TRAINING SET CLEANSING OF BACKDOOR POISONING BY SELF-SUPERVISED REPRESENTATION LEARNING

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ABSTRACT

A backdoor or Trojan attack is an important type of data poisoning attack against deep neural network (DNN) classifiers, whereby the training dataset is poisoned with a small number of samples that each possesses the backdoor pattern (usually a pattern that is either imperceptible or innocuous) and which are mislabeled to the attacker’s target class. When trained on a backdoor-poisoned dataset, a DNN behaves normally on most benign test samples but makes incorrect predictions to the target class when the test sample has the backdoor pattern incorporated (i.e., contains a backdoor trigger). Here we focus on image classification tasks and show that supervised training may build stronger association between the backdoor pattern and the associated target class than that between normal features and the true class of origin. By contrast, self-supervised representation learning ignores the labels of samples and learns a feature embedding based on images’ semantic content. Using a feature embedding found by self-supervised representation learning, a data cleansing method, which combines sample filtering and re-labeling, is developed. Experiments on CIFAR-10 benchmark datasets show that our method achieves state-of-the-art performance in mitigating backdoor attacks.

Index Terms—Backdoor; contrastive learning; data cleansing

1. INTRODUCTION

It has been shown that Deep Neural Networks (DNNs) are vulnerable to backdoor attacks (Trojans) [1]. Such an attack is launched by poisoning a small batch of training samples from one or more source classes chosen by the attacker. Training samples are poisoned by embedding innocuous or imperceptible backdoor patterns into the samples and changing their labels to a target class of the attack. For a successful attack, a DNN classifier trained on the poisoned dataset: i) will have good accuracy on clean test samples (without backdoor patterns incorporated); ii) but will classify test samples that come from a source class of the attack, but with the backdoor pattern incorporated (i.e., backdoor-triggered), to the target class. Backdoor attacks may be relatively easily achieved in practice because of an insecure training out-sourcing process, through which both a vast training dataset is created and deep learning itself is conducted. Thus, devising realistic defenses against backdoor poisoning is an important research area. In this paper, we consider defenses that operate after the training dataset is formed but before the training process. The aim is to cleanse the training dataset prior to training of the classifier.

We observe that, with supervised training on the backdoor attacked dataset, a DNN model learns stronger “affinity” between the backdoor pattern and the target class than that between normal features and the true class of origin. This strong affinity is enabled (despite the backdoor pattern typically being small in magnitude) by mislabeling the poisoned samples to the target class. However, self-supervised contrastive learning, does not make use of supervising class labels; thus, it provides a way for learning from the training set without learning the backdoor mapping.

Based on this observation, a training set cleansing method is proposed. Using the training set $D$, we first learn a feature representation using self-supervised contrastive loss. We hypothesize that, since the backdoor pattern is small in magnitude, self-supervised training will not emphasize the features of the backdoor pattern contained in the poisoned samples. Working in the learned feature embedding space, we then propose two methods (kNN-based and Energy based) to detect and filter out samples whose predicted class is not in agreement with the labeled class. We then relabel detected samples to their predicted class (for use in subsequent classifier training) if the prediction is made “with high confidence”. An overview of our method is shown in Fig. 1. Unlike many existing backdoor defenses, Our method requires neither a small clean dataset available to the defender, nor a reverse-engineered backdoor pattern (if present), nor a fully trained DNN classifier on the (possibly poisoned) training dataset. Also, ours is the first work to address the problem of backdoor samples evading (“leaking through”) a rejection filter – we propose a relabeling method to effectively neutralize this effect. A complete version of our paper with Appendix is online available.

2. THREAT MODEL AND RELATED WORKS

Consider a clean dataset $D = \{(x_i, y_i) \mid i = 1 \ldots N\}$, where: $x_i \in \mathbb{R}^{H \times W}$ is the $i$th image in the dataset with $X$, $H$ and $W$ respectively the number of image channels, height, and width; $y_i \in \{1, 2, \ldots, C\}$ is the corresponding class label, with the number of classes $C > 1$. Backdoor attacks

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are identified as “low credible” samples by the classifier, with the classifier is fine-tuned. In each iteration some samples is chosen based on BIC [17]. Instead of clustering, [16] em-
uses a Gaussian mixture model whose number of components is based on BIC [17]. Instead of clustering, [16] em-
ployed a reverse-engineered backdoor pattern estimated using a small clean dataset. DBD [18] builds a classifier based on an encoder learned via self-supervised contrastive loss; then the classifier is fine-tuned. In each iteration some samples are identified as “low credible” samples by the classifier, with their labels removed; the classifier is then updated based on the processed dataset in a semi-supervised manner.

3. METHODOLOGY

3.1. Vulnerability of supervised training

We now illustrate the vulnerability of supervised training by analysis of a simple linear model trained on a poisoned dataset, considering the case where all classes other than the target are (poisoned) source classes. The victim classifier forms a linear discriminant function for each class $s$, i.e., the inner product $f_s(x) = x \cdot w_s$, where $w_s \in \mathbb{R}^{X \times H \times W}$ is the vector of model weights corresponding to class $s$. Assume that, after supervised training, each training sample is classified correctly with confidence at least $\tau > 0$ as measured by the margin:

$$f_s(x_i) - \max_{c \neq y_i} f_c(x_i) \geq \tau, \forall (x_i, y_i) \in D.$$  \hfill (1)

Assuming that the backdoor pattern $Dx$ is additively incorporated, given an attack sample based on clean $x_s$ originally from source-class $s \neq t$, Eq. (1) implies

$$w_t \cdot (x_s + Dx) - w_s \cdot (x_s + Dx) \geq \tau.$$  \hfill (2)

If $x_s$ is also classified to $s$ with margin $\tau$, then

$$w_s \cdot x_s - w_t \cdot x_s \geq \tau. \hfill (3)$$

Adding (1) and (3) gives

$$f_t(Dx) - f_s(Dx) = (w_t - w_s) \cdot Dx \geq 2\tau.$$  \hfill (4)

This loosely suggests that, after training with a poisoned training dataset, the model has stronger “affinity” between the target class and the backdoor pattern (4) than between the source class and the class-discriminative features of clean source-class samples (3). This phenomenon is experimentally verified when the model is a DNN, as shown in Apdx. A.

However, these strong affinities are only made possible by the mislabeling of the backdoor-poisoned samples. Given that usually the perturbation $Dx$ is small, backdoor attacked images differ minutely from the original (clean) images. Thus if a model is trained in a self-supervised manner, without making use of the class labels, the feature representations of $x$ and $x + Dx$ should be quite similar/highly proximal. Thus, in the model’s representation space, poisoned samples may “stand out” as outliers in that their labels may disagree with the labels of samples in close proximity to them. This is the basic idea behind the cleansing method we now describe.

3.2. Self-supervised contrastive learning

SimCLR [19, 20] is a self-supervised training method to learn a feature representation for images based on their semantic content. In SimCLR, in each mini-batch, $K$ samples are randomly selected from the training dataset, and each selected sample $x_k$ is augmented to form two versions, resulting in $2K$ augmented samples. Augmented samples are then fed into the feature representation model, which is an encoder $E(\cdot)$ followed by a linear projector $L(\cdot)$, with the feature vector $z$ extracted from the last layer: $z = L(E(x))$. For simplicity we will refer to $L(E(\cdot))$ as the “encoder” hereon. The encoder is trained to minimize the following objective function:
\[
C = - \frac{1}{2} \sum_{i=1}^{2K} \log \frac{\exp \left( z_i \cdot z_{\alpha(i)} / \tau \right)}{\sum_{i' = 1}^{2K} \exp \left( z_i \cdot z_{i'} / \tau \right)},
\]

where \(i\) and \(\alpha(i)\) are indexes of two samples augmented from the same training sample. Consistent with minimizing (5), SimCLR trains the encoder by projecting an image and its augmentations to similar locations in the derived feature space. So, given the fact that a backdoor attack makes minor changes to a poisoned training sample while preserving the semantic content related to its source class (the label of the clean sample), it is expected that the encoder will learn to project a backdoor image into a feature space location close to clean (and augmented) images from the source class. Working in the feature representation space learned by SimCLR, a training-sample filtering and re-labeling method can thus be deployed to cleanse the training set.

### 3.3. Data filtering

We consider two options for data filtering: \(k\) Nearest Neighbor (kNN) classifier and class-based “energy” score.

**kNN:** kNN is a widely used classification model. The class of a sample is determined by the voting of its top \(k\) nearest samples in the derived feature space. Basically we want to leverage the SimCLR representations and compare the label of a data point in the training set with the labels of nearby data points in representation space to verify the class label. The class label of a training sample is accepted if its labeled class agrees with kNN’s predicted class (based on plurality voting); otherwise it is likely to be mislabelled/attacked and will be rejected. In our experiments, \(k\) is chosen to be half of the number of images from each of the classes.\(^1\)

**Energy:** Given a sample (in the embedded feature space) \(z_i\), an energy score corresponding to class \(c\) is as follows:

\[
S_c(z_i) = \log \frac{1}{|\mathcal{I}_c \setminus \{i\}|} \sum_{k \in \mathcal{I}_c \setminus \{i\}} \frac{\exp \left( z_i \cdot z_k / \tau \right)}{\sum_{k'=1, k' \neq i}^{N} \exp \left( z_i \cdot z_{k'} / \tau \right)},
\]

where \(\mathcal{I} = \{i \mid i = 1...N\}\) is the set of indices of all the samples in the training set and \(\mathcal{I}_c = \{i \mid i \in \mathcal{I}, y_i = c\}\) is the set of indices of samples from class \(c\). A class decision can be made based on a sample’s class-conditioned scores: \(c^*(z_i) = \arg \max_c S_c(z_i)\). A training sample is accepted only if its predicted class \(c^*(z_i)\) agrees with its class label.

Tab. 1 shows the performance of Energy and kNN filtering methods using the ResNet-18 encoder architecture on the CIFAR-10 dataset, when 1000 samples are poisoned. Our filtering method can filter out 97% of backdoor samples while keeping most of the clean samples. However, the leaking of even a few backdoor samples is still problematic – [1] shows that even 50 backdoor samples for the CIFAR-10 dataset can make the attack successful\(^2\). So one cannot successfully defend backdoor attacks only by data filtering.

### 3.4. Re-labeling

From the discussion in Sec. 3.2, SimCLR projects a backdoor image to a feature space location close to clean images from the source class. For a sample that is rejected with a certain level of confidence (e.g., for kNN, if all \(k\) neighbors are labeled to class 1, but the sample is labeled to class 2), it is likely that the sample is a backdoor image and that the predicted class is the source class. Also, [2] indicates that a backdoor attack can be unlearned if a model is trained on images with backdoor triggers but labeled to the true class. Thus, to neutralize the influence of the backdoor images leaked in the filtering step, we first identify samples that are rejected (samples with kNN/energy’s predictions do not agree with their class labels) with a confidence threshold \(T\). Then we re-label these samples to the predicted class. For kNN, the confidence can be measured by the fraction of samples with the predicted label amongst the \(K\) nearest neighbors; for the energy-based method, the maximum score (over all classes) can be used as the confidence measure. Note that \(T\) is a hyper-parameter – the performance of our relabeling method is sensitive to the threshold \(T\). Care should be taken when a sample is relabeled since it inevitably induces label noise – the predictions of kNN and the energy-based method are not always reliable. So it is not a good idea to pre-define a number/ratio of samples that will be relabeled given that the number of backdoor attacked samples is not known. Alternatively, the confidence can be determined based on the confidence of clean samples (here we treat all accepted samples in the filtering step as clean samples). In practice, we set the threshold as the 80-th percentile of the confidences of accepted samples.

### 4. EXPERIMENTS

Our experiments are mainly conducted on CIFAR-10 [21]. Two global backdoor patterns (additive [6] and WaNet [22]) and two local patterns (BadNet[1], blended[4]) are considered in our work. The details of those attacks can be found in Apdx. C. For all the experiments ResNet-18 is used as the model architecture. A ResNet-18 encoder is first trained for 1000 epochs on the given dataset using the SimCLR loss (Eq. 5); then the kNN or energy based filtering and relabeling are applied to clean the dataset. Finally, the classifier is trained on the cleaned dataset using Supervised contrastive loss (SupCon) [20]. The performance of a defense is evaluated by two measures: clean test accuracy (ACC) and attack success rate (ASR).\(^3\) Our method is compared with three baseline methods: DBD[18], Activation Clustering (AC)[13], and Spectral

| Clean backdoor | KNN | Energy |
|---------------|-----|--------|
| 88.95         | 3.2 | 89.14  |

**Table 1:** The percentage of clean and backdoor images remaining after filtering methods applied.

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\(^1\)We found experimentally that this large choice of \(k\) yields more accurate filtering than smaller choices of \(k\).

\(^2\)More than 90% of test images with the backdoor trigger are classified to the target class.

\(^3\)ASR: the ratio of test samples with the backdoor trigger that are classified to the target class. A lower ASR implies a better defense method.
Signature (SS) [14]. AC and SS train a ResNet-18 classifier on the poisoned dataset and then identify backdoor samples using the classifier’s internal layer activations, by activation clustering (AC) or by checking if there are abnormally large activations (SS). Notably both AC and SS assume knowledge of the attacker’s target class, and SS further assumes the number of poisoned images is known. After filtering, a new classifier is trained on the cleaned dataset using SupCon. DBD defends backdoor attacks by iteratively identifying backdoor images using a classifier (pre-trained using SimCLR at the beginning) and then fine-tuning the classifier using a semi-supervised loss (MixMatch [23]), treating the backdoor images as unlabeled data and clean images as labeled data. The methods mentioned above require careful adjusting of hyper-parameters to get good performance; by contrast, there is only one hyper-parameter in our method (the threshold $T$ in the relabeling step), which can be automatically set based on the confidence on accepted samples, as discussed above.

| Method          | ASR (%) | ACC (%) | ASR (%) | ACC (%) | ASR (%) | ACC (%) |
|-----------------|---------|---------|---------|---------|---------|---------|
| None            | 99.9    | 94.14   | 94.19   | 99.9    | 94.14   | 67.6    | 93.11   |
| AC[13]          | 100     | 92.75   | 3.2     | 94.49   | 1.7     | 94.50   | 68.9    | 87.05   |
| SS[14]          | 97.4    | 91.14   | 3.2     | 94.49   | 4.9     | 94.36   | 63.5    | 93.04   |
| DBD             | 0.7     | 92.57   | 1.5     | 91.49   | 1.4     | 91.89   | 0.7     | 91.65   |
| kNN             | 2.6     | 91.46   | 4.2     | 92.37   | 4.2     | 92.13   | 3.6     | 92.24   |
| Energy          | 2.8     | 91.91   | 4.9     | 92.12   | 2.5     | 92.10   | 1.3     | 91.25   |
| SimCLR + filtering + relabeling | 88.95 | 3.2 | 68.9 | 87.05 |
| SimCLR + relabeling | 100 | 79.8 | 94.06 |
| SimCLR + filtering + relabeling | 88.95 | 3.2 | 4.2 | 92.37 |

Table 2: ASR (%) and ACC (%) for our methods and comparison methods under different attacks.

**Performance:** The defense methods aim to achieve high ACC and low ASR. Tab. 2 shows the performance of different methods when the number of poisoned images is 1000 for additive, BadNet, and blend attacks and 5000 for the WaNet attack. AC performs well for local backdoor attacks (BadNet and blend) where a backdoor image contains mostly features from the source class (original class before attack), i.e., such that the internal layer features of the classifier are different from those of clean target class images; but when the pattern is global (additive and WaNet) the classifier trained on the poisoned data can project images with backdoor patterns into locations close to those of clean target class samples; thus the performance for these attacks is poor. Similarly, SS performs well only on BadNet and can mitigate the ASR for the blended attack, but does not work well on additive and WaNet attacks. Our method and DBD give comparable performance; however Fig. 2 shows that, with an increased number of poisoned images, DBD fails (ASR close to 100% and drop of ACC under the additive attack). The likely reason is the iterative filtering of DBD – in any iteration, if some backdoor samples are falsely identified as clean, the subsequently fine-tuned classifier may (re-)learn the backdoor pattern; thus in the next iteration more backdoor images will likely be falsely accepted as clean. However, our method performs only one filtering step. Moreover, some images will be relabeled to neutralize the influence of the backdoor samples leaked in the filtering step; thus our method achieves strong robustness against backdoor poisoning even when 10% of the training samples are poisoned. Moreover, Apdx. E considers an adaptive attack scenario, with the results showing that our method can mitigate the attack even when the attack assumes full knowledge of our defense method.

![Fig. 2: Performance of our methods and DBD [18] for different number of attack images.](image)

**Ablation study:** In our method, three main steps are deployed for data cleaning: self-supervised contrastive training (SimCLR), data filtering, and data relabeling. Here we conduct an ablation study to understand the importance of each step. For the case without SimCLR, we still need to learn an encoder for feature embedding; an auto-encoder (AE) model is used as a substitute for SimCLR. KNN is used as the filtering method. From Tab. 3, We can see SimCLR is important for getting good embedding representations to accept most clean examples. The filtering method can reject most of the backdoor images, but if used without the relabeling, the remaining backdoor images still make the ASR high (68.9%). Also, without filtering, relabeling some backdoor samples can only slightly mitigate the ASR (to 79.8%). With the combination of SimCLR, filtering, and relabeling, our method achieves robustness against attacks even with a large number of poisoned images (shown in Fig. 2).

| Method                  | ASR (%) | ACC (%) | ASR (%) | ACC (%) |
|-------------------------|---------|---------|---------|---------|
| baseline, without any step | 100     | 98.4    | 94.14   |
| AE + filtering + relabeling | 23.31  | 5.3     | 3.7     | 51.15   |
| SimCLR + filtering      | 88.95   | 3.2     | 68.9    | 91.94   |
| SimCLR + relabeling     | 100     | 79.8    | 94.06   |
| SimCLR + filtering + relabeling | 88.95 | 3.2 | 4.2 | 92.37 |

Table 3: The percentage of clean (second row) and backdoor (third row) images remaining, ASR, and ACC after applying different combinations of our algorithm’s components. 1000 images were poisoned by BadNet attack.

**5. CONCLUSIONS**

In this paper, we proposed a training set cleansing method against backdoor attacks. We discussed the vulnerability of supervised trained models and thus proposed to use self-supervised learned representation embedding coupled with data filtering and relabeling. Experiments show that our method is robust under different types of attacks and different attack strengths. In future, this approach could be investigated on other architectures like ViT and to mitigate non-backdoor data poisoning attacks, e.g., label flipping attacks.
6. REFERENCES

[1] T. Gu, K. Liu, B. Dolan-Gavitt, and S. Garg, “Bad-nets: Evaluating backdooring attacks on deep neural networks,” *IEEE Access*, vol. 7, pp. 47230–47244, 2019.

[2] B. Wang, Y. Yao, S. Shan, H. Li, B. Viswanath, H. Zheng, and B.Y. Zhao, “Neural cleanse: Identifying and mitigating backdoor attacks in neural networks,” in *Proc. IEEE Symposium on Security and Privacy*, 2019.

[3] Z. Xiang, D. J. Miller, H. Wang, and G. Kesidis, “Detecting scene-plausible perceptible backdoors in trained DNNs without access to the training set,” *Neural Computation*, vol. 33, no. 5, pp. 1329–1371, 2021.

[4] X. Chen, C. Liu, B. Li, K. Lu, and D. Song, “Targeted backdoor attacks on deep learning systems using data poisoning,” https://arxiv.org/abs/1712.05526v1, 2017.

[5] H. Zhong, C. Liao, A. Squicciarini, S. Zhu, and D.J. Miller, “Backdoor embedding in convolutional neural network models via invisible perturbation,” in *Proc. CODASPY*, 2020.

[6] Z. Xiang, D. J. Miller, and G. Kesidis, “Detection of backdoors in trained classifiers without access to the training set,” *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–15, 2020.

[7] W. Guo, L. Wang, X. Xing, M. Du, and D. Song, “TABOR: A highly accurate approach to inspecting and restoring Trojan backdoors in AI systems,” https://arxiv.org/abs/1908.01763, 2019.

[8] Y. Liu, W. Lee, G. Tao, S. Ma, Y. Aafer, and X. Zhang, “ABS: Scanning neural networks for back-doors by artificial brain stimulation,” in *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, 2019, CCS ’19, p. 1265–1282.

[9] X. Xu, Q. Wang, H. Li, N. Borisov, C.A. Gunter, and B. Li, “Detecting AI Trojans using meta neural analysis,” in *Proc. IEEE Symposium on Security and Privacy*, 2021.

[10] Hang Wang, Zhen Xiang, David J Miller, and George Kesidis, “Universal post-training backdoor detection,” arXiv preprint arXiv:2205.06900, 2022.

[11] Y. Li, X. Lyu, N. Koren, L. Lyu, B. Li, and X. Ma, “Neural Attention Distillation: Erasing Backdoor Triggers from Deep Neural Networks,” in *Proc. ICLR*, 2021.

[12] K. Liu, B. Doan-Gavitt, and S. Garg, “Fine-pruning: Defending against backdoor attacks on deep neural networks,” in *Proc. RAID*, 2018.

[13] B. Chen, W. Carvalho, N. Baracaldo, H. Ludwig, B. Edwards, T. Lee, I. Molloy, and B. Srivastava, “Detecting backdoor attacks on deep neural networks by activation clustering,” http://arxiv.org/abs/1811.03728, Nov 2018.

[14] B. Tran, J. Li, and A. Madry, “Spectral signatures in backdoor attacks,” in *Proc. NIPS*, 2018.

[15] Z. Xiang, D.J. Miller, and G. Kesidis, “A benchmark study of backdoor data poisoning defenses for deep neural network classifiers and a novel defense,” in *Proc. IEEE MLSP*, Pittsburgh, 2019.

[16] Z. Xiang, D. J. Miller, and G. Kesidis, “Reverse engineering imperceptible backdoor attacks on deep neural networks for detection and training set cleansing,” *Computers and Security*, vol. 106, 2021.

[17] G. Schwarz, “Estimating the dimension of a model,” *Annals of Stats.*, vol. 6, pp. 461–464, 1978.

[18] Kunzhe Huang, Yiming Li, Baoyuan Wu, Zhan Qin, and Kui Ren, “Backdoor defense via decoupling the training process,” in *International Conference on Learning Representations*, 2021.

[19] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton, “A simple framework for contrastive learning of visual representations,” in *Proceedings of the 37th International Conference on Machine Learning*, 2020, pp. 1597–1607.

[20] Prannay Khosla, Piotr Teterwak, Chen Wang, Aaron Sarna, Yonglong Tian, Phillip Isola, Aaron Maschinot, Ce Liu, and Dilip Krishnan, “Supervised contrastive learning,” *Advances in Neural Information Processing Systems*, vol. 33, pp. 18661–18673, 2020.

[21] A. Krizhevsky, “Learning multiple layers of features from tiny images,” *University of Toronto*, 05 2012.

[22] A. Nguyen and A. Tran, “Wanet - imperceptible warping-based backdoor attack,” in *International Conference on Learning Representations*, 2021.

[23] David Berthelot, Nicholas Carlini, Ian Goodfellow, Nicolas Papernot, Avital Oliver, and Colin A Raffel, “Mixmatch: A holistic approach to semi-supervised learning,” *Advances in neural information processing systems*, vol. 32, 2019.

[24] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and F. Li, “Imagenet: A large-scale hierarchical image database,” in *2009 IEEE Conference on Computer Vision and Pattern Recognition*, 2009, pp. 248–255.