SCNet: A Neural Network for Automated Side-Channel Attack

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1 INTRODUCTION

Deep learning models have been used in many areas, such as image classification [9, 25], object detection [16], and natural language processing (NLP) [7, 26]. While deep learning has made huge improvements on computer vision (CV) and NLP, using deep learning to perform security-related tasks is also catching people’s attention. Recently, researchers pay more attention to performing cryptanalysis using neural networks, especially side-channel attacks [17, 20, 28]. We notice that Maghrebi et. al [17] have already compared a lot of machine learning models, such as random forest, support vector machine, convolutional neural network and recurrent neural network. But they evaluate them on DPA_v2 [6] with very simple structure, which is hard to realize the full potential of neural networks. More than that, they do not design a model for side-channel attack specially.

The side-channel attack (SCA) based on power consumption [3, 14, 18] is a powerful attack method. It takes advantage of information obtained by the implementation of the security algorithms (i.e. varying power consumption when the circuit runs different operations) in order to obtain part of the secret information. One of the common targets of SCA is the key used in a block cipher [12]. A block cipher consists of an encryption algorithm $E(x, k)$ and a decryption algorithm $D(y, k)$, where $x$ is the plaintext to be encrypted, $k$ is the key, and $y$ is the ciphertext. They are all binary strings with fixed lengths. Generally $x = D(y, k)$ and $y = E(x, k)$. For example in AES-128 [12], $x, y, k$ have same length 128 bits, i.e. 16 bytes.

To obtain the key $k$ fixed in a block cipher running on a cipher chip, here we discuss two main threat models in side-channel attacks based on the power of the attackers: a) The attackers can encrypt any messages they want by any key to sample the leaked information (i.e. power consumption) from the attacked chip. So they can analyze power traces by building a power consumption model to predict the key fixed in the attacked chip. All these two threat models, the attackers build a reference model based on data from different sources.

In this paper, we propose a novel approach under threat model a) to analyze power consumption information (i.e. voltages shown in...
In order to solve this problem, we propose the sampling point embedding technique, which can automatically transfer each sampling point into a vector having a fixed length to encode the leaked information behind the point. We further propose a new deep learning model, called SCNet, to automatically perform side-channel attacks with good performance. In SCNet, we propose a dilated encoder block to generate embedding vectors for sampling points. It can obtain much more diverse features and avoid over-fitting on some sensitive noise points. At the end of the block, we stack features from each encoder in this block as a whole one. The model can learn how to generate correct embedding vectors in an end-to-end fashion.

In Figure 2, we show a system architecture of predicting the secret key byte by using SCNet. A block cipher algorithm is running in a chip which attackers can input keys and plaintexts and receive ciphertexts, i.e. threat model a) we have introduced. Attackers sample the voltage signals by using a resistor when encrypting messages and choose the sampling points related with the attacked key byte to input to the model, which are called points of interest. Then, the model automatically transfer each sampling point into embedding vector and calculate crossing information which is used to predict the probability of key byte.

The commonly used evaluation method of SCA is based on the success rate (SR) and guessing entropy (GE) [23], representing whether the model predicts the right label and the average remaining workload to predict the right one, respectively. The idea is to find the SR and GE expectations under multiple power traces through multiple attack experiments. In our experiments, we use this metrics to evaluate our model and others. Mostly, we compare SCNet with ASCAD CNN model [21]. According to the result shown in [21], ASCAD CNN has better performance than template attack, VGG-16 and MLP. In addition, we compare SCNet with SCNet_seq which employs all the components in SCNet but is built in a sequential manner, i.e. without dilated blocks. In practice, we also need to consider the time complexity and storage space complexity of the attack method. Approaches that require less training and predicting data are also considered superior. Thus, we evaluate the models in terms of time consumption, model size, and number of traces required for prediction. More than that, we prefer to introduce a new view to explain how neural network can help us solve this question.

In summary, our contributions in this paper are as follows:

1. We propose SCNet. To the best of our knowledge, it is the first time to explain the reason why we can use deep learning models to help us analyze side-channel traces. And it is designed for side-channel attacks specially, so it is more powerful to attack block ciphers with defense.

2. We design dilated encoder blocks and sampling point embedding techniques to accurately obtain the crossing information between sampling points and the secret key.

3. Extensive experimental evaluations using real-world public datasets including ASCAD [21] and DPA_v4.2 [1] demonstrate that our approach is reasonable for building the attacking model.

The rest of this paper are organized as follows. Section 2 reviews related works in areas concerning techniques involved in the proposed approach. Section 3 introduces how we assume the properties of the sampling points and propose a new method to analyze the points based on their properties. Section 4 discusses the details of the proposed SCNet. Section 5 introduces the experiment settings and interprets the experimental evaluation results. Finally, in Section 6, we conclude the paper and discuss potential future...
research directions. And you can find our models and dataset from https://github.com/GuanlinLee/SCNet.

2 RELATED WORK

In this section, we review related work in areas concerning techniques involved in the proposed approach.

2.1 Side-Channel Attacking Technologies

2.1.1 Differential Power Analysis (DPA). DPA measures power levels at different parts of the cipher chip and applies statistical analysis to overcome countermeasures, such as added noise, that are applied to obscure individual bits [13, 14]. Specific operating information can be obtained by DPA to recover the secret key. Firstly, the attacker obtains many encryption traces about different plaintexts at random. Some of the traces are related with one specific bit, which is label 0; while others are related with label 1 of this bit. The positions having huge difference between 0’s traces and 1’s traces are the most related to the secret information. Then, the attacker can guess some values of the secret key and find the most related one.

2.1.2 Correlation Power Analysis (CPA). CPA was proposed by [2]. To predict the secret key, the adversary needs to model the leaking information. Usually, the adversary analyzes the correlation between a distribution \( t \) of sampling points and a distribution \( HW(y) \) of the Hamming Weight of the intermediate results of cryptography by using:

\[
C(t, y) = \frac{E[t \cdot HW(y)] - E[t]E[HW(y)]}{\sqrt{Var[t]Var[HW(y)]}}.
\]

By analyzing \( C(t, y) \), the adversary can find the most related intermediate results to obtain the secret key. Firstly, we need to measure the actual power consumption of the chip when it encrypts multiple different plaintexts. Then, we calculate power consumption which we guess is true according to the power leakage model [19]. Finally, in order to restore the secret key, we analyze the correlation between the two kinds of power consumption.

2.1.3 Template Attack. Template attack is a powerful type of side-channel attack. In order to implement a template attack, the attacker first needs to create templates of different secret keys [22] by finding a set of functions to fit the collected traces with different keys. It is common for an attacker to analyze a same device as the one being attacked. By modeling and analyzing the templates, the traces of the attacked device are further compared, and the key information can be obtained by using maximum likelihood analysis.

2.1.4 ASCAD. Prouff et al. [21] proposed the ASCAD dataset, which is a public side-channel attack dataset. In this dataset, SCA is implemented by the Advanced Encryption Standard (AES) [12]. A mask is employed to lower the correlation between the power consumption and the intermediate value of the algorithm by randomizing certain values in the AES program. The traces of masked AES in the dataset are synchronized, and no specific hardware countermeasure is activated on the ATMega8515. Only the 700 points of interest are kept in each trace. There are 50,000 traces in the train set and 10,000 traces in the testing set. They propose to use AlexNet to perform key recovery with the 2-D convolution replaced by a 1-D convolution. They compared their model with a baseline neural network (e.g. vanilla NN) and conventional methods. The results show that CNNs are much better than NNs and conventional methods.

2.2 Deep Learning Technologies

2.2.1 Neural Network. Neural network (NN) is models composed of neural units. Units are separated into many groups. Each group corresponds to a layer. NN may have hundreds of layers in a model, which includes millions of units in it. After each layer there is a non-linear activation function, e.g., Sigmoid, Tanh, ReLU [5], which introduce more non-linear characteristic to the model.

\[
\text{Sigmoid}(x) = \frac{1}{1 + \exp(-x)}
\]

\[
\text{Tanh}(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}
\]

\[
\text{ReLU}(x) = \max(x, 0)
\]

To train a NN having ability to achieve special task, we need a dataset named train set. And to validate the generalization of other datasets, we also need a valid set and a test set. During the training process, we feed the network with input data from train set to calculate the output. And the label from train set and the output are sent to the loss function which is used to obtain a objective value. Then a process named backward propagation [15] starts to compute the gradients of the units layer by layer and use the gradients to update each unit’s value. After training, the network would have a good performance on both valid set and test set.

2.2.2 Dilated Convolutions. The main application of the dilated convolution is the density prediction: computer vision applications where the projected object has a similar size and structure to the input image [27]. The filters of dilated convolution are similar to the ones in ordinary convolution, while they skip some points during convolution, which directly lead to the increase of the receptive field. In implementations, it can also decrease the number of parameters ensuring that the model has much lower over-fitting risk. By using dilated convolution, the convolutional layer can capture farther spatial information and richer semantic information.

2.2.3 Long Short Term Memory (LSTM). LSTM is a kind of the recurrent neural network (RNN), which is usually used to handle sequential data. A standard LSTM unit is called a cell, which has an input gate, an output gate, and a forget gate [10]. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of data into and out of the cell, which can reduce the influence of gradient vanishing. LSTM is currently widely used in text translation, speech synthesis, and other fields. With the deepening of the research, there are various versions of LSTM, such as GRU [4] and Bidirectional LSTM [8].

3 ATTACKING ASSUMPTIONS

In this section, we introduce some assumptions of the traces, i.e. sampling point sequences. In [14], a DPA test can be summarized as follows: let \( T_{[i, \ldots, m]}[1, \ldots, k] \) denote \( m \) traces, which consist of \( k \) sampling points. Let \( T_c[i] \) denote the \( i \)-th point within the
trace $T_c$. Let $C_1, \ldots, C_m$ denote $m$ known inputs or outputs for the traces with $C_c$ corresponding to $T_c$. Let $B(C_c, K_n)$ denote a binary valued selection function with input $C_c$ and $K_n$ as the guessed key byte. Each point $i$ in the differential trace $\Delta B_i$ for the guess $K_n$ is computed as follows:

$$\Delta B_i = \frac{\sum_{c \in 1}^m B(C_c, K_n) T_c[i]}{\sum_{c \in 1}^m B(C_c, K_n)} - \frac{\sum_{c \in 1}^m (1 - B(C_c, K_n)) T_c[i]}{\sum_{c \in 1}^m (1 - B(C_c, K_n))}.$$ 

We use the traditional methods to guide us to analyze the traces, but using a neural network.

3.1 Waveform Resolving

Suppose that the traces comprise of various kinds of operating information, such as XOR and S-Box (i.e. a nonlinear transform) [12], which satisfies:

$$x_i = \sum_{j=0}^{p-1} \sum_{l=0}^{N-1} x_{i,j,l} + \sum_{l=0}^{p-1} \epsilon_i,l,$$

$$x_{i,j} = \{x_{i,j,0}, x_{i,j,1}, \ldots, x_{i,j,N-1}\},$$

$$\epsilon_i = \{\epsilon_{i,0}, \epsilon_{i,1}, \ldots, \epsilon_{i,p-1}\},$$

where $x_{i,j}$ represents the $j$-th operating information concerning the $i$-th sampling point, and $x_{i,j}$ is an $N$-dimensional vector. $p$ is the number of different operations. $\epsilon_i$ is a $p$-dimensional noise vector. For every sampling point, there is a noise feature for each operation vector. $x_i$ is a direct representation for the information carried by the $i$-th sampling point.

For the aligned sub-traces $X$, $X'$ from two different traces, the sampling points at the same coordinate are related to the encrypting bits. That is to say when the operating bits, i.e. the intermediate results in the block cipher, are the same, the difference between the two sub-traces should only be the noise distribution:

$$X[a, b] = \{x_a, x_{a+1}, x_{a+2}, \ldots, x_b\},$$

$$X'[a, b] = \{x'_a, x'_{a+1}, x'_{a+2}, \ldots, x'_b\},$$

$$\forall (x_i - \epsilon_i), (x'_i - \epsilon'_i) \in \text{opset}_{i,k},$$

for the same intermediate results in the block cipher, $x_i - x'_i \sim (\epsilon_i - \epsilon'_i)$, where $\text{opset}_{i,k}$ denotes a set of the $k$-th ($k \leq p$) available operation at position $i$. It is assumed that every sampling point can be represented by an $N$-dimensional vector.

3.2 Waveform noise model

In template attacks [22], the multivariate Gaussian distribution is proposed to model the noise. However, here we choose to use the Wiener process to model noise to leverage temporal information. For each dimension in the $p$-dimensional vector, we assume that the noise is sampled from a same Wiener process. The Wiener process in each dimension is independent and identical:

$$\epsilon_{i,h}(t) - \epsilon_{i,h}(s) \sim N\left(0, \sigma_h 2^{(t-s)}\right),$$

for $t > s > 0$, $h \leq p - 1$.

More than that, the noise distribution between sampling points from any two different sub-traces is:

$$\forall (x_i - \epsilon_i), (x'_i - \epsilon'_i) \in \text{opset}_{i,k},$$

and $N(\mu_0, \mu_1, \mu_2, \ldots, \mu_{p-1}; \sigma_0^2, \sigma_1^2, \sigma_2^2, \ldots, \sigma_{p-1}^2)$.

4 SCNET

To obtain the crossing information automatically, we design an encoder group and stack those having different hyperparameters to build an encoding block, which is powerful enough to extract the crossing information hidden in the traces. And the model has the capability to project the sampling points to multi-scale embedding information through the encoders. The embedding vectors between different sampling points in same trace usually are various, because at different times the chip may perform a different operation or just wait for the next operation. Moreover, the waveforms of different traces vary with the plaintexts and keys. When we fix the plaintext and key, the waveform is only related to noise corresponding to the chip. So the distribution of them is $P_{\text{trace}}(X|\text{plaintext, key, noise})$.

In addition, the distribution of sampling points in the traces is $P_{\text{point}}(x_i|X, i)$. And our model estimates a distribution:

$$P(\text{key byte}|X) = P(\text{labels}|x_0, x_1, x_2, \ldots, x_{M-1}),$$

where $X$ is a trace consisted of sampling points $x_0, x_1, x_2, \ldots, x_{M-1}$, and $\text{key byte}$ is the part of the key (one byte) used to produce these points. To train the model, we adopt the multi-class cross-entropy function as the loss function:

$$\text{Loss} = -\frac{1}{\text{BatchSize}} \sum_{v=0}^{255} \sum_{z=0}^{255} (y_{v,z} \log (y'_{v,z}))$$

since there are 256 $(2^8)$ labels for each key byte.

In practice, one way to obtain the crossing information is to utilize fully connected layers. Another way is to skip some points by using dilated encoder. Both methods have their advantages and disadvantages. The first method can completely obtain the information we need. However, too many parameters make the network prone to over-fitting on noise signal. The second method avoids using too many parameters. However, the dilated encoder may avoid too many crucial points, which makes it fail to predict the key. But in order to follow the conventional methods, we decided to adopt the dilated encoder. And using a group of dilated encoders together can make sure that all crucial points will make contribution to the final output.

As we mentioned, a group of dilated encoders is used to build a encoder block. For a dilated encoder, it can bypass some values and encode the rest. But it will be very unstable if we use a hyperparameter to decide which values to ignore according to their positions or features. It is much better to use convolution layers to calculate the crossing information, because the sliding window will obtain all combination situations if there are enough layers. To bypass some values, we can pad some zeros on filters. We obtain the $i$-th output after performing an $r$-dilated encoding operation on the input $X$.
with $l$-size kernel $f$:

$$output_i = \sum_{k=0}^{l-1} x_{i+rk} * f_k,$$

where $\ast$ is the convolution operator.

According to the property mentioned in Section 3.2 of the Wiener process [24], we can use LSTM to denoise signal vectors. The structure of SCNet is shown in Figure 3. In SCNet, we incorporate six similar dilated encoder groups into each block to resolve sampling points at the same time. The LSTM layers reduce the number of feature maps after each block and ensure that the output channels are fewer than the feature maps of the next block to forget most of the duplicate and useless features.

5 EXPERIMENTAL EVALUATION

We conduct experiments based on real-world datasets to evaluate the performance of the proposed SCNet and compare with others.

5.1 Datasets

We use ASCAD dataset, which is a public side-channel dataset, to test the models. This dataset contains 50,000 items (i.e. traces) for training, which we split into the train set and the validation set; and another 10,000 items for testing. Each item has exactly 700 sampling points. All traces are generated by using different keys. The datasets has three versions with different offsets, which means these traces are not aligned and with most 0, 50 and 100 points deviation, respectively: 1) ASCAD Desync0, 2) ASCAD Desync50 and 3) ASCAD Desync100. It is suitable for evaluating the performance of models under complex conditions.

We also use DPA_v4.2 [1] to test the models. We split the raw DPA_v4.2 dataset into two parts. The first part contains 75,000 items for training, which we split into the train set and the validation set. The second part contains 5,000 items for testing. Each item has exactly 300 sampling points which are related to the 11-th byte of the AES secret key. In the train set, the items are generated by using 15 different keys. In the testing set, all the traces are generated by using a same key. Both of the datasets are acquired by the software implementing the AES algorithm with a mask.

5.2 Comparison Models

Since we evaluate our model on ASCAD as a main result, it is necessary to compare with a well designed and trained neural network as well as a traditional template attack. Thus, we adopt the ASCAD
Figure 4: The structure of SCNet_seq. The model is built in a sequential manner with the same components as in SCNet.

(a) Different number of dilated encoder groups without LSTM.
(b) Different number of dilated encoder groups with three LSTMs.
(c) Different numbers of LSTMs with same encoder groups.

Figure 5: Ablation study on DPA_v4.2 dataset.

| Model Name   | Sliding Windows Size | Dilation Rate | LSTM Dimension | Feature Maps |
|--------------|----------------------|---------------|----------------|--------------|
| SCNet        | [7;7;7]              | [15,13,11;9,7,5,5,2,1] | [16;64;256]    | [8;32;92]    |
| SCNet_seq    | [11;11;9]            | [13,11,9;13,11,9;13,11,9] | [64;128;512]  | [32,48,64;96,112,128;192,224,256] |

Table 1: The Hyperparameters of SCNet_seq and SCNet

CNN as the comparison model, in order to illustrate the effects of our design choices. Another baseline model is SCNet_seq, which is showed in Figure 4. It employs all the components in SCNet, but the whole model is built in a sequential manner. It has less dilated encoders and wider LSTM layers than SCNet. Additionally, to test the effect of LSTM layers, we compare SCNet with 6Group and 3Group. 6Group has the same block structure as SCNet, but does not contain any LSTM layer. 3Group reduces the number of dilated encoder groups in each block by 50%, and with no LSTM layer. The parameters of SCNet and SCNet_seq are shown in Table 1.

5.3 Ablation Study
To validate the effectiveness of SCNet, we perform ablation experiments on DPA_v4.2 dataset. In all experiments, we use the same
Table 2: A comparison between models and traditional method template attack. The models are trained on GTX TITAN X. "XXX Required" is the minimum number of traces for dataset "XXX", which are required to get 100%-correct forecast. "None" means that the model cannot get 100%-correct forecast within 5000 traces. [23]

|                         | ASCAD CNN | SCNet_seq | SCNet | 6Group | 3Group | Template Attack |
|-------------------------|-----------|-----------|-------|--------|--------|----------------|
| Training Time (sec)     | 14,250    | 1,000     | 1,675 | 816    | 510    | -              |
| Model Size (MB)         | 508.0     | 26.5      | 16.6  | 36.0   | 16.7   | -              |
| ASCAD Desync0 Required  | 150       | 80        | 160   | None   | None   | 190[21]        |
| ASCAD Desync50 Required | 4,570     | 1,970     | 530   | None   | 4270   | 3200[21]       |
| ASCAD Desync100 Required| None      | 2,760     | 3,700 | None   | None   | None[21]       |
| DPA_v4.2 Required       | None      | 1,690     | 1,200 | 4760   | 3,200  | 10             |

More specifically, we evaluate networks using the same sliding windows size and dilation rate without the LSTM layers at first. The experiments study the effect of different number of dilated encoder groups in each block, as shown in Figure 5a. "rank" is the position where the correct byte appears in the output, which is sorted in descending order of the probability [23]. The smallest number of traces that can reach rank 0 is the only metric in our experiments. The best result of the network without using LSTM layers is achieved by the network with three dilated encoder groups. Even we use same number of encoder groups, the one without LSTM layers can not beat the SCNet. And it is clear that without LSTM layers, the prediction curves do not decline as smoothly as the one of SCNet. This means that it is hard for the models to decrease the guess entropy by using more traces, directly. The LSTM layers can make sure that the model predicts unchanging distribution so that when predicting on more traces, it achieves better results.

Then, we evaluate networks with three LSTM layers. The experiments study the effect of the number of dilated encoder groups in each block, as shown in Figure 5b. The results achieved by the networks with between 2 to 4 groups are not good. SCNet, which uses 6 groups in each block, achieves the best result. For networks with less groups in each block, the crossing information hidden behind the traces is hard to exact. And the lowest rank appears in
each predict curve is related with the number of groups. The more groups are used, the less traces are needed to achieve the lowest point. However the lowest point is not related with the number of groups. And the model needs more groups to obtain the crossing information we need to predict the distribution.

Finally, we evaluate networks which have the same number of dilated encoder groups in each block. The experiments study the effect of different numbers of LSTM layers. The results are shown in Figure 5e. For networks with less LSTM layers, it is hard to denoise the traces. And the lowest rank appears in each predict curve is related with the number of LSTM layers, which is quite similar with the relation of the number of groups. The more LSTM layers are used, the less traces are needed to achieve the lowest point. However the model without any LSTM layer has better result than the one with one or two LSTM layers. When the model is equipped with not enough LSTM layers, the quality of the prediction distribution is not as good as the one without LSTM layers. And the model needs as much as possible LSTM layers to guarantee that the noise is denoised.

5.4 Results

We perform extensive experiments comparing the ASCAD CNN, template attack and our proposed models. Table 2 shows a detailed comparison between them. SCNet_seq and SCNet have fewer parameters than ASCAD CNN (26.5MB and 16.6MB vs 508.0MB with an almost 95% reduction) and are faster in terms of training (1,000s and 1,675s vs 14,250s with an almost 90% reduction). To compare the results, we use the same test code which is provided by [21]. Both of two models achieve significantly better performance than ASCAD CNN even template attack. For the ASCAD Desyn0 dataset, which is an aligned dataset, our two networks only need to use around a hundred traces (80 or 160) to obtain the key byte. More traces (1,970 or 530) are needed for the ASCAD Desyn0 dataset, which is a lightly unaligned dataset. Even more traces (2,760 or 3,700) are needed for the ASCAD Desyn100 dataset, which is a heavily unaligned dataset. For the DPA_v4.2 dataset, which is an aligned dataset, around one thousand traces are needed (1,690 or 1,200).

To increase the credibility of the results, we also compare SCNet with 6Group and 3Group. And the results shows that the SCNet has better performance on all datasets. The 6Group and the 3Group can only achieve relatively good results on DPA_v4.2. And on ASCAD, all three sub-datasets are extremely challenging for the 6Group and the 3Group.

Figures 6a, 6b, 6c show the performance of SCNet_seq, SCNet and ASCAD CNN on the three ASCAD datasets, respectively. In Figure 6a, there is no significant difference between the number of traces the models use to predict the key correctly. All curves are very smooth without large fluctuations. However, the biggest value of guessing entropy achieved by SCNet is lower than those of the other two approaches. In Figure 6b, SCNet achieves significantly better results than the others. And the curve of ASCAD CNN repeatedly rises and falls sharply between 300 traces and 1,500 traces. Between 1500 traces and 4,000 traces, it has a small change. In Figure 6c, SCNet_seq is better than SCNet and ASCAD CNN. The ASCAD CNN is the worst one, which can not reduce the guessing entropy to 0 in 5,000 traces. Although the ASCAD CNN curve declines, it remains within a relatively stable range finally. And the one of SCNet falls quickly at first, but it rises to a very high value and falls again. After fluctuating within a certain range, it reduces to 0 when using 3,700 traces and stays at 0. The SCNet_seq outperforms others on this dataset. The curves of it falls quickly to 0 after using 2760 traces which is about 1,000 traces less than SCNet and stays at 0 stably. In Figure 7, we only show results of SCNet_seq and SCNet, while the ASCAD CNN cannot provide the correct prediction after training. The SCNet achieves better result than SCNet_seq. The curve of SCNet shows that the guessing entropy at start is very low and it falls to 0 quickly after using 1,200 traces and does not rise again. But the SCNet_seq one is very unstable at first. It starts at a higher point and falls firstly but then rises up very fast. After rising to the highest point, it falls to 0 slowly. Finally, it stays at 0 after using 1,690 traces. Additionally, it is much easier to train models on datasets with smaller offsets, as expected.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we propose SCNet. It takes the sampling point sequences as the input and obtains the key byte, which is used in the block cipher algorithms. To obtain the key byte, SCNet adopts dilated encoders and sampling point embedding vectors to capture the cross information (high order relationship). Extensive experiments on the ASCAD and the DPA_v4.2 datasets show that SCNet can restore key bytes with significantly fewer traces than ASCAD CNN. The outcomes from this research is very useful for both attack and defense in block cipher security.

And in the future, our model may could be used to obtain the data running in GPUs when people train other models. This is a huge threat for those sensitive information and privacy. In future research, we will study how to adapt SCNet to compromise the security of today’s federated machine learning (FML) systems, thereby finding ways to improve their robustness.

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