ABSTRACT

This technical report describes a new feature of the CleverHans (Papernot et al., 2018) library called attack bundling. Many papers about adversarial examples present lists of error rates corresponding to different attack algorithms. A common approach is to take the maximum across this list and compare defenses against that error rate. We argue that a better approach is to use attack bundling: the max should be taken across many examples at the level of individual examples, then the error rate should be calculated by averaging after this maximization operation. Reporting the bundled attacker error rate provides a lower bound on the true worst-case error rate. The traditional approach of reporting the maximum error rate across attacks can underestimate the true worst-case error rate by an amount approaching 100% as the number of attacks approaches infinity. Attack bundling can be used with different prioritization schemes to optimize quantities such as error rate on adversarial examples, perturbation size needed to cause misclassification, or failure rate when using a specific confidence threshold.

1 INTRODUCTION

Many papers about adversarial examples present lists of error rates corresponding to different attack algorithms. A common approach is to take the maximum across this list and compare defenses against that error rate. We argue that a better approach is to use attack bundling: the max should be taken across many examples at the level of individual examples, then the error rate should be calculated by averaging after this maximization operation. Reporting the bundled attacker error rate provides a lower bound on the true worst-case error rate. The traditional approach of reporting the maximum error rate across attacks can underestimate the true worst-case error rate by an amount approaching 100% as the number of attacks approaches infinity. Attack bundling can be used with different prioritization schemes to optimize quantities such as error rate on adversarial examples, perturbation size needed to cause misclassification, or failure rate when using a specific confidence threshold. We contribute attack bundling to the cleverhans (Papernot et al., 2018) library.

2 COMMON REPORTING PRACTICES

In papers about adversarial examples, it is common to see tables such as Table 1. We call this a Many Attack Table (MAT). MATs report the error rate when the model is used to classify many different kinds of adversarial examples, but there is no attempt to report the worst-case performance of the model. MATs can be used to make some scientific points. For example, the MAT can be used to show that the model performs well against one attack and poorly against another attack. If the model performs well against gradient-based attacks but poorly against transfer-based attacks, a MAT could be used to argue that the model suffers from gradient masking (Papernot et al., 2017). MATs are often used to argue that a specific defense is strong because the defense performs well on many different kinds of attacks. This is an incorrect use; if the defense performs badly on even one kind of attack within the threat model under consideration, then the model performs badly. Attackers will
Table 1: Error rates under different adversarial attacks. This table is a hypothetical illustration of a Many Attack Table (MAT) that should not be used to argue that a defense is strong. This hypothetical table reports error rates for several different adversarial attacks, rather than choosing the strongest attack against each example and then reporting the resulting error rate. Showing multiple attacks without any report of the result of the maximization operation can create the misleading impression that the defense performs well because it performs well against several attacks. The existence of one successful attack in fact shows that the defense has failed.

| Attack     | No attack | Attack 1 | Attack 2 | Attack 3 |
|------------|-----------|----------|----------|----------|
|            | 1%        | 3%       | 11%      | 99%      |

Table 2: Error rates under different adversarial attacks, and the maximum error rate taken across different attacks in the table. This table is a hypothetical illustration of a Worst Attack Table (WAT) that we argue should not be used to argue that a defense is strong. This WAT does a much better job of showing that the proposed defense is broken than the MAT in Table 1 did. Unfortunately, WATs can arbitrarily underestimate the true error rate. WATs provide a lower bound on the true error rate but this bound may be very loose, so they are useful for showing that defenses are broken but not for showing that defenses work.

| Attack     | No attack | Attack 1 | Attack 2 | Attack 3 | Max |
|------------|-----------|----------|----------|----------|-----|
|            | 1%        | 3%       | 11%      | 99%      | 99% |

choose the most effective attack, not a random attack drawn from a long list of mostly ineffective attacks.

Another common type of table used in adversarial example papers is illustrated in Table 2. We call this a **Worst Attack Table** (WAT). WATs are better than MATs: they attempt to describe the worst case by taking the max across each row of a MAT. This models a scenario where the attacker tries out many attack algorithms and then deploys the single attack algorithm that causes the highest error rate. We argue that WATs are still not the correct reporting format; they can underestimate the true error rate arbitrarily badly.

Unfortunately, WATs can badly underestimate the true error rate. In general, attack algorithms can provide only a lower bound on the error rate under a particular threat model: if you run an attack and the attack fools the model, you know the model can be fooled in at least that instance, but if you run an attack and the model is not fooled, you don’t know whether or not there exists a different attack that can fool the model for this example. Unfortunately, attack algorithms remain the most popular method for evaluating the robustness of models to adversarial examples. As long as this is the case, it is important to design attack-based evaluation methodology to obtain the tightest possible lower bound on the error rate.

**Goodfellow et al. (2018)** introduced the concept of **attack bundling**. In the attack bundling approach, many different attacks are run against each example, just like when creating a MAT or a WAT. The difference is that all of these attacks are then combined to create a single stronger attack, in which the attacker chooses the best adversarial example for each clean example. Given a set of $n$ attack algorithms, the “max” column of a WAT produces a tight lower bound on the true error rate if there exists one algorithm that has optimal 0/1 loss for every example. Attack bundling produces a bound that is at least as tight as the WAT bound. The attack bundling bound is tight if for every example there exists one algorithm that has optimal 0/1 loss for that example. Table 3 shows an example dataset and illustrates how WAT can underestimate the error rate as well as how attack bundling can obtain a tighter estimate of the error rate.

In the worst case, a WAT can underestimate the true error rate by an amount approaching 100%. Suppose that there is a dataset containing $n$ examples and there is a WAT reporting the error rate for $n$ attacks. Suppose that attack $i$ results in misclassification of example $i$ and correct classification of all other examples. The error rate for each attack is thus $\frac{1}{n}$ and the max error rate across attacks is also $\frac{1}{n}$ but the error rate for attack bundling is 1. Because $\lim_{n \to \infty} \frac{1}{n} = 0$, the WAT can provide an estimate of approximately 0% error rate when the true worst-case error rate is 100%.
Table 3: An example situation where reporting the max error rate attacks underestimates the true worst-case error rate badly, but attack bundling finds the true error rate. In this example, we have a test set containing two examples, example 1 in the first row and example 2 in the second row. We have two attack algorithms, Attack 1 and Attack 2. In the second and third column where show an indicator variable describing whether the model makes an error on adversarial examples created by these algorithms. Attack 1 causes an error on example 1 and attack 2 causes an error on example 2, but the model gets the remaining adversarial examples correct. Now consider the bundled attack, where the attacker tries out both attacks and chooses the better one. As shown in the rightmost column, this causes an error for both examples. In the bottom row, we see the error rate for Attack 1 and Attack 2, as well as for the bundled attack. Because Attack 1 and Attack 2 both get an error rate of 50%, a WAT would report an estimated worst-case error rate of 50%. The bundled attack reveals that the worst-case error rate in this case is actually 100%.

3 DISCUSSION OF THREAT MODELS

Attack bundling assumes that the attacker can try many attacks on one example and see which is the most successful.

Under some black box threat models, this may not be the case. However, there is not yet any clear methodology for how to evaluate defenses in the black box setting. [Athalye et al. (2018)] thus recommend evaluating defenses primarily in the white box setting. Even in the most limited black box settings, attackers could apply the principle of fooling large ensembles of models (Liu et al., 2016) to the bundling problem. For example, the bundling algorithm could select the adversarial version of each example that fools the most ensemble members, in hopes of increasing the probability that the chosen adversarial example will also fool the completely unknown target model.

Some black box threat models do provide partial access to the model. For example, the threat model may allow the attacker to send inputs to the model and observe its output. This allows the attacker to try out all the attacks in the bundle and then use the best one.

Some defenses are designed to interfere with the attacker in ways that could interfere with attack bundling. For example, defenses based on using a stochastic model make it impossible to know exactly which output will be obtained when running a specific input. Trying $n$ attack points and then choosing the best input to re-deploy may thus not perform as well as expected, because a different output will be obtained on re-deployment. Attack bundling can still be used in these cases, for example by choosing the attack point that performs the best averaged across $m$ calls to the stochastic model. See [Carlini & Wagner (2017)] for an example of how attackers can circumvent stochastic defenses.

Some defenses try to discourage exploratory attacks by imposing negative consequences for attackers who are detected. For example, an account may be banned from a service if the account seems to be trying out multiple attacks in order to bundle them. Attackers in the white box setting can evade these kinds of defenses by running the attacks on their own copy of the model, and then deploying only the chosen attack against the target model.

The bundled attack also assumes that the attacker can try many attacks before committing to one. Real attackers may not be so powerful, even in a white box setting. For example, if the attacker has a perfect copy of the model but the starting point $x$ is not known ahead of time, and the attacker has limited time to produce an adversarial example, the attacker may not be able to bundle many attacks.
Many threat models in the adversarial example literature are based on an attacker that can make norm-constrained perturbations of clean examples. Attack bundling works in these threat models but also many other more realistic threat models. It is mostly agnostic to the action space of the attacker.

4 CONFIGURING AN ATTACK BUNDLER

Attack bundling algorithms can be configured with many different goals. When an attacker attacks a batch of clean examples using a finite amount of computation, the attacker must decide how to budget computation time for each example.

An attacker who wants to maximize error rate should clearly stop spending computation on an example after a misclassified adversarial example has been found for that particular example. Between two potential adversarial examples, the attacker prefers one that results in misclassification.

For an attacker who wants to maximize failure rate (Goodfellow et al., 2018) of a confidence thresholding defense, the attacker prefers to spend computation on examples that do not yet exceed the confidence threshold. An attacker who wants to maximize the failure rate (Goodfellow et al., 2018) of a model that uses confidence thresholding as a defense faces some special considerations. When attacking an individual example, it is not necessary to know the defender’s specific threshold \( t \) so long as \( t \geq \frac{1}{2} \). When attacking a batch of several examples, the attacker can obtain a better failure rate if the attacker knows \( t \) and spends more computation on examples for which the confidence of incorrect predictions does not yet exceed \( t \). When choosing between two potential adversarial examples, the attacker prefers the one with higher confidence.

Attackers can also use different example prioritization schemes and adversarial selection schemes to achieve other goals, such as minimizing the perturbation size needed for misclassification. Finding minimum-norm adversarial examples can be useful because the examples can be sorted by perturbation norm and used to make a plot with error rate on the vertical axis and the size of the norm ball allowed by the threat model on the horizontal axis.

Attack bundling can also be used to re-implement existing adversarial example strategies. For example, using \( n \) random restarts of gradient-based optimization (Madry et al., 2017) or \( n \) random points in a random search procedure (Athalye et al., 2018) can be regarded as bundling \( n \) different attacks.

5 EXAMPLE: ATTACKING AN MNIST MODEL

As an example, we show how attack bundling can be used to attack an MNIST model. Here we used the regularized model of Goodfellow et al. (2018), which shows some resistance to \( L^\infty \)-constrained adversarial examples. We use a \( L^\infty \) constraint \( \epsilon \) of 0.3 for MNIST digits with values in \([0, 1]\). We also clip the adversarial perturbations to this range.

6 RELATED WORK

The general principle of choosing the strongest attack for each specific context rather than evaluating each attack across all contexts is common in computer security. We are not aware of the specific origin of this idea. Athalye et al. (2018) briefly described this principle in the context of adversarial accuracy evaluations. Our contributions are to: (1) provide a general, extendable implementation in a standard library, (2) name the technique, (3) quantify the amount that the alternative techniques can underestimate, (4) describe how bundling algorithms apply to quantities other than accuracy, e.g. for making success-fail curves, (5) describe how to apply bundling in the black box setting, and (6) describe how bundling algorithms can prioritize spending computation attacking different examples.
Figure 1: We compare the MaxConfidence procedure (Goodfellow et al., 2018) using two different single attacks to the same procedure using bundled attacks. Both of the single attacks are randomly initialized projected gradient descent. We use two configurations of the attack: one that is relatively cheap using only 40 steps with step size 0.1, and another that is relatively expensive using 1000 steps with step size 0.04. The expensive attack is stronger than the cheap attack. However, a bundled attack using both of these and uniform noise attacks (to mitigate gradient masking) is just slightly stronger. Bundling multiple restarts rather than just a single start per attack results in greater strength. Rather than reporting each of these curves, and creating the psychological impression that the model performs as well as the upper-leftmost curve indicates, a paper evaluating this method as a defense should really report just the strongest bundled curve, since it has the tightest lower bound on the true failure rate. Reporting multiple curves in a separate graph may be useful for diagnosing gradient masking, etc., but is only distracting when the purpose is to argue that the defense is strong. See (Goodfellow et al., 2018) for more information about how to read these success-fail curves.


7 CONCLUSION

Attack bundling is now available as part of the cleverhans library (Papernot et al., 2018). Papers evaluating defenses by running them against attacks should switch to the new methodology.

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