A Partial Break of the Honeypots Defense to Catch Adversarial Attacks

Nicholas Carlini (Google Brain)

Abstract—A recent defense proposes to inject “honeypots” into neural networks in order to detect adversarial attacks. We break the baseline version of this defense by reducing the detection true positive rate to 0%, and the detection AUC to 0.02, maintaining the original distortion bounds. The authors of the original paper have amended the defense in their CCS’20 paper to mitigate this attacks. To aid further research, we release the complete 2.5 hour keystroke-by-keystroke screen recording of our attack process at [https://nicholas.carlini.com/code/ccs_honeypot_break](https://nicholas.carlini.com/code/ccs_honeypot_break)

I. INTRODUCTION

Shan et al. [2] (CCS’20) recently proposed a honeypots-based defense against adversarial examples. This defense injects a backdoor into a neural network during training, and then shows that adversarial examples generated on this classifier share similar activation patterns to backdoored inputs—and can therefore be detected with near-perfect accuracy.

The authors of this paper provided us with early access to an implementation of this defense. We find that the baseline version of this defense is completely ineffective. We reduce the AUC to below 0.02 (random guessing gives 0.50), for a true positive of 0% at a false positive rate of 10%. In response, the authors have amended the defense introducing additional randomness and layers that mitigate this attack. This short paper analyzes the baseline version of the defense.

II. ATTACKING THE HONEYPOT DEFENSE

We assume familiarity with prior work on adversarial examples [3], and breaking adversarial examples detectors [1]. We use \( f(x) \) to denote a trained neural network evaluated on input image \( x \). An adversarial example is an input \( x' \) so that \( \|x - x'\| \) is small (under some \( \ell_p \) norm) but \( f(x) \neq f(x') \).

The Honeypot Defense injects a backdoor perturbation \( \Delta \) during the neural network training process so that for all inputs \( x \), the classifier will consistently and predictably misclassify \( f(x + \Delta) \). As a result of this backdoor, standard methods to generate adversarial examples will create examples \( x' \) that have “characteristics” of the backdoored inputs.

These characteristics are formalized by comparing the cosine similarity between the hidden vectors \( h(x') \) and the average backdoored hidden vector \( \phi = \mathbb{E}_{x \in X}(h(x + \Delta)) \). That is, for a given input \( x \), the defense computes

\[
\text{sim}(h(x), \phi) = \frac{h(x) \cdot \phi}{\|h(x)\| \|\phi\|}
\]

and rejects an input \( x \) as adversarial if \( \text{sim}(h(x), \phi) > \tau \).

Threat Model. This defense argues robustness under the \( \ell_\infty \) norm threat model (\( \epsilon = 8/255 \)) for both (a) a full white-box threat model, and (b) a limited white-box threat model where the adversary has access to the trained model \( f_0 \) but not the signature \( \phi \). The defense reports a 0.97 minimum AUC across all prior attacks, and claims a 0.76 AUC against the strongest adaptive attacks that allow a 6.3x larger distortion bound.

A. Initial White-Box Attack: Reducing AUC to 0.46

Following recent advice [4], we design a loss function to be as simple as possible to make it easy to diagnose difficulties in optimization. Thus, we adopt the most common attack technique, and minimize a weighted sum of the misclassification loss and the detection-evading loss:

\[
\arg\max_{\delta: \|\delta\|_{\infty} \leq \epsilon} \left( L_{ce}(f(x + \delta), y) - \lambda \cdot L_d(h(x + \delta), \phi) \right) \tag{1}
\]

where \( L_{ce} \) is standard cross-entropy loss, \( L_d = \text{sim}(h(x), \phi) \) is the loss of the detector (defined on the signature \( \phi \) for the hidden vector \( h(\cdot) \)), and \( \lambda \) is a hyperparameter controlling the relative importance of the two terms.\(^1\) We directly minimize this loss function with 100 iterations of \( \ell_{\infty} \)-regularized gradient descent with a step size of 0.1.

This form of loss function is not new: we used it extensively in prior work [1], and the honeypot defense paper used it to perform its own adaptive attack [2]. Nevertheless, the attack is effective at reducing the defense AUC to 0.46—below the threshold of 0.5 corresponding to random guessing. We are unable to explain why our attack succeeded when the authors attempt at this exact formulation failed.

B. Improved White-Box Attack: Reducing AUC to 0.02

The above loss formulation has a weakness: an optimal attack method should satisfy three constraints simultaneously. The final generated adversarial example:

- should introduce a sufficiently small perturbation;
- should be misclassified as a particular target class; and,
- should not be detected as adversarial by the detector.

Solving Equation\(^1\) guarantees that the perturbation is bounded correctly (because of the hard constraint), but does not guarantee the other two properties. When minimizing Equation\(^1\) we might over-optimize the cross-entropy loss at the expense of the detection loss (if \( \lambda \) is too small) or instead that we

\(^1\)We set \( \lambda = 8 \) for our attacks. Manual binary search determined that \( \lambda = 5 \) was too small and \( \lambda = 10 \) was too large. Setting \( \lambda = 8 \) was just right.
might might over-optimize the detection loss (if $\lambda$ is too big). Instead, we would like to ensure that whenever the input already adversarial, all available distortion “budget” goes into fooling the detector (and vice versa).

We thus consider an improved attack that alternates between two gradient descent procedures. As long as the input $x + \delta$ is misclassified, i.e., $f(x + \delta) \neq y$, we perform straightforward gradient descent minimizing the detection loss:

$$
\delta \leftarrow \text{proj}_{\|\delta\|\leq \varepsilon} (\delta - \eta \cdot \nabla L_d(h(x + \delta), \phi))
$$

(2)

taking steps of size $\eta$ and ensuring the perturbation remains bounded within the $\ell_\infty$ box with norm $\varepsilon$.

Alternatively, if instead $f(x + \delta) = y$, then we minimize the cross-entropy loss. As a first attempt we update with

$$
\delta \leftarrow \text{proj}_{\|\delta\|\leq \varepsilon} (\delta + \eta \cdot \nabla L_e(f(x + \delta), y)).
$$

(3)

By doing this, we can ensure that every gradient descent step is helpful: when $x + \delta$ is misclassified we take steps to reduce the likelihood it is detected; when $x + \delta$ is not misclassified we take steps to increase the cross entropy loss.

This has one drawback: often these two steps point in opposite directions. Progress is then slow, with each step “undoing” the progress made in the prior step. To alleviate this, whenever we take steps to make the input more adversarial, we ensure that doing so does not also make the input more detectable. This is achieved by ensuring that all cross-entropy steps are orthogonal to the detection gradient direction. Formally, let

$$
g_e = \nabla L_e(f(x + \delta), y)
$$

(4)

$$
g_d = \nabla L_d(h(x + \delta), \phi)
$$

(5)

then we replace Equation (3) with

$$
\delta \leftarrow \text{proj}_{\|\delta\|\leq \varepsilon} \left( \delta + \eta \cdot \left( g_e - g_d \frac{g_d \cdot g_e}{\|g_d\|} \right) \right).
$$

(6)

These two approaches are identical when allowed a sufficient number of iterations of gradient descent. However, it is easy to see why this procedure is more efficient for a limited number of gradient descent steps: for sufficiently small step sizes $\eta$, the update rule in Equation (6) is guaranteed to be orthogonal the gradient direction from Equation (5). Therefore, we never make negative progress on steps in this direction. This improved attack reduces the classifier AUC to 0.02.

C. Attacking without Signature Knowledge

The defense also claims robustness against an adversary who is not aware of the signature $\phi$. Unfortunately, the defense is also broken under this threat model. Because of the intuition of the defense—that typical adversarial examples will have a signature similar to $\phi$—it is possible to estimate it through

$$
\hat{\phi} = \mathbb{E}_{x \in \mathcal{X}}(h(A(x))
$$

where $A(x)$ generates an adversarial example on input $x$. Then we run exactly the prior attack substituting $\hat{\phi}$ for $\phi$.

More generally, consider an adversary who computes two adversarial examples $x'$ and $x''$ for a given input $x$ such that $h(x') \cdot h(x'') = 0$. Then by randomly returning one of these inputs as the result of $A(x)$, is will be definitionally impossible for the classifier to obtain greater than a 50% true positive rate.

D. Mitigating this Attack

The honeypot defense authors have mitigated this attack in the final version of their paper. We do not analyze the robustness of this modified scheme, and refer the reader to the updated paper for details on how the scheme has been modified. It is an interesting and open question to study if the improved defense could be evaded with a stronger attack.

III. Discussion

The attacks presented above are simple modifications of well-known methods, and apply gradient descent to a well-crafted loss function. This phenomenon is not new—an appropriate implementation of gradient descent has sufficed for breaking many defenses published over the last several years [4].

Although we should not require that published defenses be perfect and resist all attack, we should hope that attacks on published defenses require novel attack approaches. Even when defenses can be broken, if they require sophisticated attacks then they can be extremely valuable in order to help better understand what are and are not fundamental properties of adversarial examples. However, when breaks amount to “apply gradient descent”, there are few generalizable lessons other than that one particular idea does not work.

In order to provide more perspective, we recorded our 2.5 hour attack, keystroke-by-keystroke, to document the steps we follow. (This two and a half hours goes from first inspecting the code to the final break, and is not an atypical amount of time; attacks in [4] took similarly long.) We hope this additional artifact might prove useful for developing improved procedures for assessing performance of studied defenses:

https://nicholas.carlini.com/code/ccs_honeypot_break

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