Hardening Deep Neural Networks via Adversarial Model Cascades

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Abstract

Deep neural networks (DNNs) have been shown to be vulnerable to adversarial examples - malicious inputs which are crafted by the adversary to induce the trained model to produce erroneous outputs. This vulnerability has inspired a lot of research on how to secure neural networks against these kinds of attacks. Although existing techniques increase the robustness of the models against white-box attacks, they are ineffective against black-box attacks.

To address the challenge of black-box adversarial attacks, we propose Adversarial Model Cascades (AMC); a framework that performs better than existing state-of-the-art defenses, in both black-box and white-box settings and is easy to integrate into existing set-ups. Our approach trains a cascade of models by injecting images crafted from an already defended proxy model, to improve the robustness of the target models against adversarial attacks. To the best of our knowledge, ours is the first work that provides a defense mechanism that can improve robustness against multiple adversarial attacks simultaneously. We conducted an extensive experimental study to prove the efficiency of our method against multiple attacks; comparing it to numerous defenses, both in white-box and black-box setups.

1 Introduction

In the last few years, machine learning has become ubiquitous. Machine learning (ML) models, especially deep neural networks (DNNs) are used to solve complex problems in a wide range of areas; including computer vision, natural language processing, computational biology, as well as sensitive applications such as autonomous navigation, computational finance, etc. DNNs have been shown to be vulnerable to adversarial examples. Adversarial examples can thus be used to mislead ML models (neural networks in specific, which are widely used), which form the backbone of several sensitive applications. This creates a new class of security and privacy issues.

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Furthermore, adversarial examples that fool one model are often successful in deceiving other models which are trained to perform the same task; irrespective of their architectures or the datasets used to train either of them.\cite{Papernot et al., 2017}. Attackers may, therefore, conduct an attack with minimal or no knowledge about the target model (black-box attack), by training their substitute model to craft adversarial examples and use those examples to exploit the target model, even when they do not have access to the target model’s training data.\cite{Papernot et al., 2017}.

The above vulnerabilities have inspired a lot of research on how to secure neural networks against such attacks. Many of the earlier attempts have resulted only in a marginal increase in the robustness of neural networks.\cite{Huang et al., 2015, Gu and Rigazio, 2014}. Defensive Distillation\cite{Papernot et al., 2016b} and Adversarial Training\cite{Shaham et al., 2015} are among the well-known techniques to harden neural networks against adversarial attacks. Although these methods increase the robustness against white-box attacks (where the adversary has access to the target model’s architecture, weights, and data on which it was trained), they are ineffective against black-box attacks.\cite{Papernot et al., 2017}.

Liu et al. analyze the transferability of attacks for black-box scenarios\cite{Liu et al., 2016}. They provide an ensemble-driven method for generating images at the adversary’s end and claim higher attack rates. Bhagoji et al. propose a gradient estimation technique, which they claim performs as good as white-box attacks\cite{Bhagoji et al., 2017}. However, there is no record of research on defense mechanisms, that work well for unseen attacks. Tramer et al. use an ensemble of models to increase the robustness of the target model\cite{Tramer et al., 2017}. However, they use pre-trained models for transferring examples, and do not consider the scenario involving adaptive adversaries.

One of the key contributions of our paper is the fact that in addition to the traditional white-box setting, we also consider an adaptive black-box adversary that makes use of queries to the target model’s prediction function to train a proxy model. To the best of our knowledge, ours is the first work that provides a defense mechanism that can improve robustness against multiple adversarial attacks simultaneously, in both white-box and black-box settings; for attacks which the target model has been defended against, as well as those for which it hasn’t. In addition to this, we also provide an in-depth study...
2 Background

2.1 Neural Networks

A neural network is a function \( f(\vec{x}; \theta) = p \) that accepts an input \( \vec{x} \in \mathbb{R}^n \) and produces an output \( p \in \mathbb{R}^m \). The model \( f \) also implicitly depends on some model parameters \( \theta \). In this paper we focus on neural networks used as an \( m \)-class classifier, where output is computed using the softmax function. The output vector \( p \) is thus treated as a probability distribution, i.e., \( p_i \) is treated as the probability that input \( x \) has class \( i \). The classifier assigns the label \( y = \arg \max_i f(\vec{x}; \theta) \) to the input \( \vec{x} \). Let \( y_{true} \) be the correct label of \( x \). The inputs to the softmax function are called logits.

We define \( f \) to be the full neural network including the softmax function, \( Z(\vec{x}) = z \) to be the output of all layers except the softmax (so \( z \) are the logits), and \( f(\vec{x}; \theta) = \text{softmax}(Z(\vec{x})) = p \)

A neural network typically consists of layers \( f = \text{softmax} \circ f_n \circ f_{n-1} \circ \ldots \circ f_1 \)

where, \( f_i(\vec{x}) = \sigma(\theta_i \cdot \vec{x}) + b_i \)

for some non-linear activation function \( \sigma \), some matrix \( \theta_i \) of model weights, and some vector \( b_i \) of model biases. Together \( \theta \) and \( b \) make up the model parameters.

2.2 Threat Model

Given a clean (no adversarial noise) sample \( (\vec{x}, y) \sim D' \), where \( D' \) is a proxy for an unknown distribution \( D \), from which the set of samples used to train the target model \( f(\vec{x}; \theta) \) is drawn; an adversary tries to create a malicious sample \( \vec{x}_adv \) by adding a small perturbation to \( \vec{x} \), such that \( \vec{x} \) and \( \vec{x}_adv \) are close, according to some distance metric (either \( L_1 \), \( L_2 \) or \( L_\infty \) norm), and \( f(\vec{x}_adv) \neq y \). In each domain, the distance metric that we must use is different. In the space of images, which we focus on in this paper, we rely on previous work that suggests that various \( L_n \) norms are reasonable approximations of human perceptual distance.

We consider the traditional white-box adversary that has access to the target model’s weights and architecture and an adaptive black-box adversary that interacts with the model only through its predictive interface. This adaptive black-box adversary trains a proxy model \( f_{P}(\vec{x}; \theta') \) on the set \( S' = \{(\vec{x}^i, y_i')\}_{i=1}^n \) , where \( \vec{x}^i \)'s are drawn i.i.d from distribution \( D' \) and \( y_i = f(\vec{x}^i; \theta) \). In this setting, the adversary crafts adversarial examples \( \vec{x}_adv \) on the proxy model \( f_{P}(\vec{x}; \theta') \), using white-box attack strategies and uses these malicious examples to mislead the target model \( f(\vec{x}; \theta) \).

2.3 Practical Implications

Machine learning is being used in an increasing array of settings to make potential security/critical decisions: self-driving cars, drones, robots, anomaly detection, malware classification, speech recognition and recognition of voice commands, and many more. Consequently, understanding the security aspects of deep learning has become a crucial question in this area. The extent to which we can construct adversarial examples influences the settings in which we may (or may not) want to use neural networks.

In the speech recognition domain, recent work has demonstrated that it is possible to generate audio that sounds like speech to machine learning algorithms but not to humans [Carlini et al., 2016]. This can be used to control users’ devices without their knowledge. Evtimov et al. show that stickers attached to any object can be used to fool sophisticated image-recognition systems, which are extensively used in autonomous vehicles [Evtimov et al., 2017].

Given these threats, there have been various attempts to construct defenses that increase the robustness of a neural network; defined as its accuracy on adversarial examples.

2.4 Adversarial Examples

We consider two classes of adversarial examples, namely targeted and untargeted.

Given a clean sample \( \vec{x} \) and a target \( y_{target} \neq f(\vec{x}; \theta) \), it is often possible to find a malicious sample \( \vec{x}_adv \), such that \( f(\vec{x}_adv; \theta) = y_{target} \), and \( \vec{x}_adv \) is close to \( \vec{x} \) according to some distance metric (either \( L_1 \), \( L_2 \) or \( L_\infty \) norm). Such examples are called targeted adversarial examples (e.g. Jacobian-based Saliency Map Attack). Additionally, we could also generate untargeted adversarial examples \( \vec{x}_adv \) where \( f(\vec{x}; \theta) \neq f(\vec{x}_adv; \theta) \) and \( \vec{x} \) is close to \( \vec{x}_adv \) (e.g. Fast Gradient Sign Method). In practice, it has been observed that the untargeted attacks are usually less powerful than targeted attacks.

For our analyses, we consider the following attacks:

- **Jacobian-based Saliency Map Attack (JSMA)**: Uses saliency maps to pick critical pixels and modify them, constrained by \( L_0 \) norm [Papernot et al., 2016a].
- **Fast Gradient Sign Method (FGSM)**: Uses the gradient of a modified loss function to modify samples, constrained by \( L_\infty \) norm [Goodfellow et al., 2014].
- **Virtual Adversarial Perturbations (VAP)**: VAP perturbs \( \vec{x} \) in the direction that can most severely damage the probability that the model correctly assigns the label \( y \) to \( \vec{x} \) [Miyato et al., 2015].
- **Carlini & Wagner (C&W) L2 Attack**: C&W attack uses a \( L_2 \)-regularized loss function based on the logit layer representation [Carlini and Wagner, 2017].
- **Elastic Adversarial Perturbations (EAP)**: EAP is based on elastic-net regularization, using a mixture of \( L_1 \) and \( L_2 \) penalty functions [Chen et al., 2017].
- **Projected Gradient Method (PGM)**: Uses projected gradient descent (PGD) on the negative loss function [Madry et al., 2017].

Examples for each of these attacks are shown in Figure 1.
Adversarial Training
Adversarial training hardens the model against malicious examples by either re-training the model on an augmented set containing the training data and the adversarial examples or learning using the modified objective function:

$$J(\theta; \bar{x}, y) = \alpha . J(\theta; \bar{x}, y) + (1 - \alpha) . J(\theta; \Delta \bar{x}, y)$$

where $J(\theta; \bar{x}, y)$ is the original loss function. This defense aims to increase the model’s robustness by ensuring that it predicts the same class for a clean example and its corresponding example with adversarial perturbation. Adversarial training has been proved to be easily bypassed in practice; this has been attributed to the sharpness of the loss around the training examples.

Defensive Distillation
Defensive distillation hardens the model in two steps: first, a DNN with identical architecture is trained in a standard manner and during training, its soft-max layer is smoothed by dividing the logits with a constant $T$ (temperature). Then, a second model is trained, using the same inputs and its corresponding soft target labels, generated by evaluating the DNN over each of the training instances and taking the corresponding output probabilities. The second model behaves like the first one, as the soft labels convey additional hidden knowledge learned by the first model. It has been shown that similar behavior can be obtained by converting class labels into soft targets: having values close to 1 for the target class and the rest of the mass distributed on the other classes, and use these new values for training the model instead of the true labels [Warde-Farley and Goodfellow, 2016].

Although these techniques increase the robustness of the models against white-box attacks, they are ineffective against adaptive black-box attacks.

3 Approach
As described earlier, defending against adversarial examples is not an easy task; existing defense methods are only able to increase model robustness in certain settings and to a limited extent. To address this challenge, we propose Adversarial Model Cascades (AMC) which can help us secure models against adaptive black-box attacks. Our approach is to train a cascade of models by injecting images crafted from an already defended proxy model to improve the robustness against adversarial attacks. In the next section, we describe the critical steps involved in our approach; namely the construction of the proxy models and the adversarial model cascades.

3.1 Proxy Models
One of the critical steps in our proposed approach is to train a proxy (or surrogate) model to mimic the target model. The strategy is to train a proxy for the target model using unlabeled examples from the proxy distribution $D'$ and labels obtained by observing the target model's output on these examples. Then, adversarial examples are crafted using this proxy. We expect the target model to misclassify examples due to transferability between architectures [Papernot et al., 2017]. One may believe that the choice of a neural network architecture plays a vital role in the effectiveness of the proxy model and the adversary might find it hard to decide on a suitable one. However, the adversary has some partial knowledge of the oracle input (e.g., images, text) and expected output (e.g., classification) at the very least. The adversary can thus use an architecture adapted to the input-output relation. Adversaries can also consider performing an architecture exploration and train several substitute models before selecting the one yielding the highest attack success. In our research, we use an architecture similar to one of those proposed by Urban et al., which they have shown to be effective in training surrogate models (via distillation) and replicating the predictive performance of the target model [Urban et al., 2016].

3.2 Adversarial Model Cascades
Inspired by the observation that adversarial examples transfer between defended models, we propose adversarial model cascades (AMC); which trains a cascade of models by injecting examples crafted from a local proxy model (or the target model itself). The cascade trains a stack of models built sequentially, where each model in the cascade is more robust than the one before. The key principle of our approach is that each model in the cascade is optimized to be secure against a single type of attack and the knowledge from the previous model is leveraged via parameter transfer while securing the model for subsequent attacks. This technique increases the robustness of the next layer of the cascade, which ultimately yields a model which is robust to all the attacks it has been hardened against via the algorithm. We also accumulate data generated by attacks over iterations to prevent overfitting on the examples corresponding to the attack under consideration in that iteration. A high-level overview of the AMC framework is summarized in Algorithm 1.

In the case of a white-box adversary, adversarial examples $X_{adv}$ are crafted for the corresponding model $M'$ (AMC, target-hardened). For the case of an adaptive black-box adversary (AMC, local proxy), adversarial examples are crafted using an identical local proxy model $P'_1$ (whose training data...
input: Undefended model $M^0$, corresponding training set $T$ on which $M^0$ was trained

begin
  for each level (attack) $i \leftarrow 0$ to $T - 1$ of the cascade do
    Initialize model parameters of $M^{i+1}$ to $\theta_{M^i}$;
    Re-train the model on the set $T' = T \cup X_{adv}$, where $X_{adv}$ are adversarial examples, generated using the $i^{th}$ attack for which $M^{i+1}$ is optimized to be robust against;
  end

Predict using the final level: $\hat{y} = \arg\max_y M_T(x)$;

end

Algorithm 1: A high-level overview of the AMC framework. The algorithm works by transferring knowledge for a specific attack and building upon it iteratively to increase robustness.

was constructed by querying $M^i$). It is important to note that, for our approach to work on in adaptive black-box scenario, we just need access to the prediction interface of model $M^i$, which is available by default.

4 Experiments

4.1 Datasets
To measure the performance of our proposed technique, we run our experiments on three datasets standard in the computer vision/machine learning community: MNIST [Lecun and Cortes, 1998], SVHN [Netzer et al., 2011] and CIFAR-10 [Krizhevsky, 2009].

For training proxy models, we used the following datasets:

- MNIST: we generated additional data using the technique described by Loosli et al. [Loosli et al., 2007].
- SVHN: we used images from the additional set of examples available in the SVHN dataset.
- CIFAR-10: we used images from STL-10 [Coates et al., 2011] dataset corresponding to labels that are present in CIFAR-10. For the remaining classes (‘frog’), we picked images from Imagenet [Russakovsky et al., 2015] database. All of these were down-sampled to 32×32 pixels.

To ensure a fair comparison, all the target (including AMC), as well as proxy models, were trained such that they all had accuracies within the same ballpark (Table 1).

4.2 Data Preprocessing
All pixels are scaled to [0, 1]. We employ the following split strategies for all of the three datasets:

- Training data from the original dataset is split in the ratio 0.8 : 0.2 (standard split used while splitting data into train and test sets). The target model uses the larger set for training itself and the remaining data to test itself.
- Test data from the original dataset is split into two halves. The attacker model uses one half for crafting adversarial inputs, while the other half is reserved for use by the target model if and when it hardens itself.

- The attacker obtains data at its level for training and testing itself (dataset-wise, described in Section 4.1).

The data used at any stage is balanced class-wise. Data-augmentation, similar to that described by Urban et al., is used for CIFAR10 and SVHN to help prevent over-fitting [Urban et al., 2016].

4.3 Experimental Setup
We evaluate the effectiveness of our approach against adaptive black-box adversaries as follows:

1. We train two local proxy models ($P'$ & $P''$): ($P'')$ is used to strengthen (or harden) the target model and ($P''$) is used to measure the robustness of the hardened models to adversarial attacks. These models are replicas of each other since they have the same architecture and are trained over the same dataset.

2. To test the effectiveness of the model hardening algorithms, we generate adversarial examples for the local proxy model $P''$, using white-box strategies and attack the target model with these examples.

Adversarial images generated during hardening are from a set which is different from both the test and training set (Section 4.2). We observe that this practice prevents the model from over-fitting over the adversarial examples.

| Model            | MNIST | SVHN | CIFAR10 |
|------------------|-------|------|---------|
| Undefended       | 0.988 | 0.942| 0.854   |
| Defensive Distillation | 0.989 | 0.941| 0.852   |
| AMC, target-hardened | 0.987 | 0.932| 0.857   |
| AMC, local proxy | 0.989 | 0.935| 0.861   |
| Proxy (logits)   | 0.986 | 0.978| 0.829   |

Table 1: Test accuracies for various target and proxy models trained by us. Proxy(logits) corresponds to the proxy trained with access to class conditional probabilities.

Proxy Model Architecture
The architecture of the proxy model comprises 4 convolutional layers and 2 dense layers, using ReLU activations and dropout [0.4, 0.3, 0.2], along with 2 × 2 max pooling after every 2 convolutional layers. This architecture is similar to the one mentioned in Section 5.1. The same architecture is used for all three datasets, with changes in input shape accordingly.

Black Box Model Architectures
The architecture described by Clevert et al., which is the state-of-the-art for CIFAR-10, is used as the black-box architecture for CIFAR-10 and SVHN [Clevert et al., 2015]. The architecture for the MNIST-based model, however, is designed by the authors. The designed architecture is close to state-of-the-art, so not much exploration has been done for this dataset. Dropout of [0.1, 0.2, 0.2, 0.2, 0.5] is used.
Table 2: Error rates (lower is better) for various defenses against white-box and black-box attacks for MNIST, SVHN and CIFAR10. Adversarial Training[P] signifies hardening with examples generated with a local proxy for the corresponding attack. We can see AMC performing better than most defenses. Attacks \{J, F, E, C, P, V\} here correspond to \{JSMA, FGSM, EAP, C&W, PGM, VAP\} respectively.

Table 3: Error rates (lower is better) for models trained via AMC for \(n - 1\) of the attacks and tested against the \(n^{th}\) attack, for white-box and black-box settings for MNIST, SVHN and CIFAR10. We can see AMC performing better against an unseen attack than an undefended model. U, T and P correspond to the cases of unhardened, AMC target-hardened and AMC local-proxy respectively.

4.4 Empirical Results

We conducted an extensive experimental study, proving the efficiency of our method against multiple attacks, comparing it to numerous defenses, both in white-box and black-box set-ups. AMC, target-hardened uses adversarial examples generated from the target model and AMC, local proxy generates them using a local proxy. We evaluated the performance of our approach against popular defense strategies (namely adversarial training and defensive distillation) on all the three datasets listed above, for popular white-box attack algorithms such as FGSM, JSMA, and compared them with both variations of our proposed framework (Section 3.2). Defensive distillation is approximated using label noise while training the target model. Adversarial training is done by fine-tuning the plain target model with examples generated for the corresponding attack (concatenated to original training data). This technique is tried for two cases: the target model creating those examples, and a local proxy creating them. Accuracies for the models used in our experiments are given in Table 2. Note that there is no drop in accuracies for the case of adversarial hardening (for any of the attacks).

Note that the parameters for the attacks we tested were decided upon after analyzing the adversarial images produced, using them. We visually inspected some of the generated examples to make sure that they are not just noise, while at the same time trying to maximize error induced in the target model.

White-Box Attacks

We compared our proposed framework (both variations mentioned in Section 3.2) with existing defense methods. Both variations of models trained via AMC, on an average, give
higher robustness (accuracy on adversarial examples) than other defense methods. We observe that the improvement for CIFAR-10 is not appreciable, but nonetheless, it is more robust than a undefended model (Table 2). We also observed that models obtained via adversarial hardening against one kind of attack did not improve robustness against another kind of attack, whereas our models are robust against all the attacks we considered.

**Black-Box Attacks**

For the adversary’s proxy models, we consider proxies trained using three possible predictive interfaces. Given an example \( x \), the target models predictive interface returns:

1. only the most likely label \( \hat{y} \),
2. only the most likely label \( \hat{y} \) and adds label noise to it, and
3. a vector of tuples containing class conditional probabilities \( p(y_i|x) \) and the corresponding label \( y_i \).

Our proposed AMC framework outperforms existing defense methods for black-box attacks as well, irrespective of the predictive interface made available by the target model. Results for the third type of proxy (the most powerful one, having access to prediction probabilities from the target model) are summarized in Table 2. We observed similar trends for the other two kinds of proxy models. As expected, these other proxies are less successful while fooling the target model, which is explained by the higher information transfer while training the proxy with access to prediction probabilities from the target model. Robustness of models trained with AMC (both AMC,target-hardened and AMC,local proxy) is, on average, higher than other defense methods. We also observed that attacks like C&W and EAP (Section 2.4) do not generalize well from proxy to target models, giving error rates close to expected error rates for unperturbed images (1-classification accuracy).

**Generalizing to Unseen Attacks**

To study the capability of models trained via AMC to generalize, we test them on unseen attacks: we use \( n-1 \) attacks for running AMC, and the \( n^{th} \) one for performing attacks. We try this for all \( n \) possible attacks. We observe that models trained via our proposed framework outperform undefended models in terms of robustness, for both white-box and black-box settings (Table 3). In fact, the performance of AMC for unseen attacks is comparable to models hardened against those specific attacks, as well as defensive distillation.

**Variations of AMC**

To assert the importance of parameter transfer and accumulation of data across iterations in our AMC algorithm, we ran the following variations (Algorithm 1) as well:

1. No parameter transfer (\( M_{i+1} \leftarrow \theta_{M^i} \)) or accumulation of data across runs (\( T' = T \)).
2. Parameter transfer (\( M'_{i+1} \leftarrow \theta_{M^i} \)), but no accumulation of data across runs (\( T' = T \)).
3. Accumulation of data across runs (\( T' = T \cup X_{adv} \), but no parameter transfer (\( M'_{i+1} \leftarrow \theta_{M^i} \)).

We observed that having either one of parameter transfer or accumulation of data across runs by themselves give a negligible increase in robustness. Thus, we conclude that it is a combination of both these that helps the final model achieve its robustness.

**5 Discussion**

As we observe in our experiments, there doesn’t exist any defense technique that works against all adversarial attacks; hardening a model for a specific attack does not necessarily lead to an increase in robustness against future attacks of that kind. Adversarial hardening, as we observed, increased robustness only against the attack it is hardened against and did not increase robustness against other attacks. Defensive distillation was observed to increase robustness against more than one kind of attack. However, it too did not work well against all attacks; in fact, in some cases, it decreased the robustness of the target model.

Key contributions of the AMC framework proposed in the paper are as follows:

1. AMC provides robustness against all the attacks it is hardened against, thus making it an all-in-one defense mechanism against several attacks.
2. It increases the robustness of the target model against both black-box and white-box attacks, for attacks against which the model has been hardened, as well as for those against which it hasn’t been.
   - In the case of white-box attacks, AMC provides an increase in robustness of 8.175% & 7.115%, in comparison to defensive distillation and adversarial hardening.
   - In the case of black-box attacks, AMC provides an increase in robustness of 30.218% & 4.717%, in comparison to defensive distillation and local-proxy based adversarial hardening.
3. It is easy to incorporate into already trained models. As the intermediate step in building the model cascades only involves fine-tuning, it is much faster than existing defensive methods which require training from scratch.
4. The resultant model does not compromise on predictive performance since it is comparable to the original model which AMC starts with as shown in Table 1.
5. We observed that the order of attacks against which AMC is hardened does not significantly affect the resultant model’s robustness or performance. Thus, trying different orders of attacks to run this framework is not necessary.

To the best of our knowledge, ours is the first work that provides a defense mechanism that can improve robustness against multiple adversarial attacks simultaneously; in both white-box and black-box settings. We conclude that the transfer of parameters (thus transfer of knowledge) while training via our framework, as hypothesized earlier, helps increase the target model’s robustness against all attacks seen by it, and also makes it better suited for any unseen attacks in the future.
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