RETHINKING THE NECESSITY OF LABELS IN BACKDOOR REMOVAL

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ABSTRACT

Since training a model from scratch always requires massive computational resources recently, it has become popular to download pre-trained backbones from third-party platforms and deploy them in various downstream tasks. While providing some convenience, it also introduces potential security risks like backdoor attacks, which lead to target misclassification for any input image with a specifically defined trigger (*i.e.*, backdoored examples). Current backdoor removal methods always rely on clean labeled data, which indicates that safely deploying the pre-trained model in downstream tasks still demands these costly or hard-to-obtain labels. In this paper, we focus on how to purify a backdoored backbone with only unlabeled data. To evoke the backdoor patterns without labels, we propose to leverage the unsupervised contrastive loss to search for backdoors in the feature space. Surprisingly, we find that we can mimic backdoored examples with adversarial examples crafted by contrastive loss, and erase them with adversarial finetuning. Thus, we name our method as *Contrastive Backdoor Defense* (CBD). Against several backdoored backbones from both supervised and self-supervised learning, extensive experiments demonstrate that our proposed CBD, without using labels, achieves comparable or even better defense performance compared to the ones using labels, which allows practitioners to safely deploy pre-trained backbones on downstream tasks without extra labeling costs.

1 INTRODUCTION

Deep neural networks (DNNs) have achieved promising performance on various tasks, including computer vision (He et al., 2016) and natural language processing (Floridi & Chiriatti, 2020). Unfortunately, their success heavily relies on a huge amount of data, intensive computing resources, and the careful tuning of hyper-parameters. Thus, it becomes popular to download a pre-trained backbone and deploy it on several downstream tasks in recent years (Newell & Deng, 2020). These backbones can be trained in any training paradigms, including supervised learning and self-supervised learning (Chen et al., 2020; He et al., 2022), and then be open-sourced on third-party platforms.

While providing convenience, they also bring potential risks such as backdoor attacks. Numerous works (Gu et al., 2017; Turner et al., 2019) pointed out this threat easily occurs in supervised learning, and recent studies (Saha et al., 2022; Jia et al., 2022) started to pay attention to that in self-supervised learning. Specifically, a backdoored model always predicts a predefined label for target inputs with a specific trigger, which causes severe security problems.

Many defense methods have been proposed to address this security issue (Zeng et al., 2022; Wang et al., 2019; Wu & Wang, 2021), but they mainly focus on backdoor defense inside supervised learning by building a classification-based loss. In the popular deployment scheme from the pre-trained backbone to downstream tasks, the practitioners might have few costly labeled data, fail to obtain a classifier head (*e.g.*, a self-supervised backbone) to compare with the true label, or hard to design a classification-based loss (*e.g.*, tasks for detection or segmentation). To break through

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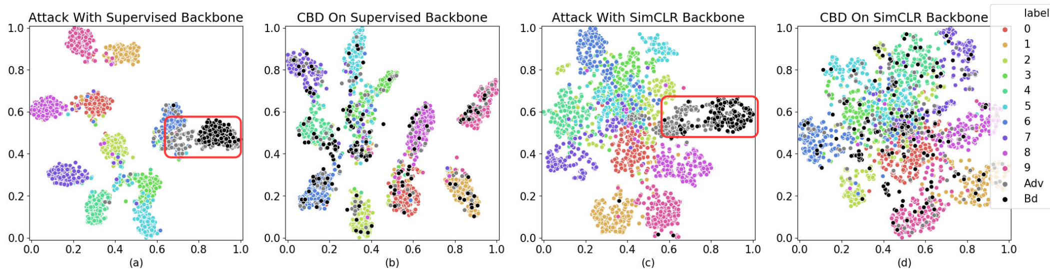

Figure 1: The t-SNE visualization of samples in feature space on CIFAR-10. All backbones are backdoored by the Blend Attack with class 6 as the target class. **(a)-(b)**: supervised backbone. **(c)-(d)**: self-supervised backbone. **(a)&(c)**: backboored backbone. **(b)&(d)**: backbone after proposed CBD. *Bd*: backdoor examples; *Adv*: contrastive adversarial examples.

these restrictions, we first consider the following question: *do we really need labels for backdoor removal?*

In this paper, we focus on how to purify a backdoored backbone with only unlabeled data. Regarding the backdoor trigger as a "shortcut" (Wang et al., 2019) in decision boundary (a small trigger is enough to change outputs for many backdoored models), the traditional methods (Wang et al., 2019; Zeng et al., 2022) attempt to make the prediction deviate from the ground-truth label as far as possible using a small perturbation in inputs, so as to evoke the backdoor behavior and then erase it. Unfortunately, we have no access to any labels, or even the prediction results when the backbone lacks a classifier head. To evoke the backdoor behavior without labels, we propose to leverage the unsupervised contrastive loss to search for the backdoor in the feature space, *i.e.*, making the output feature as different from its original feature as possible using a small perturbation. Surprisingly, we find that we can easily mimic backdoored examples with adversarial examples crafted by contrastive loss. Based on this finding, we propose to erase the backdoor behaviors by letting these contrastive loss-based adversarial examples have similar features as their clean counterpart using fine-tuning. Thus, we term our method as Contrastive Backdoor Defense (CBD), which successfully defends against backdoor attacks without any labeled data.

2 Contrastive Backdoor Defense without Any Labeled Data

In this section, we first define our problem setup. Then, we analyze how to discover potential backdoored features with unsupervised contrastive loss. Finally, based on this observation, we propose a novel fine-tuning method for a pre-trained feature extractor.

Defense Setup. Here, we consider a typical setting for post-processing backdoor removal, where one practitioner downloads a pre-trained backbone from an untrustworthy source and defends against potential backdoor attacks before deploying it. It is important to note that the pre-trained backbone in our setting can be trained through supervised or self-supervised methods. While for defense, with only accessing some unlabeled data, there are not any labels or label-related information. This is very different from existing backdoor removal methods that rely on clean labeled data.

Visualization of Backdoor Attacks. Starting from the supervised learning backbone, a successful backdoor attack misclassifies triggered samples into the target class. As shown in Figure 1(a), the clean samples from the target class (blue circles) and the backdoor samples (black circles) are located in two separate clusters, though they are classified into the same class. For the self-supervised learning backbone, without knowing the downstream task, a successful backdoor attack can only be verified by a disparity between benign features and backdoor features (Carlini & Terzis, 2022). As shown in Figure 1(c), the backdoor cluster (black circles) is also obviously separated from clean clusters. This consistent phenomenon inspires a potential defense via identifying the backdoor cluster and removing it, which is easy to realize when labels are available (Wang et al., 2019). However, when there are not any labels, we need to think how to identify the separated backdoor cluster.

Covering Backdoor Cluster via Adversarial Examples. Inspired by the "shortcut" in supervised learning (Wang et al., 2019), here we attempt to find the "shortcut" in contrastive manner. By creating two views on an instance, we aim to discover a small perturbation to make the view with the perturbation and the benign view as different as possible in the hidden feature space. Specifically, given an image x and a pair of augmentations $(\tilde{x_i}, \tilde{x_j})$, we maximize the contrastive loss between features of augmentation $\tilde{x_j}$ and augmentation $\tilde{x_i} + \delta_i$ from backbone $f(\cdot)$ using PGD attack (Madry et al., 2018) as

$$\max_{\|\delta_i\|_p \le \epsilon} \ell_{cl}(f(\tilde{x_i} + \delta_i), f(\tilde{x_j})), \tag{1}$$

where ϵ is perturbation budget and contrastive loss is defined in Appendix B.

As shown in Figure 1 marked by the red rectangle, generated adversarial features (grey circle) in either supervised backbone (Figure 1(a)) or self-supervised backbone (Figure 1(c)) attempt to cover the region of backdoor examples (black circles). This indicates the separated backdoor cluster in feature space can be approached by instance-wise contrastive-loss-based adversarial examples.

2.1 The Proposed Method

Finding that the adversarial cluster approaches the backdoor cluster, our goal is to eliminate the "shortcut" for defense.

Backdoor-to-Standard Pulling. We first illustrate how to mitigate the trigger-sensitive "shortcut". In supervised learning, the backdoor attack mainly builds a strong connection between the trigger and its target class (Huang et al., 2022). Thus, connecting the trigger to all the classes can effectively break the backdoor attack. However, this approach is infeasible in our setting since we do not use labeled data. Instead, we need to cover the gap between backdoored features and clean features. Based on the experiments above, those generated instances that approach the backdoor cluster can act as a substitution of backdoored images. Thus, pulling adversarial images toward their benign parts can mitigate backdoor effects as we align the potential backdoor features and clean features. Specifically, for each image x, in addition with $(\tilde{x_i}, \tilde{x_j})$, we generate another view $\tilde{x_k}$, and find its perturbation δ_k by Eq. 1. Then we treat $\tilde{x_k} + \delta_k$ as a trigger recovered image, and our Backdoor-to-Standard Pulling will be:

$$\ell_{pull}(x) = \ell_{cl}(\text{freeze}(f(\tilde{x_i})), f(\tilde{x_k} + \delta_k)), \tag{2}$$

where we freeze the feature of $\tilde{x_i}$.

Embedding Distillation. In addition to removing backdoor behaviors inside a backbone, we still demand the backbone to have high performance on benign inputs (the utility of the backbone). Here, we discuss how to preserve such utility. Note that Backdoor-to-Standard Pulling not only changes the mimic features of backdoor examples, *i.e.*, adversarial features, but also the features of benign examples, which may hurt the feature representation of benign data. As a result, we propose to keep the benign feature representation by distilling the embedding of benign data from the original backdoored backbone to our purified backbone. Specifically, we use the backdoored model as a teacher and our current model during purifying as a student through the Embedding Distillation loss to align the benign feature representation between the backdoored backbone and the purified backbone as follows,

$$\ell_{kd}(x) = \ell_{cl}(f(\tilde{x_i}), f^*(\tilde{x_i})), \tag{3}$$

where $f^*(\cdot)$ is the backdoored backbone. Note that this distillation will not preserve the backdoored feature distribution since our given data is clean.

Standard Fine-tuning. Finally, to retain the benign representations close, aligning the variants of different clean augmentation would be helpful. This is similar to standard contrastive fine-tuning between benign augmentations on trained backbones. Therefore, our Standard Fine-tuning will be:

$$\ell_{sft}(x) = \ell_{cl}(f(\tilde{x_i}), f(\tilde{x_j})). \tag{4}$$

Overall. The final loss on sample x is a combination of three items:

$$\ell_{total} = \lambda_1 \ell_{pull}(x) + \lambda_2 \ell_{kd}(x) + \lambda_3 \ell_{sft}(x), \tag{5}$$

where λ_1, λ_2, and λ_3 are positive hyper-parameters with $\lambda_1 + \lambda_2 + \lambda_3 = 1$.

3 Experiments

Setups. We evaluate our method on CIFAR-10 (Krizhevsky et al., 2009) with the backbone of ResNet-18 (He et al., 2016) trained by supervised and self-supervised (SimCLR (Chen et al., 2020)) methods. We use BadNets (Gu et al., 2017), Blend (Chen et al., 2017), and SIG (Barni et al., 2019),

Table 1: Results on CIFAR-10 with models trained by supervised methods. Accuracy (Acc) of the clean test data, Attack Sucess Rate (ASR) on poisoned test data with target labels, and Patched Accuracy (PA) on poisoned test data with original labels.

Attacks	Metrics	No Defense	ANP	FP	FT	NAD	CBD (ours)
BadNets	ACC	93.25	91.34	91.11	**91.52**	90.76	89.74
	ASR	99.95	0.10	1.72	7.59	1.58	**1.07**
	PA	0.05	89.77	88.89	85.59	89.19	**89.34**
Blend	ACC	94.23	88.94	91.54	**92.38**	89.32	91.81
	ASR	100.00	37.41	54.02	98.89	72.97	**4.98**
	PA	0.00	38.83	32.31	1.07	20.26	**81.33**
SIG	ACC	94.45	89.43	91.09	**92.26**	89.28	90.89
	ASR	99.29	2.08	4.38	5.24	**2.97**	4.98
	PA	0.67	82.57	80.59	**81.11**	78.62	78.88

Table 2: Results on CIFAR-10 with models trained by self-supervised methods SimCLR.

Defenses	BadNets			Blend			SIG		
	Acc	ASR	PA	Acc	ASR	PA	Acc	ASR	PA
No Defense	85.68	28.73	61.10	85.36	43.01	23.12	85.43	33.34	56.97
FT	64.94	**5.20**	53.32	63.83	3.79	20.93	66.59	7.97	47.93
CBD (ours)	**81.77**	6.70	**76.20**	**80.07**	**3.67**	**70.69**	**80.51**	**6.64**	**66.34**

as our attack baselines. For other post-processing backdoor removal methods, we select fine-tuning and state-of-the-art defenses including ANP (Wu & Wang, 2021), NAD (Li et al., 2021), and Fine-pruning (Liu et al., 2018) as our baselines, though they need labels. For our proposed CBD, we set the default hyper-parameters to $\lambda_1 = 0.3$, $\lambda_2 = 0.5$, and $\lambda_3 = 0.2$. We generate adversarial examples with perturbation budget $\epsilon = 8$, step size 0.1, and 20 steps for the supervised trained backbone and 100 steps for the self-supervised trained backbone. To evaluate the utility of purified backbone, we use the clean accuracy (ACC). While evaluating the defense against backdoor attacks, we use two different metrics: 1) standard attack success rate (ASR) which measures the ratio of backdoor samples that are misclassified as the target label; and 2) patched accuracy (PA) which measures prediction accuracy of backdoor samples (*i.e.*, images patched with the trigger) to the ground-truth label. Note that $\text{ASR} + \text{PA} \leq 1$. More details can be found in Appendix C.

Results. The visualizations of our method are shown in Figure 1(b)&(d). By using our method, we break the clustering of generated adversarial examples (gray circle) as well as the backdoor cluster (black circle). To further demonstrate the effectiveness of our method, we first compare CBD with four defense baselines under models pretrained by supervised methods. For the trade-off of getting costly labeled data, we compare these methods on 1% clean labeled data (these baselines need labels to do backdoor defense) and 5% clean unlabeled data for our method (we do not use labels to do defense even though labels are given) in Table 1. Our method successfully purified different attacks even without labeled data and the classifier head. The attack success rate in all cases is less than 5%. Also, the gap between the original clean performance and our purified clean performance is less than 5%. Overall, our method reaches comparable results without accessing any labeled data.

As we know the features learned by self-supervised methods are different from supervised ones, we additionally evaluate our proposed CBD on the self-supervised backbone in Table 2. Here only unlabeled data are available, we use contrastive fine-tuning (FT) as a comparison. All the performances of backbones are tested under a linear classifier with 1% training data. While maintaining high clean accuracy, CBD successfully defends all attacks and recovers the patched accuracy. Compared with contrastive fine-tuning which greatly downgrades the clean performance and achieves low patched accuracy, we verify the effectiveness of CBD under contrastive learning. More results for additional setups, high-resolution datasets, and ablation studies can be found on Appendix D and Appendix E.

4 Conclusion

In this paper, we investigated how to erase the backdoor behaviors inside pre-trained backbones without using any labels. We first demonstrate the potential threat of backdoor attacks on current contrastive pre-trained backbones. Then, we analyzed the behaviors of backdoored examples and proposed a contrastive way to mimic them, based on which, we proposed Contrastive Backdoor Defense (CBD) without needing any labeled data, achieving comparable even superior defense than supervised ones.

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A Related work

Backdoor Attack. Backdoor Attack is a newly risen security concern on DNNs (Gu et al., 2017), in which the adversary can manipulate the model to predict a target class as long as a predefined trigger pattern appears in the image. This backdoor behavior can be easily injected inside DNNs by poisoning some data pairs. Specifically, (1) **poison-label attack**: the attacker randomly adds the trigger pattern into samples from all classes and changes their label to the target class (Gu et al., 2017; Chen et al., 2017; Nguyen & Tran, 2021; Zbontar et al., 2021; Doan et al., 2021)). (2) **clean-label attack**: the adversary only adds the trigger pattern into the samples from the target class, which is more stealthy since their annotation is correct (Turner et al., 2019). Recent studies start to pay attention to backdoor attacks on self-supervised learning frameworks, especially on contrastive learning methods (Saha et al., 2022; Jia et al., 2022). This emerging threat is challenging for DNN models and attracts researchers' attention.

Backdoor Removal. Meanwhile, numerous backdoor removal methods are proposed, which can be mainly grouped into two categories, including (1) **training-time defense** (Huang et al., 2022; Gao et al., 2021): the defender can access training data and train a model based on various defense strategies. For instance, Gao et al. (2021) utilized adversarial training to train a robust model against backdoor triggers; (2) **post-processing defense** (Liu et al., 2018; Wang et al., 2019; Wu & Wang, 2021; Zeng et al., 2022; Li et al., 2021): the defender sanitize the models with tiny amounts of data with no access to the training process and training data. Thus, post-processing defense can be applied in a wider range of scenarios, *e.g.*, purifying backbones from the Internet before deploying them in downstream tasks. However, almost all these methods rely on enough amount of labeled clean data and classification loss, while labeled data may be hard to obtain, the backbone may have no classifier head, or it is hard to design classification-based loss for defense (*e.g.*, defense for object detection or segmentation). In this work, we focus on how to purify backdoored backbone without the help of any labels.

B Backbone Training

For the backbone $f(\cdot, \theta)$ from supervised learning, its parameters are usually trained based on a K-class classification problem. Given a labeled training dataset $\mathcal{D}_l = \{(x_1, y_1), \cdots, (x_N, y_N)\}$, which contains N inputs $x_i \in \mathbb{R}^d, i = 1, \cdots, N$, and the corresponding ground-truth label $y_i \in \{1, \cdots, K\}$, the cross-entropy loss for a single data pair (x_i, y_i) can be calculated as follows,

$$\ell_{ce}(x_i) = -\log g_{y_i}(f(x_i, \theta)), \tag{6}$$

where the $g(\cdot)$ is the classifier head for this classification task and $g_{y_i}(\cdot)$ indicates the outputted probability that x_i belongs to class y_i from the classifier. The training process attempts to find an optimal model parameter θ to minimize the average loss on the whole training data.

By contrast, the backbone $f(\cdot, \theta)$ from self-supervised learning is trained without any classifier head. The training process optimized the model parameters, so as to let the similar sample pairs stay close to each other while dissimilar ones are far apart in the embedding space. For example, given an unlabeled dataset $\mathcal{D}_u = \{x_1, \cdots, x_N\}$, the normalized temperature-scaled contrastive loss for the sample x_i is

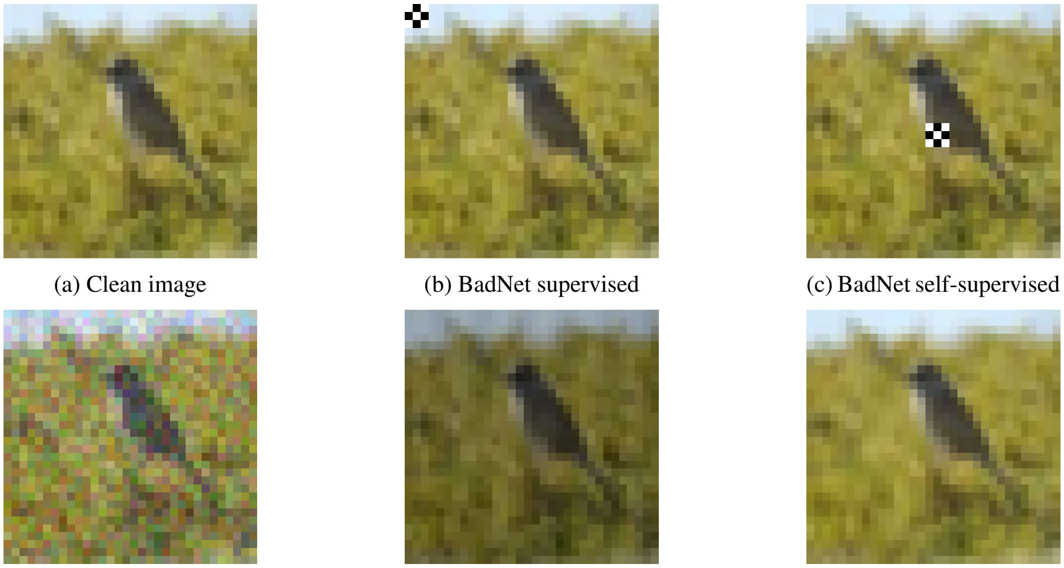
$$\ell_{cl}(f(\tilde{x}_i, \theta), f(\hat{x}_i, \theta)) = -\log \frac{\exp(\text{sim}(\tilde{z}_i, \hat{z}_i)/\tau)}{\sum_{k=1}^{2N} \mathbb{I}_{[k \neq i]} \exp(\text{sim}(\tilde{z}_i, \tilde{z}_k)/\tau)}, \tag{7}$$

where $\tilde{z}_i = f(\tilde{x}_i, \theta), \hat{z}_i = f(\hat{x}_i, \theta), \tilde{z}_k = f(\tilde{x}_k, \theta)$, $\text{sim}(\cdot, \cdot)$ is the cosine similarity and τ is the temperature hyper-parameter. $\tilde{x}_i$ and $\hat{x}_i$ (positive samples) are two augmented samples from the same sample x_i, while $\tilde{z}_k$ (negative samples) is the projection of any other augmented samples. The self-supervised training process attempts to find an optimal model parameter θ to minimize the average loss over all possible positive pairs on the unlabeled dataset.

C More Implementation details for Backdoor Attacks and Defenses

C.1 Datasets and DNNs.

We evaluate the performance of our method on **CIFAR-10** (Krizhevsky et al., 2009) and **ImageNet-100** (Tian et al., 2020; Deng et al., 2009). We use ResNet-18 (He et al., 2016) as the backbone



(a) Clean image (b) BadNet supervised (c) BadNet self-supervised

(d) Blend (e) SIG (f) WaNet

Figure 2: Examples of CIFAR-10 backdoored images.

for both supervised and CL models and select SimCLR (Chen et al., 2020) as our CL method. On CIFAR-10, we train 200 epochs for supervised backbones and 1000 epochs for SimCLR. For ImageNet-100, we train 90 epochs and 400 epochs for supervised backbones and self-supervised backbones, respectively.

C.2 Backdoor attacks implementations

In this part, we present the detailed configurations of our attacks. The backdoor triggers are presented in Figure 2. We set the target label to 6 (frog in CIFAR-10 and lorikeet in ImageNet-100). The poisoning ratio across all supervised settings is 6% of the dataset (60% of target label 6 for CLA). To create backdoor on self-supervised models, we poison 60% of target label 6[1], which is 6% of all data for CIFAR-10 and 0.6% for ImageNet-100.

- **BadNets (Gu et al., 2017)**: We implant a 3×3 black-white patch for CIFAR-10 and 32×32 patch introduced in (Saha et al., 2022) for ImageNet-100 as our triggers. For supervised backbones, we put the trigger on the top-left. We inject it into the center of the image to achieve a better attack success rate on self-supervised backbones.
- **Blend (Chen et al., 2017)**: We mix the data with a 32×32 and a 224×224 noise image for CIFAR-10 and ImageNet-100, respectively. We achieve good attack results in supervised and self-supervised settings with blend ratio $\alpha = 0.2$. In addition, Blend Attack can result in bad patched accuracy in self-supervised backbones even with a low attack success rate. Note that general Gaussian blur augmentation is not presented when training Blend with SimCLR.
- **SIG (Barni et al., 2019)**: We generate SIG trigger with $f = 6$ and $\Delta = 20$. We blend it to the target image with a blend ratio $\alpha = 0.3$. Note that we use poison-label attack setting for SIG in supervised learning.
- **WaNet (Nguyen & Tran, 2021)**: We use the default configurations and code of WaNet except for the poisoning ratio in supervised backbones. In particular, we poison 6% of training data and set the noise rate $p_n = 2$, $s = 0.5$, and $k = 4$. We implement WaNet based on the original code for self-supervised learning. However, we did not show the results of WaNet on self-supervised backbones as it can not build an effective backdoor with or without noise mode.

[1]Without any labels, this is the same as injecting backdoor to frog images for CIFAR-10 and lorikeet images for ImageNet-100 on the self-supervised setup

Table 3: Additional results on CIFAR-10 with models trained by supervised methods.

Attacks	Metrics	No Defense	ANP	FP	FT	NAD	CBD (ours)
WaNet	ACC	93.67	93.41	**93.37**	91.99	88.88	88.81
	ASR	94.88	0.99	**0.28**	7.67	1.01	3.82
	PA	4.94	92.56	**91.49**	83.64	87.08	85.98
CLA	ACC	87.86	84.13	81.70	77.60	73.79	**81.72**
	ASR	99.96	10.62	4.92	45.58	4.40	**2.22**
	PA	0.04	77.21	77.68	48.40	71.48	**81.40**

- **CLA (Turner et al., 2019)**: We are using the same 3×3 black-white patch in BadNets. To generate perturbations, we have untargeted PGD with $L_\infty, \epsilon = 16, \text{step} = 7$. Since CLA is sensitive to data augmentation, we did not use any of them in our training. This is the reason for low clean accuracy of the backdoored backbone

C.3 Backdoor Defense implementations

To compare our results with state-of-the-art defense methods, we modify the code from open-source BackdoorBenchmark (Wu et al., 2022). To ensure the fairness of the comparison, we use 1% of labeled data and 5% of pseudo-labeled data respectively. Specifically, for pruning-based ANP (Wu & Wang, 2021), we maintain the default setting reported in the paper. When evaluating ANP, we make a trade-off between clean accuracy and attack success rate. We finetune a teacher model with 10 epochs and run NAD (Li et al., 2021) defense for 20 epochs. It is worth noting that we only count the last block of ResNet-18 as the attention layer with $\beta = 1000$ as suggested in the BackdoorBenchmark. For fine-pruning (Liu et al., 2018), we also implement it with the suggested setting from the BackdoorBenchmark, where we stop pruning and finetune it with 50 epochs when the clean accuracy is dropped lower than 90% of total clean accuracy. We keep the same setting for the baselines on ImageNet-100.

For our proposed CBD on CIFAR-10, we finetune the backbone with 15 epochs by using SGD optimizer with 0.02 learning rate, 0.9 momentum, and 5×10^{-4} weight decay. Then, we attach a linear classifier to the frozen purified feature extractor and use another 1% clean data to do linear probing as suggested in other self-supervised works (Saha et al., 2022; Chen et al., 2020). We set the batch size of our defense to 128 and temperature to 0.5. On ImageNet-100, we use 0.05 learning rate. We set the $\lambda_1 = 0.3, \lambda_2 = 0.7$ and use adversarial examples with $\epsilon = 16$ and step $= 20$, and keep the other parts same.

D Additional Experiments

D.1 Experiments on more attacks

As shown in Table 3, we also evaluate our proposed CBD with advanced WaNet (Nguyen & Tran, 2021) and Clean-label Attack (Turner et al., 2019). For the Clean-label Attack, our CBD outperforms all other methods across all three metrics. Moreover, CBD continues to exhibit satisfactory performance even in the most challenging case of WaNet. However, performance improvements can be achieved by adjusting the weight of losses or adopting different adversarial strategies, as demonstrated in Section E.

D.2 ImageNet-100 experiments

To examine the effectiveness of our method in real-world datasets, we compare our method using ImageNet-100 (Tian et al., 2020; Deng et al., 2009) in Tables 4 and 5. We poison 60% of the lorikeet images in ImageNet-100 (0.6% of all data) to create the backdoor. We are comparing BadNets and Blend Attack on both supervised and self-supervised backbones using the same baselines. Since ImageNet-100 is much more complex, our proposed CBD set the $\lambda_1 = 0.3, \lambda_2 = 0.7$ and not using Standard Fine-tuning. In addition, we are leveraging the same unlabeled data to train a projection head from scratch for the stability of self-supervised backbones. For all the supervised backbones, our method achieves superior performance. By using 5% of unlabeled data, we successfully achieve the best clean accuracy, attack success rate, and patched accuracy in the real-world dataset. Also, our method purifies the self-supervised a backbones with huge improvement of Patched Accuracy while only losing less than 5% of clean accuracy. Overall, these experiments can demonstrate the capability of our proposed method when other methods failed in the real-world dataset.

Table 4: Results on supervised ImageNet-100.

Attacks	Metrics	No Defense	ANP	FP	FT	NAD	CBD
BadNets	ACC	78.15	65.14	50.00	61.40	55.08	**66.43**
	ASR	99.90	49.45	19.88	97.35	80.08	**13.39**
	PA	0.10	41.23	28.97	85.59	13.21	**59.84**
Blend	ACC	80.06	69.42	50.08	61.48	56.62	**75.39**
	ASR	99.48	18.16	18.38	40.10	26.61	**0.12**
	PA	0.40	27.66	14.81	21.15	16.97	**70.77**

Table 5: Results on SimCLR ImageNet-100.

Defenses	BadNets			Blend		
	Acc	ASR	PA	Acc	ASR	PA
No Defense	61.52	38.56	35.45	59.86	0.02	40.06
FT	38.22	5.24	32.63	34.72	0.58	21.82
Our method	57.42	9.57	49.84	56.39	0.44	54.36

Also, we provide a case study for object detection in Table 6. The evaluation metric for object detection is average precision (AP) and patched average precision (PAP). In this case study, we demonstrate the effects of backdoor attack on the backbone and improve the Patched AP with our CBD. We use the pre-trained SimCLR backbone with Blend Attack on ImageNet-100. Then, we train and test the Fast-RCNN (Ren et al., 2015) with this backbone on PascalVOC-2007 (Everingham et al., 2009) dataset. We freeze the first two layers of our backbone and deploy it as the initial parameter of Faster-RCNN. Note that even without poisoning, Blend Attack can disturb the results of object detection. Thus, for better comparison, we also add a clean pre-trained SimCLR backbone and test it on Blend Attack. Even in the downstream object detection setting, while reaching a similar AP, we mitigate the backdoor effects and bring the Patched AP even higher to that of the clean backbone. These results point out the emergent threat of backdoored pre-trained backbone and verify the effectiveness of our method.

Table 6: Case study for object detection on PascalVOC-2007. Clean Model is a pre-trained backbone without backdoor. Average Precision **(AP)** is the evaluation metric for object detection. Patched Average Precision **(PAP)** is the patched AP for our backdoor evaluation.

Defenses	VOC2007		
	Clean Model	No Defense	Our Method
AP	65.86	65.00	64.65
PAP	37.06	30.64	43.82

D.3 Comparisons using pseudo-label

Although being attacked, a modern supervised DNN can still retain high clean accuracy. Thus, if a user wants to get a clean supervised model, instead of collecting costly labeled data, they can also leverage the classification results of the backdoored model as pseudo-labels. Under this scenario, the user can use other baseline methods on unlabeled data. We conduct experiments of other baselines on 5% unlabeled data with generated pseudo labels in Table 7. Note that this practice is only applicable when the classifier head is retained and clean accuracy is high (*e.g.*, CIFAR-10). Even though the generated pseudo labels are mostly accurate, the existing noise of these labels deteriorates other defense baselines. In particular, Fine-tuning and NAD lost their ability to defend SIG, and the ASR of fine-tuning-based methods in most cases is increased. Moreover, despite comparable results on SIG for ANP, the patched accuracy on other attacks is decreased. These results demonstrate the weakness of using pseudo-labels to defend against backdoor attacks.

E Ablation studies

E.1 Ablation studies of supervised backbone

Effects on different adversarial examples The quality of adversarial examples that mimic backdoored features plays an important role in our method. Among different adversarial settings, PGD20 attack with L_∞ norm, 0.1 step size, and $\epsilon = 8$ is the default in our supervised setting. Please note that our default settings are not the best; we have made some trade-offs. As shown in Table 8,

Table 7: Results for pseudo-label data. We leverage the prediction of the poisoned model on clean unlabeled data to generate pseudo-labels and performance baselines on them.

Attacks	Metrics	No Defense	ANP	FP	FT	NAD	CBD
BadNets	ACC	93.25	91.54	92.54	92.71	**92.94**	89.74
	ASR	99.95	0.08	4.12	11.33	6.20	**1.07**
	PA	0.06	87.49	**89.51**	83.98	88.26	89.34
Blend	ACC	94.23	87.92	93.11	**93.47**	93.43	91.81
	ASR	100.00	48.69	75.30	60.73	66.72	**4.98**
	PA	0.00	31.07	20.84	27.92	24.01	**81.33**
SIG	ACC	94.45	90.66	**93.13**	92.55	92.73	90.89
	ASR	99.29	2.10	10.46	72.44	57.53	**4.98**
	PA	0.67	84.98	77.31	25.78	39.91	**78.88**
WaNet	ACC	93.67	92.03	**93.59**	89.94	91.57	88.81
	ASR	94.88	0.69	**0.19**	0.96	0.69	3.82
	PA	4.94	90.67	**92.49**	88.18	89.86	85.98
CLA	ACC	87.86	84.16	**82.90**	80.88	79.7	81.72
	ASR	99.96	2.18	0.64	2.49	**0.28**	2.22
	PA	0.04	82.61	**82.99**	81.65	81.91	81.40

Table 8: Ablation studies with different adversarial settings on CIFAR-10 supervised backbones.

Attacks	Metrics	Before	$\epsilon = 2$	$\epsilon = 4$	$\epsilon = 16$	$L_2 1024$	PGD100	CBD (ours)
BadNets	ACC	93.25	89.86	89.72	89.82	**92.16**	88.62	89.74
	ASR	99.95	1.14	1.24	**1.06**	4.65	1.22	1.07
	PA	0.06	89.38	89.12	**89.48**	88.73	88.19	89.34
Blend	ACC	94.23	91.22	91.16	92.21	**93.03**	90.99	91.81
	ASR	100.00	10.76	8.50	3.35	**3.12**	4.91	4.98
	PA	0.00	73.93	76.13	**84.29**	82.43	81.90	81.33
SIG	ACC	94.45	91.09	90.79	90.98	**92.96**	89.51	90.89
	ASR	99.29	5.01	**4.49**	5.58	43.54	4.95	4.98
	PA	0.67	78.29	**78.90**	78.46	51.83	77.73	78.88
WaNet	ACC	93.67	89.20	88.33	88.25	**90.51**	86.57	88.81
	ASR	94.88	1.17	1.22	1.65	**1.15**	2.02	3.82
	PA	4.94	88.93	87.99	87.66	**89.90**	85.60	85.98
CLA	ACC	87.86	**81.92**	81.68	81.72	84.91	80.77	81.72
	ASR	99.96	2.14	2.54	**2.07**	38.54	3.61	2.22
	PA	0.04	81.54	80.96	**81.56**	56.98	78.11	81.40

we present the results with different budgets ($\epsilon = 2, 4, 16$), steps (PGD100), and norm (L_2 norm with $\epsilon = 1024$). The carefully selected results can reach state-of-the-art without any labeled data. Based on the results of these adversarial examples, they successfully reach backdoored features with instance-wise contrastive loss.

Effects on different losses. Our proposed CBD is composed of three losses. To verify the effectiveness of these losses, we test our methods on four different variants. Specifically, we adjust the hyper-parameters of these losses accordingly. These variants include (1) Standard Fine-tuning ($\lambda_3 = 1$), (2) Backdoor-to-Standard pulling & Embedding Distillation ($\lambda_1 = 0.5, \lambda_2 = 0.5$), (3) Backdoor-to-Standard pulling & Standard Fine-tuning ($\lambda_1 = 0.5, \lambda_3 = 0.5$), and (4) Backdoor-to-Standard pulling ($\lambda_1 = 1$). We can verify their contributions to our method on Table 9. In most cases, our default setting reaches the best performance. However, the ablation studies indicate that Standard Fine-tuning is less important for our method and is optionally compared with Backdoor-to-Standard pulling and Embedding Distillation.

E.2 Ablation studies of self-supervised backbone

In this part, we provide ablation studies for self-supervised backbone. Similar to the supervised backbones, we conduct CIFAR-10 experiments on different adversarial strategies in Table 10 and losses in Table 11. We adopt the same setting as the supervised backbone except we are using PGD100 attack to find backdoored features.

Table 9: Ablation studies of different losses on CIFAR-10 supervised backbones. SFT is Standard Fine-tuning, KD is Embedding Distillation, and Pull is Backdoor-to-Standard pulling.

Attacks	Metrics	Before	SFT	Pull & KD	Pull & SFT	Pull	CBD (ours)
BadNets	ACC	93.25	88.55	88.84	80.65	71.76	**89.74**
	ASR	99.95	12.01	1.18	3.23	4.18	**1.07**
	PA	0.06	77.83	88.59	80.08	71.28	**89.34**
Blend	ACC	94.23	89.21	91.03	85.68	75.70	**91.81**
	ASR	100.00	91.89	5.18	5.59	6.77	**4.98**
	PA	0.00	6.99	81.10	76.34	67.34	**81.33**
SIG	ACC	94.45	89.38	89.78	84.12	74.39	**90.89**
	ASR	99.29	14.00	5.22	5.50	7.32	**4.98**
	PA	0.67	69.54	78.40	70.61	59.13	**78.88**
WaNet	ACC	93.67	69.80	86.42	59.81	54.90	**88.81**
	ASR	94.88	3.91	**1.66**	6.20	5.78	3.82
	PA	4.94	69.76	**86.37**	58.72	51.70	85.98
CLA	ACC	87.86	40.39	80.05	35.79	27.80	**81.72**
	ASR	99.96	12.49	**1.87**	12.77	10.18	2.22
	PA	0.04	38.11	80.03	34.00	26.56	**81.40**

Table 10: Ablation studies of our methods on self-supervised backbones. The default defense for self-supervised backbone is PGD100 and PGD20 for others.

Attacks	Metrics	Before	$\epsilon = 2$	$\epsilon = 4$	$\epsilon = 8$	$\epsilon = 16$	$L_2 1024$	CBD (ours)
BadNets	ACC	85.68	81.69	81.91	**81.99**	81.90	81.93	81.77
	ASR	28.73	14.38	12.42	10.63	**4.01**	8.46	6.70
	PA	61.10	69.32	71.30	72.84	**78.16**	75.21	76.20
Blend	ACC	85.36	79.45	79.69	80.25	80.10	79.97	**80.7**
	ASR	43.01	17.27	12.58	5.26	2.74	**2.23**	3.67
	PA	23.12	49.67	57.82	68.28	72.53	**72.67**	70.69
SIG	ACC	85.43	80.42	80.54	80.66	**80.77**	80.68	80.51
	ASR	33.34	14.59	13.92	14.09	11.52	26.59	**6.64**
	PA	56.97	62.47	62.39	61.81	62.81	55.52	**66.34**

Table 11: Ablation studies of different losses on self-supervised backbones.

Attacks	Metrics	Before	SFT	Pull & KD	Pull & SFT	Pull	CBD (ours)
BadNets	ACC	85.68	64.94	80.74	65.78	42.73	**81.77**
	ASR	28.73	5.20	6.73	2.27	**0.82**	6.70
	PA	61.10	53.32	74.83	59.78	39.56	**76.20**
Blend	ACC	85.36	63.83	78.63	59.57	38.22	**80.7**
	ASR	43.01	3.79	2.88	**0.81**	2.25	3.67
	PA	23.12	20.93	**70.97**	51.84	32.46	70.69
SIG	ACC	85.43	66.59	79.13	66.48	45.14	**80.51**
	ASR	33.34	7.97	5.42	**1.35**	1.99	6.64
	PA	56.97	47.93	65.88	54.42	40.61	**66.34**