BATT: BACKDOOR ATTACK WITH TRANSFORMATION-BASED TRIGGERS

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ABSTRACT

Deep neural networks (DNNs) are vulnerable to backdoor attacks. The backdoor adversaries intend to maliciously control the predictions of attacked DNNs by injecting hidden backdoors that can be activated by adversary-specified trigger patterns during the training process. One recent research revealed that most of the existing attacks failed in the real physical world since the trigger contained in the digitized test samples may be different from that of the one used for training. Accordingly, users can adopt spatial transformations as the image pre-processing to deactivate hidden backdoors. In this paper, we explore the previous findings from another side. We exploit classical spatial transformations (\textit{i.e.}, rotation and translation) with the specific parameter as trigger patterns to design a simple yet effective poisoning-based backdoor attack. For example, only images rotated to a particular angle can activate the embedded backdoor of attacked DNNs. Extensive experiments are conducted, verifying the effectiveness of our attack under both digital and physical settings and its resistance to existing backdoor defenses.

Index Terms— Backdoor Attack, Physical Attack, Backdoor Learning, Trustworthy ML, AI Security

1. INTRODUCTION

Currently, deep neural networks (DNNs) have been widely adopted in many applications, such as facial recognition \cite{1, 2, 3}. However, their success relies heavily on large amounts of training data and massive computational power that are not readily available to all researchers and developers. Accordingly, people usually adopt third-party training data, outsource their training process to third-party computational platforms (\textit{e.g.}, Google Cloud or Amazon Web Services), or even directly use third-party models. However, when using these resources, the training procedures are no longer transparent to users and may bring new security threats.

Backdoor attack is one typical training-phase threat \cite{4, 5, 6}. It is also the main focus of this paper. Specifically, backdoor adversaries poison a few training samples by adding pre-defined trigger patterns to their images and modifying their labels to a specific target label. These generated poisoned samples and remaining benign samples will be used to train victim DNNs. In this way, the attacked model will learn hidden backdoors, \textit{i.e.}, the latent connections between trigger patterns and the target label. In the inference process, the adversaries can use pre-defined trigger patterns to activate hidden backdoors, leading to malicious model predictions.

Currently, most of the existing backdoor attacks are static \cite{4, 7, 8}, where adversaries adopted the same trigger patterns in the inference process as those used in the training process. Recent research \cite{9} demonstrated that these attacks are vulnerable to spatial transformations (\textit{e.g.}, flipping and shrinking) that can change the location or the appearance of trigger patterns in the poisoned images. Accordingly, existing attacks have minor effects in the physical world. The difference is mostly caused by the change in distance and angle between the camera and the target object, which is similar to introducing spatial transformations. In this paper, we explore these findings from another side:

\textit{Can we use the transformations as triggers to design more effective and stealthy attacks?}

The answer to the aforementioned question is positive. In this paper, we design a simple yet effective method, dubbed backdoor attack with transformation-based triggers (BATT)\textsuperscript{1}. Specifically, we transform a few images with a specific parameter (\textit{e.g.}, rotate to a particular angle) and change their labels to the target label. We also transform the images of remaining samples with other random parameters while keeping their labels unchanged, to encourage that only the transformations using this adversary-specified parameter can activate model backdoors. Our attack is stealthy, since spatially transformed images are still natural to human inspection while it can naturally circumvent many backdoor defenses. In particular, our BATT is still effective in the physical world, where spatial transformations are also feasible.

\textsuperscript{1}Note that there is a concurrent research \cite{10} having similar attack approaches, although with different motivations.
In conclusion, our main contributions are three-fold. 1) We reveal that users can also adopt spatial transformations to design feasible backdoor attacks (instead of backdoor defenses). 2) We design a simple yet effective attack (i.e., BATT) with transformation-based triggers that are also feasible under the physical setting. It is a new attack paradigm whose triggers are not designed in a simple pixel-wise manner. 3) We conduct extensive experiments on benchmark datasets, verifying attack effectiveness under both digital and physical settings and its resistance to existing defenses.

2. THE PROPOSED METHOD

2.1. Threat Model

In this paper, we focus on the poison-only backdoor attack in image classification. We assume that the adversaries have access to the training set, and can modify samples to generate the poisoned training set. However, they have no information about and cannot change other training components (e.g., training loss and model structure).

In general, the backdoor adversaries have three main targets. Firstly, the backdoored models should correctly classify benign data. Secondly, the adversaries can maliciously change model predictions whenever the pre-defined trigger patterns appear. Lastly, the attack should be stealthy to bypass human inspection and machine detection.

2.2. Designing the Backdoor Attack with Transformation-based Triggers (BATT)

In this section, we first briefly review the main pipeline of poison-only backdoor attacks and then illustrate the technical details of our proposed BATT method. The main pipeline of our attack is shown in Figure 1.

The Main Pipeline of Poison-only Backdoor Attacks. Poisoning a few training data is the most direct and classical method to implant hidden backdoors. Let $D_o = \{(x_i, y_i)\}_{i=1}^N$ indicates the original training dataset containing $N$ samples. The adversaries will first randomly select a subset $D_o$ from $D_o$ to generate its modified version $D_m$ by adding trigger patterns to their images and change all labels to the pre-defined target label $y_t$, i.e., $D_m = \{(G(x), y_t) | (x, y) \in D_o\}$ where $G$ is the adversary-specified poisoned image generator. For example, $G(x) = x + t$ in the ISSBA [11], where $t$ is the trigger pattern. After that, they will combine $D_o$ and remaining benign samples $D_o - D_m$ to generate the poisoned dataset $D_p$, which will be released to victim users to train their models. In particular, $\gamma = \frac{|D_p|}{|D_o|}$ is called poisoning rate.

In general, the differences between our method and existing attacks lie in two main aspects, including the generation of poisoned samples and the poisoned dataset, as follows:

Generating Poisoned Samples. Different from previous attacks adding trigger patterns in a simple pixel-wise manner (e.g., patch replacement [4] or pixel-wise perturbation [11]), we use spatial transformations that could happen in the physical world with the specific parameter $\theta^*$ to design poisoned samples. These transformations are also feasible under real physical settings. Specifically, we consider two classical transformations, including 1) rotation and 2) translation, in this paper. We call them BATT-R and BATT-T, respectively. Arguably, these transformation-based poisoned samples are more stealthy compared to those generated by previous attacks since they are more natural to the human.

Generating the Poisoned Dataset. We adopt randomly transformed benign samples instead of the original ones (i.e., $D_o - D_m$) to generate the poisoned dataset. Specifically, let $T(\cdot; \theta)$ denotes the adversary-specified transformation (with parameter $\theta$), we have $D_p = D_m \cap D_t$ where $D_t = \{(T(x_i; \theta_i), y_t) | (x_i, y_t) \in (D_o - D_m), \theta_i \sim \Theta\}$ and $\Theta$ is the pre-defined value domain. This approach is to encourage that only the transformation with parameter $\theta^*$ instead of all parameters can activate model backdoors.

Fig. 1: The main pipeline of our BATT. In the first stage, our BATT first transforms a few randomly selected images with a specific parameter (e.g., rotation with a particular angle) and changes their labels to the target label. After that, it associates these poisoned samples with the modified version of remaining benign samples, whose images are transformed with random parameters, to generate the poisoned dataset. In the second stage, victims train their models on the poisoned dataset. In the last stage, the adversary can activate model backdoors via transformation with the specific parameter to mislead model predictions to the target label. Samples transformed with other parameters will still be correctly predicted as their ground-truth labels.
Table 1: The main results of methods on the CIFAR-10 and GTSRB datasets.

| Dataset | Metric | No Attack | BadNets | Blended | WaNet | ISSBA | PhysicalBA | BATT-R (Ours) | BATT-T (Ours) |
|---------|--------|-----------|---------|---------|-------|-------|------------|--------------|--------------|
| CIFAR-10 | BA (%) | 92.26 | 91.95 | 91.62 | 91.04 | 88.33 | 91.62 | 90.35 | 91.74 |
|         | ASR (%) | 9.98 | 97.24 | 84.40 | 96.81 | 99.99 | 94.82 | 99.70 | 99.66 |
| GTSRB   | BA (%) | 97.51 | 97.39 | 97.53 | 97.02 | 98.27 | 92.23 | 99.32 | 96.77 |
|         | ASR (%) | 5.75 | 94.79 | 85.39 | 67.66 | 100.00 | 90.32 | 99.97 | 99.92 |

3. EXPERIMENTS

3.1. Main Experimental Settings

Dataset and Model. In this paper, we conduct experiments on two benchmark datasets, including GTSRB [12] for classifying traffic signs and CIFAR-10 [13] for nature images classification. We resize all images to $3 \times 32 \times 32$. We use ResNet-18 [14] as the model structure on both datasets.

Baseline Selection. We compare our BA TT with five representative baseline attacks, including 1) BadNets [4], 2) backdoor attack with blended strategy (dubbed ‘Blended’) [15], 3) WaNet [7], 4) ISSBA [11], and 5) physical backdoor attack (dubbed ‘PhysicalBA’) [9]. We also provide the results of the model trained on benign samples (dubbed ‘No Attack’) as another baseline for reference.

Attack Setup. For all attacks, we set the poisoning rate as 5% and the target label as ‘1’ on both datasets. Specifically, in our BATT-R, we used a counterclockwise rotation with $\theta_r = 16^\circ$ to generate poisoned samples and assign $\Theta_r = [-10^\circ, 10^\circ]$; We translate images to the right-side with $\theta_t = 6$ (pixels) and set $\Theta_t = [-3, 3]$ (pixels) in our BATT-T. We implement all baseline methods based on BackdoorBox [16].

Evaluation Metric. We use attack success rate (ASR) and benign accuracy (BA) to evaluate the effectiveness of methods [5]. The higher the ASR and the BA, the better the attack.

3.2. Main Results in the Digital Space

As shown in Table 1, the performance of our BATT-R and BATT-T (with adversary-specified parameter $\theta^*$) is on par with or better than that of all baseline methods. Specifically, their attack success rate (ASR) is greater than 99.5% while their benign accuracy (BA) is larger than 90% in all cases.

In particular, we present the results of our attacks on poisoned testing samples generated by the same transformation but with different parameters, to verify that only the adversary-specified $\theta^*$ instead of all parameters can activate model backdoors. As shown in Figure 2, the ASR decreases significantly when using parameters inconsistent with $\theta^*$. However, we notice that some parameters may also trigger relatively high ASR, especially those near $\theta^*$. We will discuss how to further alleviate this problem in our future work.

3.3. Main Results in the Physical Space

As illustrated in Section 2.2, rotations and translations are the feasible approximation to the transformations involved in the physical world. In this section, we verify the effectiveness of our BATT in the physical space.

For simplicity, we take our BATT-R on GTSRB as an example for the discussion. Specifically, we take photos of some real-world traffic signs with different angles, based on the camera in iPhone (as shown in Figure 3). We adopt the attacked model obtained in Section 3.2 to predict the label of all captured images. The results show that all images with the specific angle (those in the last column) are predicted as the target label, while the predictions of images with other angles (second to fourth columns) are their ground-truth labels.

Fig. 2: The performance of BATT-R and BATT-T w.r.t. different transformation parameters used in the inference process on GTSRB. The dashed lines indicate adversary-specified parameter $\theta^*$ used for training backdoored DNNs.

Fig. 3: Digital samples and their physical versions taken by a camera with different angles. All images with the specific angle (last column) are predicted by our BATT-R as the target label, while the predictions of images with other angles (second to fourth columns) are their ground-truth labels.
3.4. Ablation Study

Effects of the Trigger Pattern. Here we discuss whether our methods are still effective with different trigger patterns (i.e., different $\theta^*$. As is shown in Figure 4, our attacks are still effective as long as $|\theta^*| \gg 0$. If the $|\theta^*|$ are too small, the poisoned samples will serve as the outliers since the target label is usually different from their original label, resulting in relatively low benign accuracy and attack success rate.

Effects of the Target Label. In this part, we discuss whether our methods are still effective with different target labels $y_t$. As shown in Table 2, our attacks can reach high BA and ASR in all cases, although there may have some fluctuations.

3.5. The Resistance to Potential Defenses

The Resistance to Trigger-synthesis-based Defenses. Here we discuss whether our methods are still effective with different trigger patterns (i.e., different $\theta^*$. As is shown in Figure 4, our attacks are still effective as long as $|\theta^*| \gg 0$. If the $|\theta^*|$ are too small, the poisoned samples will serve as the outliers since the target label is usually different from their original label, resulting in relatively low benign accuracy and attack success rate.

Effects of the Target Label. In this part, we discuss whether our methods are still effective with different target labels $y_t$. As shown in Table 2, our attacks can reach high BA and ASR in all cases, although there may have some fluctuations.

The Resistance to Classical Model-repairing-based Defenses. In this part, we explore the resistance of our attacks to two representative backdoor defenses, including fine-tuning [19] and model pruning [20], which aim to remove backdoors in a trained model. As shown in Figure 5, fine-tuning has minor effects in reducing ASR even after 30 epochs. Model pruning can significantly reduce the ASR when the pruning rate is greater than 95% whereas the BA also degrades largely. These results show that our attacks are also resistant to fine-tuning and model pruning.

The Resistance to Advanced Model-repairing-based Defenses. In this part, we demonstrate that our attacks are also resistant to two advanced model-repairing-based defenses, including MCR [21] and NAD [22], to some extent. As shown in Table 3, NAD has minor effects in reducing the ASR of our attacks, although it can successfully remove model backdoors of BadNets. MCR is more effective compared to NAD, whereas the ASR is still larger than 60% after the defense.

We will explore the resistance of our attacks to other types of defenses (e.g., [23, 24, 25]) in our future works.

4. CONCLUSIONS

In this paper, we revisited the influences of spatial transformations on backdoor attacks. We designed a simple yet effective poison-only attack (dubbed BATT) using specific transformations as triggers. It is a new attack paradigm whose triggers are not designed in a simple pixel-wise manner. In particular, we demonstrated that the proposed BATT is highly effective under both digital and physical-world settings and is resistant to representative backdoor defenses.
References

[1] Zhongying Deng, Xiaoliang Peng, Zhifeng Li, and Yu Qiao, “Mutual component convolutional neural networks for heterogeneous face recognition,” IEEE Transactions on Image Processing, vol. 28, no. 6, pp. 3102–3114, 2019.

[2] Xiaolong Yang, Xiaohong Jia, Dihong Gong, Dong-Ming Yan, Zhifeng Li, and Wei Liu, “Larnet: Lie algebra residual network for face recognition,” in ICML, 2021.

[3] Haibo Qiu, Dihong Gong, Zhifeng Li, Wei Liu, and Dacheng Tao, “End2end occluded face recognition by masking corrupted features,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.

[4] Tianyu Gu, Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg, “Badnets: Evaluating backdooring attacks on deep neural networks,” IEEE Access, vol. 7, pp. 47230–47244, 2019.

[5] Yiming Li, Yong Jiang, Zhifeng Li, and Shu-Tao Xia, “Backdoor learning: A survey,” IEEE Transactions on Neural Networks and Learning Systems, 2022.

[6] Xiangyu Qi, Tinghao Xie, Yiming Li, Saeed Mahloujifar, and Prateek Mittal, “Revisiting the assumption of latent separability for backdoor defenses,” in ICLR, 2023.

[7] Tuan Anh Nguyen and Anh Tuan Tran, “Wanet-imperceptible warping-based backdoor attack,” in ICLR, 2021.

[8] Yiming Li, Yang Bai, Yong Jiang, Yong Yang, Shu-Tao Xia, and Bo Li, “Untargeted backdoor watermark: Towards harmless and stealthy dataset copyright protection,” in NeurIPS, 2022.

[9] Yiming Li, Tongqing Zhai, Yong Jiang, Zhifeng Li, and Shu-Tao Xia, “Backdoor attack in the physical world,” in ICLR Workshop, 2021.

[10] Tong Wu, Tianhao Wang, Vikash Sehwag, Saeed Mahloujifar, and Prateek Mittal, “Just rotate it: Deploying backdoor attacks via rotation transformation,” in AISec, 2022.

[11] Yuezun Li, Yiming Li, Baoyuan Wu, Longkang Li, Ran He, and Siwei Lyu, “Invisible backdoor attack with sample-specific triggers,” in ICCV, 2021.

[12] Johannes Stallkamp, Marc Schlimpsing, Jan Salmen, and Christian Igel, “Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition,” Neural networks, vol. 32, pp. 323–332, 2012.

[13] Alex Krizhevsky, Geoffrey Hinton, et al., “Learning multiple layers of features from tiny images,” Technical report, 2009.

[14] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in CVPR, 2016.

[15] Xinyun Chen, Chang Liu, Bo Li, Kimberly Lu, and Dawn Song, “Targeted backdoor attacks on deep learning systems using data poisoning,” arXiv preprint arXiv:1712.05526, 2017.

[16] Yiming Li, Mengxi Ya, Yang Bai, Yong Jiang, and Shu-Tao Xia, “BackdoorBox: A python toolbox for backdoor learning,” in ICLR Workshop, 2023.

[17] Bolun Wang, Yuanshun Yao, Shawn Shan, Huaying Li, Bimal Viswanath, Haitao Zheng, and Ben Y Zhao, “Neural cleanse: Identifying and mitigating backdoor attacks in neural networks,” in IEEE S&P, 2019.

[18] Edward Chou, Florian Tramer, and Giancarlo Pellegrino, “Sentinet: Detecting localized universal attacks against deep learning systems,” in IEEE S&P Workshop, 2020.

[19] Yuntao Liu, Yang Xie, and Ankur Srivastava, “Neural trojans,” in ICCD, 2017.

[20] Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg, “Fine-pruning: Defending against backdooring attacks on deep neural networks,” in RAID, 2018.

[21] Pu Zhao, Pin-Yu Chen, Payel Das, Karthikeyan Natesan Ramamurthy, and Xue Lin, “Bridging mode connectivity in loss landscapes and adversarial robustness,” in ICLR, 2020.

[22] Yige Li, Xixiang Lyu, Nodens Koren, Lingjuan Lyu, Bo Li, and Xingjun Ma, “Neural attention distillation: Erasing backdoor triggers from deep neural networks,” in ICLR, 2021.

[23] Kunzhe Huang, Yiming Li, Baoyuan Wu, Zhan Qin, and Kui Ren, “Backdoor defense via decoupling the training process,” in ICLR, 2022.

[24] Xi Li, Zhen Xiang, David J Miller, and George Kesidis, “Test-time detection of backdoor triggers for poisoned deep neural networks,” in ICASSP, 2022.

[25] Junfeng Guo, Yiming Li, Xun Chen, Hanqing Guo, Lichao Sun, and Cong Liu, “Scale-up: An efficient black-box input-level backdoor detection via analyzing scaled prediction consistency,” in ICLR, 2023.