Verifying the Resilience of Neural Network Watermarking

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1 Introduction

DNNs are really important and conquering the world

Learning as a service paradigm: sell your almost-trained network. What if someone tries to rip you off?

Watermarking as the solution to earlier problem. But how can we be sure watermarks are good?

DNN verification is a new and promising field. We propose a novel methodology to use verification to measure and verify the robustness of watermarking techniques. Main uses of our approach: verify watermarked networks, assess efficiency of watermarking schemes.

The rest of this paper is organized as follows. In Section 2 we provide the necessary background on DNNs, watermarking, and DNN verification. Next, in Section 3 we introduce our technique for casting the watermark resilience problem into a verification problem. Section 4 describes our implementation and evaluation of the approach on several watermarked DNNs for image recognition. We discuss related work in Section 5, and conclude in Section 6.

2 Background

[2,3]

3 Finding the minimal change that will get rid of the network's WaterMark

Given a watermarked trained neural network as described here [1]. We tested what is the minimal change to the network last layer in order to "remove" some watermarks from the network.

Guy: make this a proper citation

3.1 Defining the problem

Given a neural network N with an output size m the network decision for an input x is defined as the coordinate with the maximal value, if the network output is the vector y the decision is $argmax_{i\in[m]}\left\{y_i\right\}$

Given a watermarked network N with a set of K watermarks (A set of inputs to the network) $\{x_1,\cdots,x_K\}$ we'll mark the network last layer L such that L is a $m\times n$ matrix were n is the layer's number of neurons and m is the network output size. The change to the last layer will be a matrix with the same dimension as L we'll mark as ε, such that $\varepsilon_{i,j}$ is the change to the last layer matrix entry $L_{i,j}$. Well measure the overall change to the layer as $\|\varepsilon\|_\infty = max_{i,j}\left\{|\varepsilon_{i,j}|\right\}$.

For a certain input x we're only interested in the input to the last layer we'll mark the input to the last layer v. v is a $n\times 1$ vector. So the original network output $y=Lv$ and the changed network output is $y'=(L+\varepsilon)v$. For a single input x we need to find the minimal ε so that the $argmax_{i\in[m]}\left\{y_i\right\}\neq argmax_{i\in[m]}\left\{y'_i\right\}$

Denote $d := argmax_{i\in[m]}\left\{y_i\right\}$
For some $d'\in[m]\,, d'\neq d$ finding ε with minimal $\|\varepsilon\|_\infty$ such that $y'=(L+\varepsilon)v$ and $d' = argmax_{i\in[m]}\left\{y'_i\right\}$ can be described in a Linear Programming form like so:

$$
\begin{aligned}
Minimize:\quad & c\\
Subject\ to:\quad & \forall i,j \quad -c\leq\varepsilon_{i,j}\leq c\\
& y'=(L+\varepsilon)v\\
& y'_d\leq y'_{d'}
\end{aligned}
$$

*The variables are the entries in ε and y'

Using the same method we can find how to change the network to more than one input.
Given inputs $x_1,\cdots,x_k$ and their respective inputs to the last layer $v_1,\cdots,v_k$ and their respected outputs and decisions $\{y_1,\cdots,y_k\}$ $\{d_1,\cdots,d_k\}$ we want to find ε such that
$\forall 1\leq j\leq k \quad d_j\neq argmax_{i\in[m]}\left\{\left(\left(L+\varepsilon\right)v_j\right)_i\right\}$
Assuming we choose our new desired output $\{d'_1,\cdots,d'_k\}$ And now our LP looks like this:

$$
\begin{aligned}
&\mathit{Minimize:} && c\\
&\mathit{Subject\ to:} && \forall i,j \quad -c \le \varepsilon_{i,j} \le c\\
& && \forall j \quad y'_j = (L+\varepsilon)v_j\\
& && \forall j \quad \left(y'_j\right)_{d_j} \le \left(y'_j\right)_{d'_j}
\end{aligned}
$$

*The variables are the entries in ε and y'_j

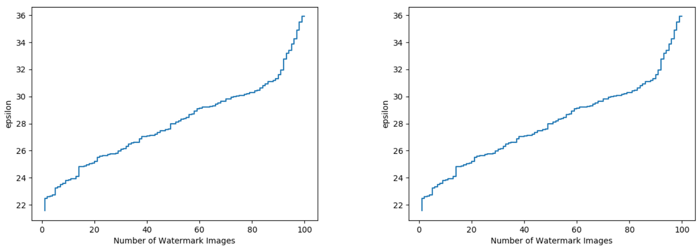
Using Marabou we can solve for the minimal ε under different norm $\|\varepsilon\|_1 = \sum_{i,j} |\varepsilon_{i,j}|$ since using this norm gives us a piece-wise linear problem.

Guy: Overall, this looks good. Some stuff will need to be moved to other sections according to the paper layout.

4 Evaluation

We tested this approach on a Neural network trained on the MNIST data set, the network was watermarked with 100 images of Gaussian noise.

Guy: I think you can start populating this section next. We will need graphs and pictures.



(a) Coffee.　　(b) More coffee.

Fig. 1: The same cup of coffee. Two times.

5 Related Work

6 Conclusion and Future Work

References

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2. G. Katz, C. Barrett, D. Dill, K. Julian, and M. Kochenderfer. Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks. In *Proc. 29th Int. Conf. on Computer Aided Verification (CAV)*, pages 97–117, 2017.
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