conin, V., Cornélie, M.A., Dassance, F., Dufresne, G., Dumas, C., Prouff, E., Venelli, A.: Deep learning to evaluate secure rsa implementations. IACR Transactions on Cryptographic Hardware and Embedded Systems **2019**(2), 132–161 (Feb 2019). https://doi.org/10.13154/tches.v2019.i2.132-161, `https://tches.iacr.org/index.php/TCHES/article/view/7388`

9. Chari, S., Rao, J.R., Rohatgi, P.: Template attacks. In: International Workshop on Cryptographic Hardware and Embedded Systems. pp. 13–28. Springer (2002)
10. Chari, S., Rao, J.R., Rohatgi, P.: Template Attacks. In: CHES. LNCS, vol. 2523, pp. 13–28. Springer (August 2002), San Francisco Bay (Redwood City), USA
11. Choudary, O., Kuhn, M.G.: Efficient template attacks. In: International Conference on Smart Card Research and Advanced Applications. pp. 253–270. Springer (2013)
12. Choudary, O., Kuhn, M.G.: Efficient template attacks. In: Francillon, A., Rohatgi, P. (eds.) Smart Card Research and Advanced Applications - 12th International Conference, CARDIS 2013, Berlin, Germany, November 27-29, 2013. Revised Selected Papers. LNCS, vol. 8419, pp. 253–270. Springer (2013)
13. Fan, R.E., Chen, P.H., Lin, C.J.: Working Set Selection Using Second Order Information for Training Support Vector Machines. J. Mach. Learn. Res. **6**, 1889–1918 (Dec 2005), `http://dl.acm.org/citation.cfm?id=1046920.1194907`
14. FIPS, P.: 180-4. Secure hash standard (SHS)," March (2012)
15. Hettwer, B., Gehrer, S., Güneysu, T.: Profiled power analysis attacks using convolutional neural networks with domain knowledge. In: Cid, C., Jr., M.J.J. (eds.) Selected Areas in Cryptography - SAC 2018 - 25th International Conference, Calgary, AB, Canada, August 15-17, 2018, Revised Selected Papers. Lecture Notes in Computer Science, vol. 11349, pp. 479–498. Springer (2018). https://doi.org/10.1007/978-3-030-10970-7_22, `https://doi.org/10.1007/978-3-030-10970-7_22`
16. Heuser, A., Picek, S., Guilley, S., Mentens, N.: Lightweight ciphers and their side-channel resilience. IEEE Transactions on Computers **PP**(99), 1–1 (2017). https://doi.org/10.1109/TC.2017.2757921
17. Heuser, A., Zohner, M.: Intelligent Machine Homicide - Breaking Cryptographic Devices Using Support Vector Machines. In: Schindler, W., Huss, S.A. (eds.) COSADE. LNCS, vol. 7275, pp. 249–264. Springer (2012)
18. Kim, J., Picek, S., Heuser, A., Bhasin, S., Hanjalic, A.: Make some noise: Unleashing the power of convolutional neural networks for profiled side-channel analysis (2019)
19. Kocher, P.C.: Timing Attacks on Implementations of Diffie-Hellman, RSA, DSS, and Other Systems. In: Proceedings of CRYPTO'96. LNCS, vol. 1109, pp. 104–113. Springer-Verlag (1996)
20. LeCun, Y., Bengio, Y., et al.: Convolutional networks for images, speech, and time series. The handbook of brain theory and neural networks **3361**(10) (1995)
21. Lerman, L., Bontempi, G., Markowitch, O.: Power analysis attack: An approach based on machine learning. Int. J. Appl. Cryptol. **3**(2), 97–115 (Jun 2014). https://doi.org/10.1504/IJACT.2014.062722, `http://dx.doi.org/10.1504/IJACT.2014.062722`
22. Lerman, L., Poussier, R., Bontempi, G., Markowitch, O., Standaert, F.: Template Attacks vs. Machine Learning Revisited (and the Curse of Dimensionality in Side-Channel Analysis). In: COSADE 2015, Berlin, Germany, 2015. Revised Selected Papers. pp. 20–33 (2015)
23. Lerman, L., Poussier, R., Bontempi, G., Markowitch, O., Standaert, F.X.: Template attacks vs. machine learning revisited (and the curse of dimensionality in side-channel analysis). In: International Workshop on Constructive Side-Channel Analysis and Secure Design. pp. 20–33. Springer (2015)
24. Maghrebi, H., Portigliatti, T., Prouff, E.: Breaking cryptographic implementations using deep learning techniques. In: Security, Privacy, and Applied Cryptography Engineering - 6th International Conference, SPACE 2016, Hyderabad, India, December 14-18, 2016, Proceedings. pp. 3–26 (2016)

25. Minka, T.P.: Automatic choice of dimensionality for pca. In: Advances in neural information processing systems. pp. 598–604 (2001)
26. Oord, A.v.d., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., Kavukcuoglu, K.: Wavenet: A generative model for raw audio. arXiv preprint arXiv:1609.03499 (2016)
27. Picek, S., Heuser, A., Guilley, S.: Profiling side-channel analysis in the restricted attacker framework. Cryptology ePrint Archive, Report 2019/168 (2019), `https://eprint.iacr.org/2019/168`
28. Picek, S., Heuser, A., Jovic, A., Bhasin, S., Regazzoni, F.: The curse of class imbalance and conflicting metrics with machine learning for side-channel evaluations. IACR Trans. Cryptogr. Hardw. Embed. Syst. **2019**(1), 209–237 (2019). https://doi.org/10.13154/tches.v2019.i1.209-237, `https://doi.org/10.13154/tches.v2019.i1.209-237`
29. Picek, S., Heuser, A., Jovic, A., Ludwig, S.A., Guilley, S., Jakobovic, D., Mentens, N.: Side-channel analysis and machine learning: A practical perspective. In: 2017 International Joint Conference on Neural Networks, IJCNN 2017, Anchorage, AK, USA, May 14-19, 2017. pp. 4095–4102 (2017)
30. Picek, S., Samiotis, I.P., Kim, J., Heuser, A., Bhasin, S., Legay, A.: On the performance of convolutional neural networks for side-channel analysis. In: Chattopadhyay, A., Rebeiro, C., Yarom, Y. (eds.) Security, Privacy, and Applied Cryptography Engineering. pp. 157–176. Springer International Publishing, Cham (2018)
31. Poussier, R., Zhou, Y., Standaert, F.X.: A systematic approach to the side-channel analysis of ecc implementations with worst-case horizontal attacks. In: Fischer, W., Homma, N. (eds.) Cryptographic Hardware and Embedded Systems – CHES 2017. pp. 534–554. Springer International Publishing, Cham (2017)
32. Prouff, E., Strullu, R., Benadjila, R., Cagli, E., Dumas, C.: Study of deep learning techniques for side-channel analysis and introduction to ascad database. IACR Cryptology ePrint Archive **2018**, 53 (2018)
33. Schnorr, C.P.: Efficient signature generation by smart cards. Journal of cryptology **4**(3), 161–174 (1991)
34. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014)
35. Standaert, F.X., Malkin, T., Yung, M.: A Unified Framework for the Analysis of Side-Channel Key Recovery Attacks. In: EUROCRYPT. LNCS, vol. 5479, pp. 443–461. Springer (April 26-30 2009), Cologne, Germany