DEEPMASK: MASKING DNN MODELS FOR ROBUSTNESS AGAINST ADVERSARIAL SAMPLES

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ABSTRACT

Recent studies have shown that deep neural networks (DNN) are vulnerable to adversarial samples: maliciously-perturbed samples crafted to yield incorrect model outputs. Such attacks can severely undermine DNN systems, particularly in security-sensitive settings. It was observed that an adversary could easily generate adversarial samples by making a small perturbation on irrelevant feature dimensions that are unnecessary for the current classification task. To overcome this problem, we introduce a defensive mechanism called DeepMask. By identifying and removing unnecessary features in a DNN model, DeepMask limits the capacity an attacker can use generating adversarial samples and therefore increase the robustness against such inputs. Comparing with other defensive approaches, DeepMask is easy to implement and computationally efficient. Experimental results show that DeepMask can increase the performance of state-of-the-art DNN models against adversarial samples.

1 INTRODUCTION

Deep Neural Networks (DNNs) have achieved great success in a variety of applications. Classifiers based on DNN models have attained great performance on multiple security-sensitive tasks (Microsoft Corporation, 2015; Dahl et al., 2013). However, recent studies show that machine learning classifiers are vulnerable to deliberate attacks. Attackers can easily generate a malicious sample by adding a small perturbation to a normal sample. Then the malicious sample can fool the classifier and force it to yield a wrong output. Such sample is called an adversarial sample. This paper focuses on finding a defensive approach that can make DNN models perform more reliable in the face of adversarial samples.

Many recent studies focused on adversarial samples, including Szegedy et al. (2013); Papernot et al. (2015); Goodfellow et al. (2014); Wang et al. (2016); Papernot et al. (2016b;a). Different algorithms for generating adversarial samples have been invented. Szegedy et al. (2013) proposed an algorithm to generate adversarial samples using Box L-BFGS method. It also showed that same adversarial sample could be transferred to fool different DNN classifiers. Goodfellow et al. (2014) purposed fast gradient sign method, which maximizes the consequence of the attack under limited size of \( L_\infty \)-norm. Papernot et al. (2015) purposed another algorithm that generates adversarial samples following the saliency value. A recent paper Papernot et al. (2016a) proposed a black-box attack, which first approximates the target classifier and then generates adversarial samples to the approximated model.

Researchers also studied how to defend attacks enforced by adversarial samples. Goodfellow et al. (2014) showed retraining a new model using adversarial samples can improve the adversarial robustness of the model. Papernot et al. (2016b) proposed defensive distillation to make the model less sensible to gradient change. Wang et al. (2016) showed that one cause of adversarial sample is those redundant features that are unnecessary to classification. A perturbation along an unnecessary feature dimension can easily fool a classifier.

In this paper, we introduce a new defensive approach for DNN models: DeepMask. The motivation of DeepMask is to increase model robustness by removing unnecessary features. Comparing to previous defensive approach, DeepMask has the following benefits: 1. DeepMask doesn’t need...
additional training process. Therefore it is computationally efficient. 2. DeepMask can be easily applied to any base DNN models.

In the rest part, Section 2 briefly introduces the background of adversarial samples and its relationship to unnecessary features. Section 3 introduces a new defensive approach DeepMask which is simple and powerful. It removes unnecessary features in a trained DNN, and thus increase the adversarial robustness. In Section 4, experiment results show that DeepMask works effectively for a state-of-the-art DNN model.

2 BACKGROUND

2.1 ADVERSARIAL SAMPLES

For the following analysis, we denote a base DNN classifier as $F(\cdot) : \mathcal{X} \to \mathcal{Y}$. $\mathcal{X}$ represents input space. $\mathcal{Y}$ denotes the output space. $x \in \mathcal{X}$ denotes a sample.

Adversarial samples are deliberately created samples. We define an adversarial sample $x'$ as:

$$
    x' = x + \Delta x, \quad |\Delta x| < \epsilon
$$

$$
    F(x) \neq F(x')
$$

(2.1)

$\Delta x$ needs to be small so that $x$ and $x'$ are imperceptible to human eyes for image classification. However, for the machine classifier $F$, it classifies $x$ and $x'$ into two different classes. Therefore, such sample $x'$ can successfully fool a machine classifier.

2.2 ADVERSARIAL SAMPLES AND UNNECESSARY FEATURES

Wang et al. (2016) show that the effectiveness of adversarial samples is related to extra unnecessary features extracted by the machine classifier. If a classifier extracts many unnecessary features in the training process, it will be vulnerable to adversarial attacks. An example of this vulnerability is shown in Appendix Section 6.2.

To solve this problem, we then propose an approach that can reduce the number of unnecessary features. Presented in Figure 6.2, the basic motivation is that the distance between an adversarial sample and its seed example will be small along relevant feature dimension (e.g. hardly visible by humans eyes) and relatively large along the unnecessary dimensions for the current task. DNN combines feature extraction and classification in one model. Therefore, we propose to remove unnecessary features for a DNN model by directly modifying its network structure.

3 METHOD: DEEPMASK

The basic idea is to remove those unnecessary features used by adversarial samples. To identify which feature is unnecessary, we test pairs of adversarial samples $x'$ and its normal seed $x$, and compare the difference between the extracted features in DNN. Those features changed rapidly are utilized by the adversary, and thus should be removed to improve the robustness of the model.

To remove those features, we insert a mask layer in DNN model, right before the linear layer handling classification. The proposed structure is shown in Figure 1.

![Figure 1: A sketch of DeepMask: A mask layer is added with weight 0 and 1 between the inspected feature extraction layer and its next layer. The mask is applied through an element-wise multiplication.](image-url)
The input of the mask layer is feature vector extracted by layers of DNN model. The weight of the mask layer is either 0 or 1. An element-wise multiplication is done in the mask layer. Therefore, the output is either the input feature or 0. Features are sorted by its sensitivity to adversarial samples, which can be measured by the distance between pairs of adversarial samples and normal samples.

The process is summarized in Algorithm 1. X can be a set of the full training set. Therefore, the process of learning the mask can be really fast. No retraining of the model is needed.

Algorithm 1 DeepMask algorithm

Input: Training set $X$, DNN classifier $F$, adversarial power $\epsilon$.

1: Initialize a vector $v$ with all 0.
2: for $\forall x \in X$ do
3: Generate an adversarial sample $x'$ using sample $x$ with power $\epsilon$.
4: Forward $x$ into the network, get the output feature vector $O_1$
5: Forward $x'$ into the network, get the output feature vector $O_2$
6: Add $|O_1 - O_2|$ into $v$.
7: end for
8: Set $v$’s top $m$ entries to 0 and the rest to 1.
9: Insert the mask layer $v$ into DNN $F$ after the inspected feature layer.

4 Experiments

4.1 Experiment Setting

• Dataset: We choose CIFAR-10 (Krizhevsky & Hinton, 2009) as the dataset of our experiment. CIFAR-10 is a image dataset with 50,000 32x32 training images and 10,000 testing images.

• We choose a Residual network with 164 layers(He et al., 2016) as our target DNN model. The model is pre-trained and achieves state-of-the-art performance on the corresponding dataset.

• Metric: We generate adversarial samples for every sample in the test set and test all adversarial samples on each DNN model. The accuracy on the adversarial sample set is reported as “adversarial accuracy” to measure the adversarial robustness of a DNN model.

4.2 Experiment Result

The result of DeepMask against adversarial samples is displayed in Table 1. DeepMask can reduce the effectiveness of such adversarial samples by 10%. The adversarial perturbation is generated using fast gradient sign method (Appendix Section 6.1).

| Nodes removed(%) | Adversarial accuracy | Relative increase | Accuracy | Relative decrease |
|------------------|----------------------|-------------------|----------|-------------------|
| 0                | 0.2961               | 0.00%             | 0.943    | 0.00%             |
| 1                | 0.3923               | 32.49%            | 0.9372   | -0.62%            |
| 2                | 0.4234               | 42.99%            | 0.9132   | -3.16%            |
| 3                | 0.414                | 39.82%            | 0.9093   | -3.57%            |
| 4                | 0.4146               | 40.02%            | 0.8954   | -5.05%            |
| 5                | 0.4229               | 42.82%            | 0.9      | -4.56%            |
| 6                | 0.4173               | 40.93%            | 0.9017   | -4.38%            |

Table 1: The result of DeepMask on Res-net against adversarial attacks.

Table 1 also indicates that only a small percentage of features are important for adversarial samples. In the figure, masking 1% of features can increase the adversarial performance by 5%. Therefore, we only need to remove a small percent of features to improve the adversarial robustness greatly, and the model still achieves high accuracy on normal test samples.

5 Conclusion

In this study, we present DeepMask, a simple and cost-efficient strategy to reduce the effectiveness of adversarial samples on DNN classifiers. Many other possible strategies can be designed, for example, by adding masks that consider the difference among output labels.
REFERENCES

George E Dahl, Jack W Stokes, Li Deng, and Dong Yu. Large-scale malware classification using random projections and neural networks. In ICASSP, 2013.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572, 2014.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778, 2016.

Alex Krizhevsky and Geoffrey Hinton. Learning multiple layers of features from tiny images. Technique report, University of Toronto, 2009.

Microsoft Corporation. Microsoft Malware Competition Challenge. https://www.kaggle.com/c/malware-classification, 2015.

Nicolas Papernot, Patrick McDaniel, Somesh Jha, Matt Fredrikson, Z Berkay Celik, and Ananthram Swami. The limitations of deep learning in adversarial settings. arXiv preprint arXiv:1511.07528, 2015.

Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z Berkay Celik, and Ananthram Swami. Practical black-box attacks against deep learning systems using adversarial examples. arXiv preprint arXiv:1602.02697, 2016a.

Nicolas Papernot, Patrick McDaniel, Xi Wu, Somesh Jha, and Ananthram Swami. Distillation as a defense to adversarial perturbations against deep neural networks. In Security and Privacy (SP), 2016 IEEE Symposium on, pp. 582–597. IEEE, 2016b.

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. arXiv preprint arXiv:1312.6199, 2013. URL http://arxiv.org/abs/1312.6199.

Beilun Wang, Ji Gao, and Yanjun Qi. A theoretical framework for robustness of (deep) classifiers under adversarial noise. arXiv preprint arXiv:1612.00334, 2016.
6 APPENDIX

6.1 FAST GRADIENT SIGN ALGORITHM

As introduced in Section 1, multiple algorithms have been proposed to generate x among them. Fast Gradient Sign Algorithm proposed by Goodfellow et al. (2014) is one efficient algorithm in creating adversarial samples. The perturbation is calculated through the following equation:

$$\Delta x = \epsilon \text{sign}(\nabla_z \text{Loss}(F(z), F(x)))$$  \hspace{1cm} (6.1)

This is motivated by controlling the $L_\infty$ norm of $\Delta x$, which results in the size of perturbation in each feature dimension are the same size. Maximizing the difference between $x$ and $x'$ while limit the $L_\infty$ norm of $\Delta x$ is to follow the gradient direction on $x$ on every dimension, which is exactly the sign of the gradient function.

6.2 EXAMPLE OF AN UNNECESSARY FEATURE CAN BE UTILIZED BY ADVERSARIAL SAMPLES

Figure 3: A sketch of the vulnerability of machine learning models when extracting unnecessary features.

Figure 6.2 shows a situation when a linear classification model faces unnecessary feature. In this case, human annotators only use one feature to do the separation. But since the machine classifier use one extra feature, the attacker can push the original sample (blue cross) along that extra feature dimension(y-axis) to generate an adversarial samples (green cross), which is misclassified by the classification model.