A Protection against the Extraction of Neural Network Models

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Abstract. Given oracle access to a Neural Network (NN), it is possible to extract its underlying model. We here introduce a protection by adding parasitic layers which mostly keep unchanged the underlying NN while complexifying the task of reverse-engineering. Our countermeasure relies on approximating the identity mapping with a Convolutional NN. We explain why the introduction of new parasitic layers complexifies the attacks. We report experiments regarding the performance and the accuracy of the protected NN.

1 Introduction

Neural Networks with high accuracy require a carefully selected architecture and a long training on a large database. Thus, NN models' architecture and parameters are often considered intellectual property. Moreover, the knowledge of both the architecture and the parameters make adversarial attacks – among other kinds of attacks – easier: an attacker can easily generate small input noise that is undetectable by the human eye but still changes the model's predictions.

Several papers [4,14,15,10] have exploited the fact that a ReLU Neural Network (NN) is a piecewise linear function to extract its underlying model. Indeed, hyperplanes – where the RELU NN is linear – split the model's input space, and recovering the formed boundaries enables its extraction.

Here, we show how to modify the naturally induced division of the input space by inserting parasitic layers between the NN layers. Our parasitic layers are going to approximate the identity function, thus leaving the flow of data within the victim NN mostly unchanged, while disrupting the geometry accessible for extraction.

After finishing this introduction, we recall the aforementioned extraction of RELU NN in Sec. 2. We show in Sec. 3 following [19], how to approximate the identity through a Convolutional NN (CNN). We then describe our protection proposal in Sec. 4. Sec. 6 reports our experiments regarding the deterioration of performances and accuracy due to the addition of parasitic layers.

1.1 Background

Today, Neural Networks (NNs) are used to perform all kinds of tasks, ranging from image processing [17] to malware detection [11]. Neural Networks are al-
algorithms that, given an input $x$, compute an output $o$ usually corresponding to either a classification or a probability. NNs are organized in layers. Each layer contains a set of neurons. Neurons of a given layer are computed based on a subset from the previous layer’s parameters and parameters called weights.

There are different types of layers. Among those are:

- **Fully connected layers**: Each neuron from a layer $l_i$ is connected to all neurons from layer $l_{i+1}$. Thus, a neuron $\eta^i_k$ in a layer $l_i$ is computed as follows: $\eta^i_k = \sum_{j=1}^{n} \eta^{i-1}_j w^i_{jk}$ where $\{\eta^{i-1}_j\}_j$ are the $n$ neurons from the previous layer and $\{w^i_{jk}\}_j$ are the layer’s weights.

- **Convolutional layers**: These layers compute a convolution between one – or several – filter $F$ and windows from the input, as follows:

$$O_{i,j} = \sum_{k=1}^{h} \sum_{l=1}^{w} X_{i+k,j+l} \cdot F_{k,l}$$

The elements of the filter are the weights of the layer. The number of filters is the number of output channels. An input can have several channels. For instance, in image processing, the input of a model is usually an image with three channels, corresponding to the RGB colors.

While the different layers of an NN are linear, each layer is followed by an activation function, applied to all of the layer’s neurons. The activation function is used to activate or, on the contrary, deactivate some neurons. The most popular activation function is ReLU, defined as the maximum between 0 and the neuron.

NNs only composed of fully connected layers are called Fully Connected Networks (FCNs), while those which are mainly composed of convolutional layers are called Convolutional Neural Networks (CNNs).

A ReLU NN is a NN constituted by linear layers followed by ReLU activation functions.

Let us note that another common layer type is the pooling layer, whose goal is to reduce the dimensionality. The attacks we consider do not take them into account, as they are not piece-wise linear. For this reason, we also put ourselves in the context where pooling layers are not considered.

### 1.2 Related Works

Different kinds of reverse engineering approaches have been introduced. Batina et al. recover NNs’ structure through side channels, i.e. by measuring leakages like power consumption, electromagnetic radiation, and reaction time [1]. These measurement attacks are common for embedded devices (e.g. smartcards). Fault attacks, which are also a typical threat to smartcards, are transposed to find NN models in [3]. A weaker approach where the victim NN shares its cache memory with the attacker in the cloud is taken in [7][18]. The protections to thwart these attacks are related to the victim NN implementation. As we here consider oracle access attacks, our countermeasures have to modify the NN’s architecture itself.
A more detailed explanation of the attacks [14,15,10] is given in the next Section.

It should be noted that the abstract model of NNs that we are looking at here has been introduced by [16] while in the different context of adversarial examples. While this is, here, out-of-scope, the application of our idea to thwart adversarial examples seems intriguing.

2 Extraction of Neural Network Models

Several attacks [14,15,10] have managed to recover a ReLU NN’s weights. These attacks rely on the fact that ReLU is piecewise linear.

The attack model in [14, 10] and [15] is as follows:

– The victim model corresponds to a piecewise linear function
– The attacker can query the model
– The attacker aims at recovering the weights (and, in some cases [15], the architecture) of the victim model

Furthermore, [15] also assumes that the attacker does not know the structure (i.e. the number of neurons per layer) of the victim NN. In the case of [4], the authors assumed that the attacker had access to the architecture, but not the weights. However, the authors mentioned their belief this was not a necessary assumption, even though they did not prove it in their paper.

This attack model corresponds to the case of online services, for instance, where users can query a model and get the output, but they do not have access to the architecture and parameters of the model.

[4] is the only paper so far that proves the practicability of its attack for more than 2 layers of a given neural network, even though the theory of [14] applies to arbitrarily deep neural networks. Moreover, [4] provides a much higher accuracy with much fewer queries to the victim model.

Let $V(\eta, x)$ denote the input of neuron $\eta$, before applying the ReLU activation function, when the model’s input is $x$. For a given neuron $\eta$ at layer $l$, let us define its critical point as follows:

**Definition 1.** When, for an input $x$, $V(\eta, x) = 0$, the neuron $\eta$ is said to be at a critical point. Moreover, $x$ is called a witness of $\eta$ being at a critical point.

Finding at least one witness for a neuron $\eta$ enables the attacker to compute $\eta$’s critical hyperplane.

**Definition 2.** A bent critical hyperplane for a neuron $\eta$ is the piecewise linear boundary $B$ such that $V(\eta, x) = 0$ for all $x \in B$.

All three attacks recover the weights of each layer thanks to the following steps:

1. Identify critical points and deduce the critical hyperplanes
2. Filter out critical points from later layers
3. Deduce the weights up to the sign and up to an isomorphism
4. Find the weight signs

Although the way critical points are found and filtered out differ from an article to the other, all methods use the piecewise linearity of the ReLU activation. The main element in those attacks resides in the fact that each neuron is associated to one bent critical hyperplane (that exists because of the ReLU activation function), corresponding to the neuron’s change of sign. That hyperplane’s equation is what enables the attacker to deduce the weights.

Let us detail the attack in [4], as it is the most accurate and requires the fewest queries to the victim model so far.

Finding critical points The attacker chooses a random line \( l \) from the input space. Looking for non linearities through binary search in a large interval in that line enables the attacker to find several critical points (see Fig. 1). However, the attacker knows neither what neurons these critical points are witnesses for, nor the said neurons’ layer. Neurons from the first layer yield unbent hyperplanes, while those in the following layers are bent by the several previous ReLUs (see Fig. 2).

Recovering the weights up to a sign As seen before, the attacker has a set of witnesses for neurons in all layers. She can then carry out a differential attack in order to recover the weights and biases up to a sign.

Let us describe the attack on a simple case where the model only has one hidden layer, and the input vector space is \( \chi = \mathbb{R}^N \). Let \( x^* \) be a witness for neuron \( \eta^* \) being at a critical point. Define \( \{e_i\} \) as the set of standard basis
vectors of $\chi$. The attacker computes:

$$\alpha^i_+ = \frac{\partial f(x)}{\partial e_i} \bigg|_{x=x^*+e_i} \quad \text{and} \quad \alpha^i_- = \frac{\partial f(x)}{\partial e_i} \bigg|_{x=x^*-e_i}$$

Then, because the activation function is $ReLU(x) = \max(0, x)$, we have that: $\alpha^i_+ - \alpha^i_- = \pm A_{j,i}^{(1)} \cdot A^{(2)}$. Thus, by computing:

$$\frac{\alpha^i_+ - \alpha^i_-}{\alpha^i_+ - \alpha^i_+}$$

for all $i$, the attacker gets the weights up to a multiplicative scalar.

In the general case where the NN is deeper, and for a layer $j$, the attacker computes second partial derivatives $y_i = \{ \frac{\partial^2 f}{\partial \delta^2 i} \}$ instead of the simple ones, where the $\delta_i$ take random values. She then solves a system of equations: $h_i \cdot w = y_i$, where $h_i$ is the value of the previous layer – after the $ReLU$ – for an input model $x^* + \delta_i$. Let us note that the attacker does not know whether neuron $\eta$ is in the current layer. She therefore solves the system of equations for all layers, and only keeps the solution that appears most often. The biases can then easily be deduced from the weights.

To differentiate critical points of the current layer from other critical points, the differential attack is carried out on all the critical points and the attacker filters out the wrong critical points by observing the resulting traces.

**Recovering weight signs** In this step, the attacker proceeds recursively. The attacker has a set $\mathcal{S}$ of witnesses for unknown neurons (as found in the previous step).

Let us suppose the attacker has managed to recover the correct model up to layer $j-1$, as well as the weights up to sign for layer $j$. Let us define the polytope at layer $j$ containing $x$ as:

$$\mathcal{S} = \{ x + \delta \text{ s.t. } sign(\mathcal{V}(\eta, x)) = sign(\mathcal{V}(\eta, x + \delta)) \}$$
Thus, this polytope corresponds to the open, convex subspace shaped by the critical hyperspaces.

The attacker can easily filter out the critical points $x$ from previous layers since she already recovered the weights and biases up to layer $j$.

To filter out witnesses from layers deeper than $j + 1$, the attacker relies on the fact that the polytopes of two distinct layers have a different shape with high probability.

Finally, the attacker recovers the sign of the weights through brute force using layer $j + 1$’s witnesses.

Thus, the attacker can recover the victim model’s parameters recursively over the depth of the considered layer as described in the previous paragraphs. Moreover, even though the number of queries is linear, the work required is exponential, as explained in the previous paragraph.

3 Approximating the Identity thanks to CNNs

Our proposal is based on adding parasitic layers to the victim model, and for those layers, we rely on a CNN approximating the identity. Even though the identity mapping is one of the easiest mathematical functions, NNs, which are intrinsically nonlinear, have a hard time simulating it. In fact, because of activation functions, NNs can only approximate the identity function, without ever reaching it. However, the approximation reached can be accurate enough. We will explain what this means in the next section.

The authors of [19] first observe that while both CNNs and FCNs could approximate the identity on digits well when trained on three training examples from the MNIST dataset [13], only CNNs generalize to examples outside of the digits scope. Moreover, they state that this bias can still be observed when the models are trained with the whole MINST training set.

In order to better characterize the bias, the authors take the worst case scenario: they only train FCNs and CNNs on a single training example. Contrary to what they expected, architectures that are not too deep manage some kind of generalization: FCNs output noisy images for inputs that are not the training example, while CNNs still manage to approximate the identity. Moreover, FCNs tend to correlate more to the constant function than to the identity. The output of CNNs’ correlation with the identity function decreases with a smaller input size and a higher filter size.

The authors of [19] show – by providing possible filter values – that in their case, if the input has $n$ channels, $2n$ channels suffice to approximate the identity mapping. They also note that adding output featuremaps does help with training. Moreover, they use $5 \times 5$ filters for all their CNNs’ layers. Finally, they explain that even though 20-layer CNNs can learn the identity mapping given enough training examples, shallower networks learn the task faster and provide a better approximation.

An example of approximated identity is given in Sec. 6.
4 Our proposal

Let us consider a victim ReLU NN. The attack scenario described in Sec. 2 is based on the bent critical hyperplanes induced by the ReLU functions in the model. In [4], the bent hyperplanes are especially used in the case of expansive NNs – i.e. for which a preimage does not always exist for a given value in the output space –, in order to filter out witnesses that are not useful to the studied layer. In order to make the attacker’s task more complex, we propose to add artificial critical hyperplanes. Thus, adding artificial hyperplanes would make the attack more complex: the attacker would have to filter out the artificial hyperplanes as well as the other layers’ hyperplanes.

As explained in Sec. 3, CNNs can provide a good approximation of the identity given enough trainable examples. Moreover, they generalize well: with only a single trainable example from the MNIST dataset, CNNs up to 5 layers deep can still reach our target goal.

For this reason, we propose to add dummy hyperplanes through the insertion of parasitic CNNs approximating the identity between two layers of the victim model. Since CNNs approximate CNNs well, we only observe a very limited drop in accuracy (see Sec. 6).

Remark 1 Note that we can think of a dynamic addition of parasitic CNNs approximating the identity. For instance, considering a client-server architecture where the server is making predictions; from a client query to another, different parasitic CNNs can be added in random places of the server’s NN architecture replacing the previous ones.

Furthermore, the small CNN we add does not act on all neurons. This yields two advantages:

– The added CNN considered can be small, implying fewer computations during inference
– We can add different CNNs to different parts of the input, to further increase the difference in behavior between neurons

Fig. 3 shows an example of adding such an identity CNN between the first and the second layer of an NN with only one hidden layer.

The CNN we add consists of two hidden layers, with $5 \times 5$ filters. Indeed, as recalled in Sec. 3 a CNN with few layers and $5 \times 5$ filters can already approximate the identity on $28 \times 28$ inputs with a single training example. Thus, such a CNN is well adapted to learning the identity mapping. When the CNN receives the set of neurons from the considered layer, it first reshapes it into a square input with one channel, so that it is adapted to convolutional layers.

Moreover, for the much harder task tackled by the authors of [19], for an input with $n$ channels, $2n$ channels in the intermediary layers are enough to get a good approximation of the identity, even though more channels improve the accuracy. Since we do not constrain ourselves to training our CNN with a single example, we can limit the number of channels in the hidden layers to two –
because we consider inputs with one channel. This enables us to minimize the number of additional computations for the dummy layers, with only a slight drop in the victim model's accuracy.

5 Complexity of Extraction in the Presence of Parasitic Layers

Adding a convolutional layer with $k$ layers as described in the previous section results in adding $k$ layers to the architecture while keeping almost the same accuracy. If those $k$ layers add critical hyperplanes, then the complexity of extraction increases.

In this section, we consider a CNN added after the first layer in the victim NN. We prove that in that case, the identity CNN does add hyperplanes with high probability.

Let us suppose we add a CNN Identity layer that takes $n \times n$ inputs, and the original input size is $m$. Let $\{F_{i,j}\}_{1 \leq i \leq k, 1 \leq j \leq k}$ be its associated filter. This would result in the following weight matrix $C$:

\[
\begin{cases}
C_{i \times n+j, (i+l) \times n+j+h} = F_{i,h} & \forall 1 \leq i, j \leq n-k+1 \text{ and } 1 \leq l, h \leq k \\
C_{i,i} = 1 & \forall i \geq (n-k+1) \times (n-k+1) \\
C_{i,j} = 0 & \text{otherwise}
\end{cases}
\]

Here, without loss of generality, we consider there is no padding.

This new layer adds at most $n \times n$ bent hyperplanes. This number decreases if two neurons $\eta_i$ and $\eta_j$ share the same hyperplane.
Let $V(\eta_i, x)$ be the value of $\eta_i$ before the activation function, if the model’s input is $x$.

We need to consider two cases:

1. $\eta_i$ and $\eta_j$ are in different layers. Let us suppose that $\eta_i$’s layer is $l$ and that $\eta_j$’s layer is $l + 1$. If the layers are not consecutive, the $\eta_j$’s hyperplane is bent by ReLUs from the layers in between, making the probability of the two hyperplanes matching very low.

2. $\eta_i$ and $\eta_j$ are in the same layer

5.1 First case: $\eta_i$ is on layer $l$ and $\eta_j$ is on layer $l + 1$

Let us suppose that $\eta_i$ is on the first layer, and $\eta_j$ is on the second one. The output $z(x)$ of the first layer, for $x \in \chi$ is:

$$z(x) = A^{(1)}x + \beta^{(1)}$$

where $A^{(1)}$ is supposed to be invertible. This is an assumption made in the considered attacks, as it does not imply any loss of generality. Indeed, the dimension of the matrix can be reduced so as to remove the colinearities.

The output of the second layer is:

$$Out = C \cdot ReLU(z(x)) + \beta^{(2)}$$

Thus, since $A^{(1)}$ is invertible, there exists a solution $x^*$ such that $z(x^*) = V$. If we select $V$ so that $V_i \geq 0 \forall i \leq m$, then $V$ is not affected by the ReLU. We can therefore select a vector $V$ such that, letting $k$ be the convolutional layer’s filter size:

$$V_{(\lfloor \frac{l}{n} \rfloor + h) \times n + j \% n + l} = 0 \forall 1 \leq l, h \leq k \text{ (where } j \% n \text{ means } j \text{ modulo } n)$$

except for one value $i'$ that is not $\eta_i$, where $V_{i'} = 1$

Since this second layer is a convolutional one, $\beta^{(2)}_{i'}$ is the same for all $i$ on a given channel, denoted $\beta$. The window considered to compute $\eta_j$ is zeroed out, except for one value. The filter weight associated to that value needs to be $-\beta$ to nullify $\eta_j$. Since we can repeat the process for all values of the window that are not $\eta_i$, all the filter weights except for that associated to $\eta_i$ need to be $-\beta$ except for the one associated with $\eta_i$. This is not the case with high probability. Thus, with high probability, $\eta_i = 0$ does not imply that $\eta_j = 0$.

For deeper layers, even though we cannot select any vector $V$, it is highly unlikely for the following equation to happen:

$$z_i(x) = 0 \iff C_jReLU(z(x) + \beta^{(2)}) = 0$$

When $\eta_i$ is not in the window used to compute $\eta_j$, it is even less likely to be the case.

Therefore, two neurons on different layers are very likely to have different critical hyperplanes.
5.2 Second case: η_i and η_j are in the same layer

Let us suppose that η_i and η_j are in layer l. Let l be the first convolutional layer. Moreover, let us suppose that the CNN is set after the victim model’s first layer. Then l’s input is:

\[ z(x) = ReLU(A^{(1)}x + \beta^{(1)}) \]

where \( x \) is the model’s input.

Let us also suppose, without loss of generality, that \( j > i \). This means that the windows used to compute the two neurons are not identical. With high probability, one of the filter values associated with the disjoint window values is nonzero. For simplicity, and without loss of generality, let us suppose, in what follows, that \( F_{1,1} \) is such a filter value. Thus, in what follows, we suppose that \( F_{1,1} \neq 0 \).

Case where \( \beta = 0 \): As explained before, we can find \( x^* \) such that \( z(x^*)_{\lfloor \frac{a}{2} \rfloor \times n+i+\%n} = 1 \) and \( z(x^*)_h = 0 \) otherwise. Since \( j > i \), \( z(x^*)_{\lfloor \frac{a}{2} \rfloor \times n+i+\%n} \) is not in the window used to compute \( \eta_j \). In this case, \( \eta_i \neq 0 \) and \( \eta_j = 0 \). Thus, \( \eta_i \) and \( \eta_j \) do not share the same critical hyperplane.

Case where \( \beta \neq 0 \): If \( \beta \neq 0 \), we cannot directly apply the previous reasoning. Let \( x^* \) be a witness for \( \eta_j \) being at a critical point. Let us show that we can find an input \( x^{**} \) such that \( \eta_j = 0 \) but \( \eta_i \neq 0 \).

If \( x^* \) already satisfies this property, our work is done. Otherwise, \( x^* \) is such that \( \eta_i = \eta_j = 0 \). As explained before, there exists an input to the NN \( x' \) such that \( (A^{(1)} \cdot x')_{\lfloor \frac{a}{2} \rfloor \times n+i+\%n} = a \) with \( a > 0 \) and \( (A^{(1)} \cdot x')_h = 0 \) otherwise. Then, by piecewise linearity of \( z \), we have, for \( a \) large enough, that \( z(x^* + x')_{\lfloor \frac{a}{2} \rfloor \times n+i+\%n} > z(x^*)_{\lfloor \frac{a}{2} \rfloor \times n+i+\%n} \). Moreover, for all other indices \( h \), \( z(x^* + x')_h = z(x^*)_h \). Let us consider \( x^{**} = x^* + x' \). We have that \( z(x^{**})_{\lfloor \frac{a}{2} \rfloor \times n+i+\%n} \) is not in \( \eta_j \)’s window, which means that \( \eta_j \) remains unchanged and \( \eta_j = 0 \) when the NN’s input is \( x^{**} \). On the other hand, \( \eta_i \)’s value changes since one of its window values changes and \( F_{1,1} \neq 0 \). Thus, \( \eta_i \neq 0 \). Therefore, we can indeed find \( x^{**} \) such that \( \eta_j = 0 \) but \( \eta_i \neq 0 \).

Let us now consider the case where \( \eta_i \) and \( \eta_j \) are on deeper layers, in which case the previous proof does not hold. Let \( i = i_1 \times n + i_2 \) and \( j = j_1 \times n + j_2 \), where \( i_1 \neq j_1 \), or \( i_2 \neq j_2 \), or both. Let also \( F \) be the filter of the considered convolutional layer, of size \( k \times k \).

If \( \eta_i \) and \( \eta_j \) share the same hyperplane, then whenever \( z \) is such that \( C_iz + \beta = 0 \), we have that:

\[
\sum_{l=1}^{k} \sum_{i=1}^{k} F_{l,k} \left( z_{(i_1+l) \times n+i_2+h} - z_{(j_1+l) \times n+j_2+h} \right) = 0 \quad (1)
\]

Since Eq. \ref{eq:1} needs to hold for all the \( z \) that are on the hyperplane, this equation is very unlikely to hold.

Therefore, with a very high probability, no two neurons in the same layer share the same hyperplane.
6 Experiments

For our CNN approximating the identity – called Identity CNN from now on, we consider a CNN with two hidden layers, $5 \times 5$ filter sizes and ReLU activations. We train this model over 10,000 random input of size $16 \times 16$, and 200 runs. We reach a mean absolute percentage error of 0.0913 between the input image and the output of the CNN. We also trained a smaller CNN, with input shape $6 \times 6$, and trained over 200 runs. Apart from the input shape, this small CNN’s characteristics are the same as the previous model. We only reach a mean absolute percentage error of 0.52 between the input image and the output of the CNN for the smaller model. We denote the first CNN $ID_l$ and the second one $ID_s$.

We consider as an example a FCN (see Fig. 3) with three hidden layers – with respectively 512, 512 and 32 neurons – for the victim model, trained for image classification. We trained the model over two datasets: MNIST and CIFAR10 [13,12]. This model’s accuracy reaches a 97.9% accuracy on MNIST, and 99.6% on CIFAR10 (but only 51.7% accuracy on CIFAR10 testing set, due to overfitting).

We evaluate the accuracy of the victim model after adding CNNs following the 8 cases:

1. $ID_l$ after the first layer, on the first $16 \times 16$ neurons
2. $ID_s$ after the first layer, on the first $6 \times 6$ neurons
3. $ID_l$ after the first layer on the first $16 \times 16$ neurons, as well as $ID_l$ on the last $16 \times 16$ neurons
4. $ID_l$ after the second layer, on the first $16 \times 16$ neurons
5. $ID_s$ after the second layer, on the first $6 \times 6$ neurons
6. $ID_l$ after the second layer, on the first $16 \times 16$ neurons, as well as $ID_l$ on the last $16 \times 16$ neurons
7. $ID_l$ after the first layer, on the first $16 \times 16$ neurons, and $ID_l$ after the second layer, on the first $16 \times 16$ neurons
8. $ID_l$ after the first layer, on the first $16 \times 16$ neurons, and $ID_l$ after the second layer, on the last $16 \times 16$ neurons

On the model trained on MNIST, the accuracy does not change in any of the aforementioned cases. On the CIFAR10 dataset, the accuracy experiences a slight drop, as summarized in Table 1.

7 Conclusion

In this paper, we introduce a simple but effective countermeasure to thwart the recent wave of attacks [4,13,15,10] aiming at the extraction of NN models through an oracle access.

As a line of further research, we want to investigate the gain we get by mounting these attacks over quantized NNs [6,8,6,20]. Indeed, in the non-quantized case, a great care should be taken dealing with floating point imprecision with real numbers machine representation, as reported, for instance, by [4]. Today,
Table 1. Accuracy on CIFAR10 (testing and training datasets) of the victim model when CNNs are added as described in Sec. 6.

| Dataset            | Original Accuracy | Case 1 | Case 2  | Case 3  | Case 4  | Case 5  | Case 6  | Case 7  | Case 8  |
|--------------------|-------------------|--------|---------|---------|---------|---------|---------|---------|---------|
| CIFAR10 Testing Set| 51.7 %            | 51.6%  | 51.69%  | 51.62%  | 51.7%  | 50.8%  | 51.06%  | 51.27%  |          |
| CIFAR10 Training Set| 99.69%           | 99.5%  | 99.69%  | 99.09%  | 99.6%  | 99.29%  | 99.28%  | 99.32%  |          |

Quantized NNs share almost the same accuracy as the floating-point ones. By doing that, we are coming a step closer to differential cryptanalysis [2] performed against symmetric ciphers and which serves as an inspiration of [4]. While our protection will still be relevant, we want to explore more cryptographic techniques as alternatives.

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