IN SEARCH OF SMOOTH MINIMA FOR PURIFYING BACKDOOR IN DEEP NEURAL NETWORKS

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ABSTRACT

The success of a deep neural network (DNN) heavily relies on the details of the training scheme; *e.g.*, training data, architectures, hyper-parameters, *etc.* Recent backdoor attacks suggest that an adversary can take advantage of such training details and compromise the integrity of DNN. Our studies show that a backdoor model is usually optimized to a *bad local minima*, *i.e.*, sharper minima as compared to a benign model. Intuitively, backdoor can be purified by re-optimizing the model to a smoother minima through fine-tuning with a few clean validation data. However, fine-tuning all DNN parameters often requires huge computational cost as well as sub-par clean test performance. To address this concern, we propose a novel backdoor purification technique—Natural Gradient Fine-tuning (NGF)—which focuses on removing backdoor by fine-tuning *only one layer*. Specifically, NGF utilizes a loss surface geometry-aware optimizer that can successfully overcome the challenge of reaching a smooth minima under one-layer optimization scenario. To enhance the generalization performance of our proposed method, we introduce a clean data distribution-aware regularizer based on the knowledge of loss surface curvature matrix, *i.e.*, *Fisher Information Matrix*. To validate the effectiveness of our method, we conduct extensive experimentation with four different datasets—CIFAR10, GTSRB, Tiny-ImageNet, and ImageNet; as well as 11 recent backdoor attacks, *e.g.*, Blend, Dynamic, Clean Label, *etc.* NGF achieves state-of-the-art performance in most of these benchmarks.

1 INTRODUCTION

Training a deep neural network (DNN) with a fraction of poisoned or malicious data is often security-critical since the model can successfully learn both clean and adversarial tasks equally well. This is prominent in scenarios where one outsources the DNN training to a vendor. In such scenarios, an adversary can mount backdoor attacks (Gu et al., 2019; Chen et al., 2017) through poisoning a portion of training samples so that the model will misclassify any sample with a *particular trigger* or *pattern* to an adversary-set label. Whenever a DNN is trained in such a manner, it becomes crucial to remove the effect of backdoor before deploying it for a real-world application.

Different defense techniques (Liu et al., 2018; Wang et al., 2019; Wu & Wang, 2021; Li et al., 2021a; Zheng et al., 2022) have been proposed for purifying backdoor. Techniques such as fine-pruning (Liu et al., 2018) and adversarial neural pruning (Wu & Wang, 2021) require a long training time due to iterative searching criteria. Furthermore, the purification performance deteriorates significantly as the attacks get stronger. In this work, we explore the backdoor insertion and removal phenomena from the DNN optimization point of view. Unlike a benign model, a backdoor model is forced to learn two different data distributions: clean data distribution and poisoned/trigger data distribution. Having to learn both distributions, backdoor model optimization usually leads to a *bad local minima* or sharper minima *w.r.t.* clean distribution. We claim that backdoor can be removed by re-optimizing the model to a smoother minima. One easy re-optimization scheme could be simple DNN weights fine-tuning with a few clean validation samples. However, fine-tuning all DNN parameters often requires huge computational cost and may result in sub-par clean test performance after purification. Therefore, we intend to *fine-tune only one layer* to effectively remove the backdoor.

Fine-tuning only one layer creates a shallow network scenario where SGD-based optimization becomes a bit challenging. Choromanska et al. (2015) claims that the probability of finding bad local minima or poor quality solution increases as the network size decreases. Even though there are

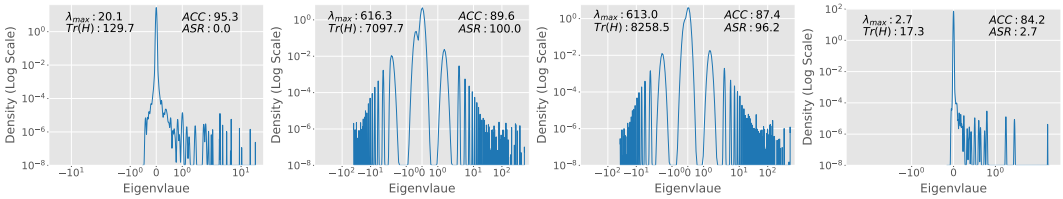
good-quality solutions, it usually requires exponentially long time to find those minima (Choromanska et al., 2015). As a remedy to this, we opt to use a curvature aware optimizer, Natural Gradient Decent (NGD), that has *higher probability of escaping the bad local minima as well as faster convergence rate*, specifically in the shallow network scenario (Amari, 1998; Martens & Grosse, 2015). To this end, we propose a novel backdoor purification technique—Natural Gradient Fine-tuning (NGF)—which focuses on removing backdoor through fine-tuning *only one layer*. However, straightforward application of NGF with simple cross-entropy (CE) loss may result in poor clean test performance. To boost this performance, we use a clean distribution-aware regularizer that prioritizes the update of parameters sensitive to clean data distribution. Our proposed method achieves SOTA performance in a wide range of benchmarks, *e.g.*, four different datasets including *ImageNet*, 11 various backdoor attacks *etc.* Our contributions can be summarized as follows:

- We analyze the loss surface characteristics of a DNN during backdoor insertion and purification processes. Our analysis shows that the optimization of a backdoor model leads to a *bad local minima* or sharper minima compared to a benign model. We argue that backdoor can be purified by re-optimizing the model to a smoother minima and simple fine-tuning can be a viable way for that. To the best of our knowledge, our study on the correlation between loss-surface smoothness and backdoor purification is novel.
- We conduct additional studies on backdoor purification process while fine-tuning different parts of a DNN. We observe that SGD-based one-layer fine-tuning fails to escape bad local minima and a loss surface geometry-aware optimizer can be an easy fix to this.
- Based on our studies, we propose a novel backdoor purification technique based on Natural Gradient Fine-tuning (NGF). In addition, we employ a clean distribution-aware regularizer to boost the clean test performance of our proposed method. NGF outperforms recent SOTA methods in a wide range of benchmarks.

2 Related Work

Backdoor Attacks: Backdoor triggers can exist in the form of dynamic patterns (Li et al., 2020), a single pixel (Tran et al., 2018), sinusoidal strips (Barni et al., 2019), human imperceptible noise (Zhong et al., 2020), natural reflection (Liu et al., 2020), adversarial patterns (Zhang et al., 2021), blending backgrounds (Chen et al., 2017), *etc.* Based on target labels, existing backdoor attacks can generally be classified as poison-label or clean-label backdoor attacks. In poison-label backdoor attack, the target label of the poisoned sample is different from its ground-truth label, *e.g.*, BadNets (Gu et al., 2019), Blended attack (Chen et al., 2017), SIG attack (Barni et al., 2019), WaNet (Nguyen & Tran, 2021), Trojan attack (Liu et al., 2017), and BPPA (Wang et al., 2022). Contrary to the poison-label attack, clean-label backdoor attack doesn't change the label of the poisoned sample (Turner et al., 2018; Huang et al., 2022; Zhao et al., 2020b). Recently, Saha et al. (2022) studied backdoor attacks on self-supervised learning.

Backdoor Defenses: Existing backdoor defense methods can be categorized into backdoor detection or purifying techniques. Detection based defenses include trigger synthesis approach (Wang et al., 2019; Qiao et al., 2019; Guo et al., 2020; Shen et al., 2021; Dong et al., 2021; Guo et al., 2021; Xiang et al., 2022; Tao et al., 2022), or malicious samples filtering based techniques (Tran et al., 2018; Gao et al., 2019; Chen et al., 2019). However, these methods only detect the existence of backdoor without removing it. Backdoor purification defenses can be further classified as training time defenses and inference time defenses. Training time defenses include model reconstruction approach (Zhao et al., 2020a; Li et al., 2021b), poison suppression approach (Hong et al., 2020; Du et al., 2019; Borgnia et al., 2021), and pre-processing approaches (Li et al., 2021a; Doan et al., 2020). Although training time defenses are often successful, they suffer from huge computational burden and less practical considering attacks during DNN outsourcing. Inference time defenses are mostly based on pruning approaches such as (Koh & Liang, 2017; Ma & Liu, 2019; Tran et al., 2018; Diakonikolas et al., 2019; Steinhardt et al., 2017). Pruning-based approaches are typically based on model vulnerabilities to backdoor attacks. For example, MCR (Zhao et al., 2020a) and CLP (Zheng et al., 2022) analyzed node connectivity and channel Lipschitz constant to detect backdoor vulnerable neurons. ANP (Wu & Wang, 2021) prune neurons through backdoor sensitivity analysis using adversarial search on the parameter space. Instead, we propose a simple one-layer fine-tuning based defense that is both fast and highly effective. To remove backdoor, our proposed method revisits the DNN fine-tuning paradigm from a novel point of view.



(a) Benign Model (b) Backdoor Model (c) Purified Model (SGD) (d) Purified Model (NGF)

Figure 1: Eigen Spectral Density plots of Loss Hessian for benign (a), backdoor (TrojanNet (Liu et al., 2017)) (b), and purified (c & d) models. In each plot, the maximum eigenvalue (λ_{max}), trace of Hessian ($\mathsf{Tr}(H)$), clean test accuracy (ACC), attack success rate (ASR) are also reported. Here, low λ_{max} and $\mathsf{Tr}(H)$ hints at the presence of smoother loss surface which often results in low ASR and high ACC. (a & b) Compared to a benign model, a backdoor model tends to reach a sharper minima as shown by the larger range of eigenvalues (x-axis). (c & d) During purification, SGD optimizer rarely escapes sharp or bad local minima (similar λ_{max} and $\mathsf{Tr}(H)$ as the backdoor model) while our proposed method, NGF, converges to a smooth minima. We use CIFAR10 dataset with a PreActResNet18(He et al., 2016) architecture for all evaluations.

3 Background

Attack Model. We consider an adversary with the capabilities of carrying a backdoor attack on a DNN model, $f_\theta : \mathbb{R}^d \to \mathbb{R}^c$, by training it on a poisoned data set $\mathbb{D}_{\mathsf{train}} = \{X_{\mathsf{train}}, Y_{\mathsf{train}}\}$. Here, θ is the parameters of the model, d is the input data dimension and c is the total number of classes. The data poisoning happens through specific set of triggers that can only be accessed by the attacker. The adversary goal is to train the model in a way such that any triggered samples $\hat{x} = x + \delta \in \mathbb{R}^d$ will be wrongly misclassified to a target label, $\bar{y}$. Here, x is a clean test sample and $\delta \in \mathbb{R}^d$ represents the trigger pattern with the properties of $||\delta|| \leq \epsilon$; where ϵ is the trigger magnitude determined by its shape, size and color. We define the *poison rate* as the ratio of poison and clean data in $\mathbb{D}_{\mathsf{train}}$. An attack is considered successful if the model behaves as: $f_\theta(x) = y$ and $f_\theta(\hat{x}) = \bar{y}$, where y is the true label for x. We use attack success rate (ASR) for quantifying such success.

Defense Goal. We consider a defender with a task to purify the backdoor model f_θ using a small clean validation set (usually $1 \sim 10\%$ of the training data). The goal is to repair the model in a way such that it becomes immune to attack, *i.e.*, $f_{\theta_p}(\hat{x}) = y$. Here, f_{θ_p} is the final purified model.

Natural Gradient Descent (NGD). Let us consider a model $p(y|x, \theta)$ with parameters $\theta \in \mathbb{R}^N$ to be fitted with input data $\{(x_i, y_i)\}_{i=1}^{|\mathbb{D}_{\mathsf{train}}|}$ from an empirical data distribution $P_{x,y}$, where $x_i \in X_{\mathsf{train}}$ is an input sample and $y_i \in Y_{\mathsf{train}}$ is its label. We try to optimize the model by solving:

$$\theta^* \in \arg\min_{\theta} \ \mathcal{L}(\theta) \tag{1}$$

, where $\mathcal{L}(\theta) = \mathcal{L}(y, f_\theta(x)) = \mathbb{E}_{(x_i,y_i)\sim P_{x,y}}[-\mathsf{log}\ p(y|x, \theta)]$ is the expected full-batch cross-entropy (CE) loss. SGD optimizes for θ^* iteratively following the direction of the steepest descent (estimated by column vector, $\nabla_\theta \mathcal{L}$) and update the model parameters by: $\theta^{(t+1)} \leftarrow \theta^{(t)} - \alpha^{(t)} \cdot \nabla_\theta^{(t)} \mathcal{L}$, where α is the learning rate. Since SGD uses Identity matrix as the pre-conditioner, it is *unaware of the geometry of loss surface*.

In NGD, however, the Fisher Information Matrix (FIM) is used as a pre-conditioner which can be defined as (Martens & Grosse, 2015),

$$F(\theta) = \mathbb{E}_{(x,y)\sim P_{x,y}}[\nabla_\theta \ \mathsf{log}\ p(y|x, \theta) \cdot (\nabla_\theta \ \mathsf{log}\ p(y|x, \theta))^T] \ \in \mathbb{R}^{N\times N}. \tag{2}$$

As FIM is a *loss surface curvature matrix*, a careful integration of it in the update eqn. of θ will make the optimizer loss surface geometry-aware. Such integration leads us to the update equation of NGD, $\theta^{(t+1)} \leftarrow \theta^{(t)} - \alpha^{(t)} \cdot F(\theta^{(t)})^{-1} \nabla_\theta^{(t)} \mathcal{L}$. Due to the surface awareness of FIM[1], in each iteration, NGD updates the parameters according to the curvature of the loss surface making a smoother loss surface around the optimization point (Amari, 1998; Park et al., 2000). To be specific, NGD-based optimization has higher probability of achieving a smoother loss surface and helps the model to gain good generalization performance.

[1]Instead of Euclidean geometry based distance in SGD update, learning rate for NGD is controlled by local distance based on the "information geometry" of the space of probability distributions, *i.e.*, KL divergence of consecutive iterations (Martens, 2020).

Table 1: Backdoor removal performance while fine-tuning (FT) different parts of a DNN. Fine-tuning only the last layer creates a shallow network scenario. In such scenario, there is a high probability that SGD does not escape bad local minima. Whereas, NGF consistently optimizes to a smooth minima (indicated by low $\lambda_{\max}$ for 6 different attacks) which results in backdoor removal, *i.e.*, low ASR and high ACC. We consider CIFAR10 dataset and PreActResNet18 architecture for all evaluations. A clean validation set is used for all purification.

FT	Badnets			Blend			Trojan			Dynamic			CLB			SIG		
Methods	$\lambda_{\max}$	ASR	ACC	$\lambda_{\max}$	ASR	ACC	$\lambda_{\max}$	ASR	ACC	$\lambda_{\max}$	ASR	ACC	$\lambda_{\max}$	ASR	ACC	$\lambda_{\max}$	ASR	ACC
Initial	573.8	100	92.96	715.5	100	94.11	616.3	100	89.57	564.2	100	92.52	717.6	100	92.78	514.1	100	88.64
Full-Net.	4.42	4.87	85.92	4.65	4.77	87.61	3.41	3.78	82.18	2.34	4.73	88.61	4.68	1.83	87.41	8.98	1.04	81.92
CNN-Bbone.	4.71	5.03	85.64	5.14	4.92	87.24	4.19	3.95	81.86	2.46	5.11	87.54	5.19	2.08	86.67	9.74	1.61	81.55
Cls. (SGD)	556.1	98.27	**90.17**	541.7	97.29	**93.48**	613.0	96.25	**87.36**	446.5	93.58	**91.36**	361.9	89.21	**91.73**	563.2	96.70	**86.92**
Cls. (NGF)	**2.79**	**1.86**	88.32	**2.43**	**0.38**	91.17	**2.74**	**2.64**	84.21	**1.19**	**1.17**	90.97	**3.13**	**1.04**	88.37	**1.48**	**0.12**	84.16

4 Smoothness Analysis of Backdoor Models

In this section, we analyze the loss surface geometry of benign, backdoor and purified models. To study the loss curvature properties of different models, we aim to analyze the Hessian of loss, $H = \nabla^2_\theta \mathcal{L}$, where we compute $\mathcal{L}$ using the *clean training set*. Hessian, H is a symmetric matrix and one can can take the spectral decomposition $H = Q\Lambda Q^T$, where $\Lambda = \mathsf{diag}(\lambda_1.\lambda_2, \ldots, \lambda_n)$ contains the eigenvalues and $Q = [q_1, \ldots, q_n]$ are the eigenvectors. As a measure for smoothness, we take the maximum eigenvalue, $\lambda_{\max}(= \lambda_1)$, and trace of hessian, $\mathsf{Tr}(H)$. Low values for these two proxies indicate the presence of highly smooth loss surface (Jastrzebski et al., 2020). The Eigen Spectral density plots in Fig. 1a- 1b tell us about the optimization of benign and backdoor models. To create these models, we use the CIFAR10 dataset and train a PreActResNet18 architecture for 200 epochs. To insert the backdoor, we use TrojanNet (Liu et al., 2017) and a poison rate of 10%. From the comparison of $\lambda_{\max}$ and $\mathsf{Tr}(H)$, we can conjecture that optimization of a benign model produces smoother loss surface. We observe similar phenomena for different datasets and architectures; details is in *Appendix F*. The main difference between a benign and a backdoor model is that the latter needs to learn two different data distributions: clean and poison. Based on our observations, we state following conjectures:

Conjecture 1. Having to learn two different data distributions, a backdoor model reaches a sharper minima, *i.e.*, large $\lambda_{\max}$ and $\mathsf{Tr}(H)$, as compared to the benign model.

We support this conjecture with empirical evidence presented in Table 1. Looking at the $\lambda_{\max}$ (Initial row) for all 6 attacks (details in *Appendix D*), it can be observed that all of these backdoor models optimizes to a sharp minima. As these models are optimized on both distributions, they also have high attack success rates (ASR) as well as high clean test accuracy (ACC). Note that, the measure of smoothness is done *w.r.t.* clean data distribution. The use of clean distribution in our smoothness analysis is driven from the practical consideration as our particular interest lies with the performance *w.r.t.* clean distribution; more details in *Appendix C*. Since high ASR and ACC indicates that the model had learned both distributions, it supports Conjecture 1.

Conjecture 2. Through *proper* fine-tuning with clean validation data, a backdoor model can be re-optimized to a smoother minima *w.r.t.* clean data distribution. Optimization to a smoother minima leads to backdoor purification, *i.e.*, low ASR and high ACC.

By *proper fine-tuning*, we imply that the fine-tuning will lead to an optimal solution *w.r.t.* the data distribution we fine-tune the model with. To support Conjecture 2, we show the removal performances of fine-tuning based purification methods in Table 1. To remove backdoor using a clean validation set ($\sim$1% of training set), we fine-tune different parts of the DNN for 100 epochs with a learning rate of 0.01. As shown in the Table 1, after proper fine-tuning (Full-Net, CNN-Bbone, and Cls. (NGF)), the backdoor model re-optimizes to a smoother minima that leads to successful backdoor removal, *i.e.*, high ACC and low ASR.

One-Layer Fine-tuning: We observe that one can remove the backdoor by fine-tuning either the full network or only the CNN backbone (using SGD). However, these methods can be computationally costly and less practical. Furthermore, such fine-tuning often leads to high drop in ACC. As an alternative, one could fine-tune only the last or classification (Cls.) layer. However, even with small validation set, a one-layer network becomes a shallow network to optimize. According to the spin-glass analogy in Choromanska et al. (2015), as the network size decreases the probability for the SGD optimizer to find *sharp local minima or poor quality minima* increases accordingly. In case of shallow network, the quality of minima is decided by their distances from the global minima.

Choromanska et al. (2015) also observes that the process of finding a path from a bad local minima to a good quality solution or global minima takes *exponentially long time*. Therefore, it is not always feasible to use the SGD optimizer for shallow network. Table 1 (row–Cls. (SGD)) corroborates this hypothesis as SGD optimizer fails to escape the sharp minima resulting in similar ASRs as the initial backdoor model. Instead of using SGD, one can use natural gradient descent (NGD) that has *higher probability of escaping the bad local minima as well as faster convergence rate*, specifically in the shallow network scenario (Amari, 1998; Martens & Grosse, 2015). Therefore, to effectively purify a backdoor model, we propose a novel Fisher Information matrix based backdoor purification objective function and optimize it using NGD optimizer.

4.1 Natural Gradient Fine-tuning (NGF)

Let us decompose the model parameters θ as,

$$\theta = \{\mathbf{W}_{1,2}, \mathbf{W}_{2,3}, \cdots, \mathbf{W}_{L-1,L}\}$$

here, $\mathbf{W}_{i,i+1}$ is the parameters between layer i and layer $i+1$, commonly termed as $(i+1)^{th}$ layer's parameters. $\mathbf{W}_{L-1,L}$ is the Lth layer's (Cls. layer) parameters and we are particularly interested in fine-tuning only this layer. Now, consider a validation set, $\mathbb{D}_{\mathsf{val}} = \{X_{\mathsf{val}}, Y_{\mathsf{val}}\}$ that contains only clean samples. We denote $\theta_L (= \mathbf{W}_{L-1,L})$ as the Lth layer's parameters. To purify the backdoor model, we formulate the following loss function:

$$\mathcal{L}_p(y, f_\theta(x)) \approx \mathcal{L}(y, f_\theta(x)) + \frac{\eta}{2} \sum_i (\mathsf{diag}(F(\bar{\theta}_L))_i \cdot (\theta_{L,i} - \bar{\theta}_{L,i})^2 \tag{3}$$

, where the first term accounts for the CE loss on the validation set. In a backdoor model, some neurons/parameters are more vulnerable than others. The vulnerable parameters are believed to be the ones that are sensitive to poison/trigger data distribution (Wu & Wang, 2021). In general, CE loss does not discriminate whether a parameter is more sensitive to clean or poison distribution. Such lack of discrimination may allow drastic/unwanted changes to the parameters responsible for learned clean distribution. This usually leads to sub-par clean test accuracy after purification and it requires additional measures to fix this issue.

Motivated by Kirkpatrick et al. (2017), we introduce a *clean distribution aware regularization* term as a product of two terms: i) an error term that accounts for the deviation of θ_L from the original backdoor parameters, $\bar{\theta}_L$ (fixed); ii) a vector, $\mathsf{diag}(F(\bar{\theta}_L))$, consisting of the diagonal elements of FIM ($F(\bar{\theta}_L)$). As the first term controls the changes of parameters *w.r.t.* $\bar{\theta}_L$, it helps the model to remember the already learned distribution. However, learned data distribution consists of clean and poison distribution both. To explicitly force the model to remember the *clean distribution*, we compute $F(\bar{\theta}_L)$ using a *clean* validation set; with similar distribution as the learned clean data. Note that, $\mathsf{diag}(F(\bar{\theta}_L))_i$ represents the square of the derivative of log-likelihood of clean distribution *w.r.t.* $\bar{\theta}_{L,i}$, $[\nabla_{\bar{\theta}_{L,i}} \log p(y|x,\theta)]^2$ (ref. eqn. 6). In other words, $\mathsf{diag}(F(\bar{\theta}_L))_i$ is the measure of importance of $\bar{\theta}_{L,i}$ towards remembering the learned clean distribution. If $\mathsf{diag}(F(\bar{\theta}_L))_i$ has a higher importance, we allow minimal changes to $\bar{\theta}_{L,i}$ over the purification process. This careful design of such regularizer improves the clean test performance significantly. We use η as a regularization constant.

Overall optimization problem using the loss-function defined in equation 3 for purifying the backdoor model f_θ is as follows:

$$\text{Objective function:} \quad \theta_p := \arg\min_{\theta_L} \mathcal{L}_p(y, f_\theta(x)); \;\; x \in X_{val}, \; y \in Y_{val} \tag{4}$$

$$\text{Update Policy:} \quad \theta_L^{(t+1)} \leftarrow \theta_L^{(t)} - \alpha F(\theta_L^{(t)})^{-1} \nabla_{\theta_L} \mathcal{L}_p \tag{5}$$

$$\text{where, } F(\theta_L) := \frac{1}{n} \sum_{j=1}^{n} \left(\nabla_{\theta_L} \log p(y_j|x_j,\theta) \cdot (\nabla_{\theta_L} \log (y_j|x_j,\theta))^T \right) \tag{6}$$

here, $F \in \mathbb{R}^{|\theta_L| \times |\theta_L|}$ is the FIM, and n is the validation set size. Notice that, as we consider fine-tune only L^{th}-layer, the computation of F and F^{-1} become tractable with a size of $|\theta_L| \times |\theta_L|$ matrix. After solving the above optimization problem, we will get modified parameters, $\overline{\mathbf{W}}_{L-1,L}$. Finally, we get the purified model, f_{θ_p} with θ_p as

$$\theta_p = \{\mathbf{W}_{1,2}, \mathbf{W}_{2,3}, \cdots, \overline{\mathbf{W}}_{L-1,L}\}$$

Table 2: Comparison of different defense methods for four benchmark datasets. Backdoor removal performance, *i.e.*, drop in ASR, against a wide range of attacking strategies show the effectiveness of NGF. For CIFAR10 and GTSRB, the poison rate is 10%. For Tiny-ImageNet and ImageNet, we employ ResNet34 and ResNet50 architectures, respectively. We use a poison rate of 5% for these 2 datasets and report performance on successful attacks (ASR close to 100%) only. Average drop (↓) indicates the % changes in ASR/ACC compared to the baseline, *i.e.*, ASR/ACC of *No Defense*. Higher ASR drop and lower ACC drop is desired for a good defense.

Dataset	Method	No Defense		Vanilla FT		MCR		NAD		ANP		**NGF (Ours)**	
	Attacks	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC
CIFAR-10	*Benign*	0	95.21	0	92.28	0	90.68	0	92.34	0	93.98	0	**94.10**
	Badnets	100	92.96	4.87	85.92	3.97	81.65	4.32	85.41	2.84	85.96	**1.86**	**88.32**
	Blend	100	94.11	4.77	87.61	32.72	80.19	5.18	84.89	3.81	89.10	**0.38**	**91.17**
	Troj-one	100	89.57	3.78	82.18	22.34	80.92	18.73	83.87	5.47	**85.20**	**2.64**	84.21
	Troj-all	100	88.33	3.91	81.95	20.45	79.63	17.21	83.16	5.53	84.89	**2.79**	**86.10**
	SIG	100	88.64	1.04	81.92	0.89	82.26	2.07	83.27	0.37	83.60	**0.12**	**84.16**
	Dyn-one	100	92.52	4.73	88.61	24.93	78.62	23.09	83.71	1.78	86.26	**1.17**	**90.97**
	Dyn-all	100	92.61	4.28	88.32	26.12	77.90	22.61	81.01	2.19	84.51	**1.61**	**90.19**
	CLB	100	92.78	1.83	87.41	35.14	79.27	17.45	83.53	1.41	85.07	**1.04**	**88.37**
	CBA	93.20	90.17	27.80	83.79	41.28	81.92	36.28	82.34	45.11	85.63	**24.60**	**85.97**
	FBA	100	90.78	7.95	82.90	33.80	81.56	29.71	82.68	66.70	**87.42**	**6.21**	86.96
	BPPA	99.70	93.82	9.94	90.23	24.36	86.41	18.63	88.15	10.46	90.57	**7.14**	**91.84**
	Avg. Drop	-	-	92.55 ↓	5.95 ↓	75.15 ↓	10.54 ↓	81.60 ↓	7.66 ↓	86.11 ↓	5.28 ↓	**94.85 ↓**	**3.46 ↓**
GTSRB	*Benign*	0	97.87	0	93.08	0	95.49	0	95.18	0	95.42	0	**95.76**
	Badnets	100	97.38	1.36	88.16	1.00	93.45	0.19	89.52	0.35	93.17	**0.24**	**94.11**
	Blend	100	95.92	5.08	89.32	6.83	92.91	8.10	89.37	4.41	93.02	**2.91**	**93.31**
	Troj-one	99.50	96.27	2.07	90.45	2.76	92.98	1.47	90.02	1.81	92.74	**1.21**	**94.18**
	Troj-all	99.71	96.08	2.48	89.73	3.25	92.18	1.88	90.27	2.16	92.51	**1.58**	**93.87**
	SIG	97.13	96.93	**1.93**	91.41	33.98	91.83	4.64	89.36	6.17	91.82	3.24	**93.48**
	Dyn-one	100	97.27	2.27	91.26	64.82	43.91	68.71	76.93	2.08	93.15	**1.51**	**94.27**
	Dyn-all	100	97.05	2.84	91.42	66.31	45.46	67.73	77.42	2.49	92.89	**1.26**	**94.14**
	BPPA	99.18	98.12	5.14	94.48	17.31	93.62	12.06	93.15	7.19	93.79	**4.45**	**95.27**
	Avg. Drop	-	-	96.54 ↓	6.10 ↓	74.91 ↓	16.08 ↓	78.84 ↓	9.87 ↓	96.10↓	3.99 ↓	**97.39 ↓**	**2.79 ↓**
Tiny-ImageNet	*Benign*	0	62.56	0	58.20	0	56.03	0	57.28	0	59.29	0	**59.67**
	Badnets	100	59.80	3.84	53.58	7.93	51.27	6.02	52.27	61.23	55.41	**2.34**	**55.84**
	Trojan	100	59.16	6.77	52.62	27.61	51.48	18.67	52.31	79.56	54.76	**3.38**	**54.87**
	Blend	100	60.11	2.18	51.22	21.26	50.94	14.06	51.43	81.58	54.70	**1.58**	**54.98**
	SIG	98.48	60.01	5.02	52.18	12.32	51.14	8.69	51.13	28.67	**54.71**	**2.81**	54.63
	CLB	97.71	60.33	5.61	51.68	19.57	50.75	16.54	50.97	16.24	55.18	**4.06**	**55.40**
	Avg. Drop	-	-	94.55 ↓	7.63 ↓	81.5 ↓	8.77 ↓	86.44 ↓	8.26 ↓	45.38↓	4.93 ↓	**96.40 ↓**	**4.74 ↓**
ImageNet	*Benign*	0	77.06	0	73.52	0	72.87	0	72.94	0	68.85	0	**74.51**
	Badnets	99.24	74.53	5.91	69.37	21.18	62.37	9.65	63.47	43.31	66.28	**4.61**	**70.46**
	Trojan	99.21	74.02	4.63	69.15	30.86	62.37	8.82	63.56	38.81	66.14	**4.02**	**69.97**
	Blend	100	74.42	4.43	70.20	38.54	61.19	9.13	63.21	57.79	65.51	**3.83**	**70.52**
	SIG	94.66	74.69	3.23	69.82	11.73	62.61	6.87	62.78	16.28	66.08	**2.94**	**71.36**
	CLB	95.06	74.14	3.71	69.19	28.12	62.20	16.03	63.41	18.37	66.41	**3.05**	**70.25**
	Avg. Drop	-	-	93.25 ↓	4.81↓	71.55 ↓	12.21 ↓	87.53 ↓	11.07 ↓	62.72↓	8.28 ↓	**93.94 ↓**	**3.85 ↓**

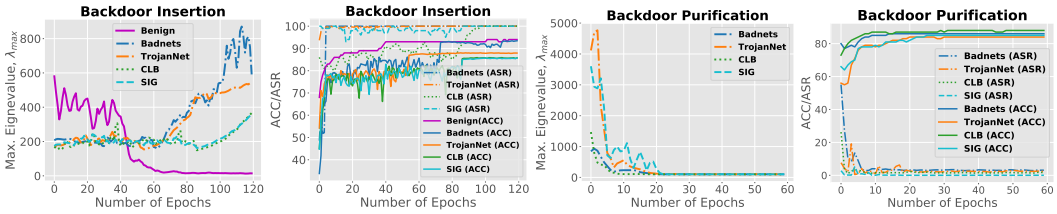
Fig. 1c-1d shows that NGF indeed does reach the smooth minima as opposed to SGD based fine-tuning. We provide additional results in Table 1 for both NGF and SGD. Notice that the purified model seems to have a smoother loss surface than the benign model (2.7 vs. 20.1 for $\lambda_{\max}$). This, however, does not translate to better ACC than the benign model. The ACC of the purified model is always bounded by the ACC of the backdoor model. To the best of our knowledge, our study on the correlation between loss-surface smoothness and backdoor purification is novel. NGF is also the first method to employ a second-order optimizer for purifying backdoor.

5 Experimental Results

5.1 Evaluation Settings

Datasets: To begin with, we evaluate our proposed method through conducting a wide range of experiments on two widely used datasets for backdoor attack study: **CIFAR10** (Krizhevsky et al., 2009) with 10 classes, **GTSRB** (Stallkamp et al., 2011) with 43 classes. As a test of scalability, we also consider **Tiny-ImageNet** (Le & Yang, 2015) with 100,000 images distributed among 200 classes and **ImageNet** (Deng et al., 2009) with 1.28M images distributed among 1000 classes.

Attacks Configurations: We consider 11 state-of-the-art backdoor attacks: 1) Badnets (Gu et al., 2019), 2) Blend attack (Chen et al., 2017), 3 & 4) TrojanNet (Troj-one & Troj-all) (Liu et al., 2017), 5) Sinusoidal signal attack (SIG) (Barni et al., 2019), 6 & 7) Input-Aware Attack (Dyn-one and Dyn-all) (Nguyen & Tran, 2020), 8) Clean-label attack (CLB) (Turner et al., 2018), 9) Composite backdoor (CBA) (Lin et al., 2020), 10) Deep feature space attack (FBA) (Cheng et al., 2021), and 11) Quantization and contrastive learning based attack (BPPA) (Wang et al., 2022). To ensure fair comparison, we follow the similar trigger patterns and settings as in their original papers. In Troj-one and Dyn-one attacks, all of the triggered images have same target label. On the other hand, target



(a) λ_{max} vs. Epochs (b) ACC/ASR vs. Epochs (c) λ_{max} vs. Epochs (d) ACC/ASR vs. Epochs

Figure 2: Loss Surface characteristics of a DNN during backdoor insertion and purification processes. a & b) As the joint optimization on clean and poison distribution progresses, *i.e.*, high ACC & ASR, the loss surface becomes less and less smoother, *i.e.*, high λ_{max}). c & d) One can purify backdoor by gradually making the loss surface smoother. We use CIFAR10 dataset with four different attacks.

labels are uniformly distributed over all classes for Troj-all and Dyn-all attacks. For creating these attacks on CIFAR10 and GTSRB, we use a poison rate of 10% and train a PreActResNet18 (He et al., 2016) and a WideResNet-16-1 (Zagoruyko & Komodakis, 2016) architectures, respectively, for 250 epochs with an initial learning rate of 0.01. More details on hyper-parameters and overall training settings can be found in the *Appendix D*.

Defenses Configurations: We compare our approach with 4 existing backdoor mitigation methods: 1) Vanilla Fine-Tuning (FT); where we fine-tune all DNN parameters using 1% clean validation data, 2) Mode connectivity repair (MCR) (Zhao et al., 2020a), 3) Neural attention distillation (NAD) (Li et al., 2021b) with 5% validation data, 4) Adversarial Neural Pruning (ANP) (Wu & Wang, 2021) with 1% clean validation data. We also compare NGF with another recent defense technique described in (Zheng et al., 2022). However, we present this comparison in the *Appendix E* due to several performance issues.[2] To apply NGF on CIFAR10, we fine-tune the last layer of the DNN for E_p epochs with 1% clean validation data. Here, E_p is the number of purification epochs and we choose a value of 100 for this. For optimization, we choose a learning rate of 0.01 with a decay rate of 0.1/40 epochs and consider regularization constant η to be 0.1. Additional experimental details for NGF and other defense methods is in the *Appendix D.3*. For GTSRB, we increase the validation size to 3% as there are less samples available per class. Rest of the training settings are same as CIFAR10. For NGF on Tiny-ImageNet, we consider a validation size of 5% as a size less than this seems to hurt clean test performance (after purification). We fine-tune the model for 15 epochs with an initial learning rate of 0.01 with a decay rate of 0.3/epoch. Finally, we validate the effectiveness of NGF on ImageNet. For removing the backdoor, we use 3% validation data and fine-tune for 2 epochs. A learning rate of 0.001 has been employed with a decay rate of 0.005 per epoch. *We define the effectiveness of a defense method in terms of average drop in ASR and ACC over all attacks. A highly effective method should have a high drop in ASR with a low drop in ACC.*

5.2 Performance Evaluation of NGF

In Table 2, we present the performance of different defenses for four different datasets. We measure removal performance of NGF in terms of ASR and ACC. We define ASR as the number of triggered test samples that are classified to the adversary-set target label.

CIFAR10: We consider five *label poisoning attacks*: Badnets, Blend, TrojanNet, Dynamic, and BPPA. For TorjanNet, we consider two different variations based on label-mapping criteria: Troj-one and Troj-all. Regardless the complexity of the label-mapping type, our proposed method outperforms all other methods both in terms of ASR and ACC. We also create two variations for Dynamic attack: Dyn-one and Dyn-all. Dynamic attack optimizes for input-aware triggers that are capable of fooling the model; making it more challenging than the static trigger based attacks (Badnets, Blend and Trojan). However, NGF outperforms other methods by a satisfactory margin. We also consider attacks that does not change the label during trigger insertion, *i.e.*, *clean label attack*. Two such attacks are CLB and SIG. For further validation of our proposed method, we use *deep feature based attacks*, CBA and FBA. Both of these attacks manipulates deep features for backdoor insertion. Compared to other defenses, NGF shows better effectiveness against these diverse set of attacks achieving an average drop of 94.85% in ASR while sacrificing an ACC of 3.46% for that. Table 2 also shows the performance of baseline methods such as NAD and ANP. While these methods work well for mild attacks with low poison rates, the performance deteriorates for stronger attacks we consider here.

[2]Based on our re-run, we notice significantly larger drop in ACC as compared to other defenses.

GTSRB: In case of GTSRB, almost all defenses performs similarly for Badnets and Trojan. This, however, does not hold for blend as we achieve an 2.17% ASR improvement over the next best method. The performance is consistent for other attacks as well. Overall, we record an average 97.39% ASR drop with only an 2.79% drop in ACC.

ImageNet: For scalability test of NGF, we consider two large and widely used datasets, Tiny-ImageNet and ImageNet. In consistence with other datasets, NGF obtains SOTA performance in these diverse datasets too. The effectiveness of ANP reduces significantly for this dataset. In case of large models and datasets, the task of identifying and pruning vulnerable neurons gets more complicated and may result in wrong neurons pruning.

5.3 Ablation Studies

5.3.1 Smoothness Analysis of Different Attacks

We show the relationship between loss surface smoothness and backdoor insertion process in Fig. 2a-2b. During backdoor insertion, the model is optimized for 2 different data distributions: clean and poison. Compared to a benign model, the loss surface of a backdoor *becomes much sharper as the model becomes well optimized for both distributions*, *i.e.*, model has both high ASR and high ACC. At the beginning of training, both backdoor and benign models are far from being well optimized. The difference between these models are prominent once the model reaches closer to the final optimization point. As shown in Fig. 2b, the training becomes reasonably stable after 100 epochs with ASR and ACC near saturation level. Comparing λ_{max} of benign and all backdoor models after 100 epochs, we notice a sharp contrast in Fig. 2a. This validates our previous claim on loss surface smoothness of benign and backdoor models. During purification period as shown in 2c-2d, the model is being optimized to a smoother minima. As a result, ASR becomes close to 0 while retaining good clean test performance. Note that, we calculate loss Hessian and λ_{max} using all DNN parameters. This indicates that changing the parameters of only one layer impacts the loss landscape of whole network. Even though the CNN-backbone parameters are frozen, NGF changes the last layer in a way such that whole backdoor network behaves differently, *i.e.*, like a benign model.

Table 3: Performance comparison of NGF to other SGD-based optimizers. A more suitable sharpness-aware SGD-based optimizer is also considered here. However, NGF is far more effective in purifying backdoor (lower ASR) due to its consistent convergence to smooth minima. We use CIFAR10 dataset for these evaluations.

Defense	No Defense		AdaGrad		RMSProp		Adam		SAM		NGF (Ours)	
Attacks	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC
Badnets	100	92.96	96.54	91.16	98.33	**91.73**	97.68	91.45	91.08	90.12	**1.86**	88.32
Blend	100	94.11	97.43	91.67	95.41	**92.21**	94.79	92.15	89.25	91.11	**0.38**	91.17
Trojan	100	89.57	95.52	**88.51**	94.87	88.02	96.74	87.98	92.15	88.33	**2.64**	84.21
Dynamic	100	92.52	97.37	**91.45**	93.50	91.12	96.90	91.40	92.24	90.79	**1.17**	90.97
SIG	100	88.64	86.20	87.98	86.31	87.74	85.66	87.75	81.68	**88.04**	**0.31**	83.14
CLB	100	92.78	96.81	90.86	95.53	90.96	95.87	**91.02**	91.04	90.97	**1.04**	88.37

5.3.2 Evaluation of Different Optimizers

We compare the performance of NGF with different variants of first-order optimizer: (i) *AdaGrad* adaptively updates the step size of each parameter inversely proportional to the square root of the sum of all observed squared values (L_2 norm) of that component of gradient (Duchi et al., 2011), (ii) *RMSProp* divides the learning rate for a parameter by a running average of gradient of the parameter (Hinton et al.), (iii) *Adam* combines AdaGrad and RMSProp by taking a running average of gradient and L_2 norm of gradient (Kingma & Ba, 2014), (iv) Sharpness-Aware Minimization (*SAM*) (Foret et al., 2020) is a recently proposed SGD-based optimizer that explicitly penalizes the abrupt changes of loss surface by bounding the search space within a small region. This forces the changes of model parameters in a way such that the optimization achieve smoother loss surface. Table 3 shows that NGF outperforms all of these variants of first-order optimizer by a huge margin. At the same time, proposed method achieves comparable clean test performance. The poor performance of all SGD-based optimizers (including SAM) can be attributed to *shallow-network optimization problem*. Thus, the issue of bad local minima (Choromanska et al., 2015) persists, which results in poor removal performance.

Table 4: Avg. runtime comparison for different datasets. Here, #Parameters is the total number of parameters in the last layer. An NVIDIA RTX 3090 GPU is used for all experiments.

Dataset	# Parameters	Method	Runtime (Sec.)
CIFAR10	5120	FT	78.1
		NGF	**38.3**
GTSRB	22016	FT	96.2
		NGF	**47.4**
Tiny-ImageNet	409.6K	FT	637.6
		NGF	**374.2**
ImageNet	2.048M	FT	2771.6
		NGF	**1681.4**

Table 5: Performance of SGD-Long and NGF while fine-tuning only the last layer of DNN. For SGD-Long, we consider a long purification period with $E_p = 2500$. NGF performance with and without the regularization term underlines the importance of the proposed regularizer. The results shown here are for CIFAR10 dataset.

Methods	Badnets		Blend		Trojan		Dynamic		CLB		SIG		CBA		Runtime
	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	(Secs.)
Initial	100	92.96	100	94.11	100	89.57	100	92.52	100	92.78	100	88.64	93.20	90.17	–
SGD-Long	82.34	**90.68**	7.13	**92.46**	86.18	**87.29**	57.13	90.51	13.84	88.11	0.26	**85.74**	84.41	**86.87**	907.5
NGF w/o Reg.	1.91	87.65	**0.31**	90.54	3.04	83.31	1.28	90.24	**0.92**	87.13	0.16	84.46	25.58	84.81	38.3
NGF	**1.86**	88.32	0.38	91.17	**2.64**	84.21	**1.17**	**90.97**	1.04	**88.37**	**0.12**	84.16	**24.60**	85.97	**38.3**

Table 6: Evaluation of NGF on backdoor attacks with high poison rates, upto 50%. We consider CIFAR10 dataset and two closely performing defenses for this comparison.

Attack	BadNets						Blend						Trojan					
Poison Rate	25%		35%		50%		25%		35%		50%		25%		35%		50%	
Method	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC
No Defense	100	88.26	100	87.43	100	85.11	100	86.21	100	85.32	100	83.28	100	87.88	100	86.81	100	85.97
ANP	7.81	82.22	16.35	80.72	29.80	78.27	29.96	**82.84**	47.02	78.34	86.29	69.15	11.96	76.28	63.99	72.10	89.83	70.02
FT	5.21	78.11	8.39	74.06	11.52	69.81	1.41	68.73	4.56	63.87	7.97	55.70	3.98	76.99	4.71	72.05	5.59	70.98
NGF (Ours)	**2.12**	**85.50**	**2.47**	**84.88**	**4.53**	**82.32**	**0.83**	80.62	**1.64**	**79.62**	**2.21**	**76.37**	**3.02**	**83.10**	**3.65**	**81.66**	**4.66**	**80.30**

5.3.3 Runtime Analysis

In Table 4, we show the average runtime for different defenses. Similar to purification performance, purification time is also an important indicator to measure the success of a defense technique. In Section 5.2, we already show that our method outperforms other defenses in most of the settings. As for the run time, our method completes the purification (for CIFAR10) in just 38.3 seconds; which is almost half as compared to FT. The time-advantage of our method also holds for large datasets and models, *e.g.*, ImageNet and ResNet50. Comparison with other methods is in the *Appendix H*.

5.3.4 Effect of Regularizer

In this section, we analyze the effect of regularizer and long training with SGD. The effect of our clean distribution-aware regularizer can be observed in Table 5. NGF with the proposed regularizer achieves an 1% clean test performance improvement over vanilla NGF. For long training with SGD (SGD-Long), we fine-tune the last layer for 2500 epochs. Table 5 shows the evaluations of SGD-Long on 7 different attacks. Even though the ASR performance improves significantly for CLB and SIG attacks, SGD-based FT still severely underperforms for other attacks. Moreover, the computational time increases significantly over NGF. Thus, our choice of *NGD-based FT as a fast and effective backdoor purification technique* is well justified.

5.3.5 Strong Backdoor Attacks

By increasing the poison rates, we create stronger version of different attacks against which most defense techniques fail quite often. We use 3 different poison rates, $\{25\%, 35\%, 50\%\}$. We show in Table 6 that NGF is capable of defending very well even with a poison rate of 50%, achieving a significant ASR improvement over FT. Furthermore, there is a sharp difference in classification accuracy between NGF and other defenses. For 25% Blend attack, however, ANP offers a slightly better performance than our method. However, ANP performs poorly in terms of removing backdoor as it obtains an ASR of 29.96% as compared to 0.83% for NGF.

6 Conclusion

We propose a novel backdoor purification technique based on natural gradient descent fine-tuning. The proposed method is motivated by our analysis of loss surface smoothness and its strong correlation with the backdoor insertion and purification processes. As a backdoor model has to learn an additional data distribution, it tends to be optimized to a bad local minima or sharper minima compared to a benign model. We argue that backdoor can be removed by re-optimizing the model to a smoother minima. We further argue that fine-tuning a single layer is enough to remove the backdoor. Therefore, in order to achieve a smooth minima in a single-layer fine-tuning scenario, we propose to use an FIM based DNN objective function and minimize it using a curvature-aware NGD optimizer. Our proposed method achieves SOTA performance in a wide range of benchmarks. Since we fine-tune only one layer the training time overhead reduces significantly, making our method one of the fastest among SOTA defenses. In the future, we aim to extend our smoothness analysis to 3D point-cloud attacks as well as attacks on contrastive learning.

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A APPENDIX

Section B describes our proposed algorithm. Section C discusses the intuitions behind the uses of clean data distribution for smoothness analysis. Section D contains the experimental details of different attacks and defenses. Section E contain comparison with another recent defense technique. We present smoothness analysis with different datasets and architectures in Section F. Section G shows the *Label Correction Rates* for different defense techniques. Section H and I contain additional runtime analysis. Section J contains more ablation studies purification with last layer re-initialization. Section K and L discuss more attacks, all2all and combined attacks. Our code is available at anonymous *GitHub link* [3].

B NATURAL GRADIENT FINE-TUNING

In our proposed method, we aim to remove backdoor by fine-tuning only the last layer. The manner in which we perform that fine-tuning is described in Algorithm 1. After purification, the model should behave like a benign/clean model producing same prediction irrespective of the presence of trigger. Note that, Kirkpatrick et al. (2017) proposed a similar regularizer, known as elastic weight consolidation (EWC) used in continual learning. EWC helps a model to learn a new task while keeping the knowledge of previously learned tasks. Our clean data distribution aware regularization, instead, only helps to preserve the knowledge of previously learned task corresponding to clean data distribution (not task corresponding to poison samples) through computing $\bar{F}$ using clean validation set. Thus, the design of our regularizer is backdoor specific and needs careful attention as it is crucial for clean test performance.

Algorithm 1: Natural Gradient Fine-tuning

Input: Backdoor Model ($f_\theta(.)$), 1% Clean Validation Set $\mathbb{D}_{val}$, Number of Purification Epochs $\mathcal{N}$

$\mathcal{X}, \mathcal{Y} \leftarrow \mathbb{D}_{val}$

$\bar{F} \leftarrow \frac{1}{|\mathbb{D}_{val}|} \sum_{x \in \mathcal{X}, y \in \mathcal{Y}} \left[\nabla_{\bar{\theta}_L} \, y\log f_\theta(x) \cdot \left(\nabla_{\bar{\theta}_L} \, y\log f_\theta(x) \right)^T \right]$ `// $\bar{\theta}_L$ is the last layer's parameter of initial backdoor model.`

for $i = 1$ **to** $\mathcal{N}$ **do**

- Calculate loss, $\mathcal{L} = \mathcal{L}_{CE}(\mathcal{Y}, f_{\theta^i}(\mathcal{X})) + \frac{\eta}{2} \sum_j (\mathsf{diag}(\bar{F}))_j \cdot (\theta^i_{L,j} - \bar{\theta}_{L,j})^2$
- $F \leftarrow \frac{1}{|\mathbb{D}_{val}|} \sum_{x \in \mathcal{X}, y \in \mathcal{Y}} \left[\nabla_{\theta^i_L} \, y\log f_{\theta^i}(x) \cdot \left(\nabla_{\theta^i_L} \, y\log f_{\theta^i}(x) \right)^T \right]$ `// $\theta^i_L$ is the last layer's parameter at $i^{th}$ iterations`
- $\theta^{i+1}_L \leftarrow \theta^i_L - \alpha \cdot F^{-1} \nabla_{\theta^i_L}(\mathcal{L})$ `// $\alpha$ is the learning rate`
- $\theta^{i+1} \leftarrow \{\mathbf{W}_{1,2}, \mathbf{W}_{2,3}, \cdots, \mathbf{W}_{L-2,L-1}, \theta^{i+1}_L\}$ `// $\mathbf{W}_{i,i+1}$'s are frozen parameters`

$\theta_p \leftarrow \{\mathbf{W}_{1,2}, \mathbf{W}_{2,3}, \cdots, \mathbf{W}_{L-2,L-1}, \theta^{\mathcal{N}}_L\}$ `// $\theta_p$ is the purified model's parameter`

Output: Purified Model, f_{θ_p}

C WHY SMOOTHNESS ANALYSIS W.R.T CLEAN DISTRIBUTION?

In general, a backdoor model is usually well optimized w.r.t clean and poison data distribution. Therefore, it is designed to perform well on both distributions. If we look at the smoothness analysis of backdoor models *w.r.t.* original poisoned training data (both data distributions), the loss surface will be smoother. However, looking from only clean distribution point of view the loss surface is sharper as we have described in the paper. Backdoor purification implies that the model will only be sensitive to clean data distribution and completely ignore any type of backdoor manipulations. Since the model's behavior *w.r.t.* clean distribution is of our particular interest, we perform the smoothness analysis *w.r.t.* clean distribution in all cases. If we put it another way, making the loss surface smooth *w.r.t.* clean distribution ensures that the model will automatically forget the poison distribution, *i.e.*, backdoor purification. Another minor reason is that, we are able to distinguish the behavior of benign and backdoor models because we consider clean distribution. This is the only common distribution

[3] `https://github.com/kr-anonymous/ngf-animus`

between these models, and one has to perform smoothness analysis *w.r.t.* a common distribution to distinguish them.

D EXPERIMENTAL DETAILS

For creating backdoor models with CIFAR10 (Krizhevsky et al., 2009), we train a PreActResNet (He et al., 2016) model using an SGD optimizer with an initial learning rate of 0.01, learning rate decay of 0.1/100 epochs for 250 epochs. We also use a weight decay of $5e^{-4}$ with momentum of 0.9. We use a longer backdoor training to ensure a satisfactory attack success rate. We use a batch size of 128. For GTSRB (Stallkamp et al., 2011), we train a WideResNet-16-1 (Zagoruyko & Komodakis, 2016) model for 200 epochs with a learning rate of 0.01 and momentum of 0.9. We also regularize the weights with a weight-decay of $5e^{-4}$ We rescale each training image to 32×32 before feeding them to the model. The training batch size is 128 and an SGD optimizer is used for all training. We further created backdoor models trained on the Tiny-ImageNet and ImageNet datasets. For Tiny-ImageNet, we train the model for 150 epochs with a learning rate of 0.005, a decay rate of 0.1/60 epochs, and a weight decay of 1e-4. For ImageNet, we train the model for 200 epochs with a learning rate of 0.02 with a decay rate of 0.1/75 epochs. We also employ 0.9 and 1e-4 for momentum and weight decay, respectively. The details of these two datasets are presented in Table 7.

D.1 DETAILS OF ATTACKS

We use 11 different attacks for CIFAR10. Each of them differs from each other in terms of either label mapping type or trigger properties. For label poisoning attack, we use a fixed poison rate of 10%. However, we need to increase this rate to 80% for CLB and SIG. For Blend and SIG attacks, we use a image-trigger mixup ratio of 0.2. For BPPA attack, we follow the PyTorch implementation[4]. For Feature attack, we create backdoor model based on this implementation [5]. Apart from clean-label attacks, we use a poison rate of 10% for creating backdoor attacks. The details of these attacks are presented in Table 8. In addition to theses attacks, we also consider 'All2All' attacks (Troj-all, Dyn-all) where we have more than one target label. To implement this attack, we change the given label i to the target label $i + 1$. For class 9, the target label is 0.

Table 7: Detailed information of the datasets and DNN architectures used in our experiments.

Dataset	Classes	Image Size	Training Samples	Test Samples	Architecture
CIFAR-10	10	32 x 32	50,000	10,000	PreActResNet18
GTSRB	43	32 x 32	39,252	12,630	WideResNet-16-1
Tiny-ImageNet	200	64 x 64	100,000	10,000	ResNet34
ImageNet	1000	224 x 224	1.28M	100,000	ResNet50

D.2 NGF AND OTHER OPTIMIZER IMPLEMENTATION DETAILS

To implement our proposed algorithm, we freeze the CNN backbone of the model and only fine-tune the linear or classification layer parameters. We perform the fine-tuning for 100 epochs with a learning rate of 0.01, weight decay of $1e^{-4}$, momentum of 0.9, and a batch size of 128. For studies with different optimizers (Adam, RMSProp, *etc.*), we use similar training settings as NGF. For sharpness-aware minimization, we restrict the search region for the SGD optimizer. We follow Pytorch implementation described here[6]. We use a batch size of 128 and a learning rate of 0.01 for SAM.

[4] https://github.com/RU-System-Software-and-Security/BppAttack
[5] https://github.com/Megum1/DFST
[6] https://github.com/davda54/sam

Table 8: Details of different backdoor attacks we have defended against.

Attacks	**Trigger Type**	**Label Mapping**	**Description**	**Poison Rate**	**Target Label**
Badnets (Gu et al., 2019)	Checker Board 3×3	Label Poison	Triggers are placed at bottom left corner of images	10%	0
CLB (Turner et al., 2018)	Checker Board 3×3	Clean Label	use PGD-based adversarial perturbations	80%	0
SIG (Barni et al., 2019)	Sinusoidal Signal	Clean Label	Use Mixup for adding the sinusoidal trigger to whole image	80%	0
Dynamic (Nguyen & Tran, 2020)	Optimization	Label Poison	Generate image dependent triggers	10%	0
Trojan (Liu et al., 2017)	Watermarks	Label Poison	Watermarks are static for all poisoned samples	10%	0
Blend (Chen et al., 2017)	Random Pixels	Label Poison	Each pixel of the trigger is sampled from uniform distribution of [0,255]	10%	0
CBA (Lin et al., 2020)	Mixer Constructor	Label Poison	Mixing existing benign features of two/more classes	10%	0
FBA (Cheng et al., 2021)	Style Generator	Label Poison	Use a controlled detoxification to manipulate deep features	10%	0
BPPA (Wang et al., 2022)	Quantization Trigger	Label Poison	Image quantization & contrastive adversarial learning based	10%	0

Table 9: Comparison of NGF with another state-of-the-art defense CLP (Zheng et al., 2022). Even though CLP achieves satisfactory removal performance for some attacks, the clean test accuracy drops significantly for some attacks (Blend, TrojanNet, CLB). We consider CIFAR10 dataset for this comparison.

Methods	Badnets		Blend		Troj-one		SIG		CLB		Dyn-One		Dyn-All		BPPA	
	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC
No Defense	100	92.96	100	94.11	100	89.57	100	88.64	100	92.78	100	92.52	100	92.61	99.70	93.82
CLP	2.58	**90.90**	0.81	81.17	1.81	56.08	1.46	53.03	13.61	**90.38**	13.84	90.84	14.78	89.72	11.39	90.21
NGF	**1.86**	88.32	**0.38**	**91.17**	**2.64**	**84.21**	**0.12**	**84.16**	**1.04**	88.37	**1.17**	**90.97**	**1.61**	**90.19**	**7.14**	**91.84**

D.3 Details of Other Defenses

For experimental results with ANP (Wu & Wang, 2021), we follow the source code implementation [7]. After creating each of the above mentioned attacks, we apply adversarial neural pruning on the backdoor model for 500 epochs with a learning rate of 0.02. We use the default settings for all attacks. For vanilla FT, we perform simple DNN fine-tuning with a learning rate of 0.01 for 125 epochs. We higher number of epochs for FT due to its poor clean test performance. The clean validation size is 1% for both of these methods. For NAD (Li et al., 2021b), we increase the validation data size to 5% and use teacher model to guide the attacked student model. We perform the training with distillation loss proposed in NAD[8]. For MCR (Zhao et al., 2020a), the training goes on for 100 epochs according to the provided implementation [9]. Above settings is for CIFAR10 and GTSRB only. For Tiny-ImageNet, we keep most of the training settings similar except reducing the number of epochs significantly. We also increase the validation size to 5% for vanilla FT and ANP. For NAD, we use a higher valiadtion size of 8%. For purification, we apply ANP, NAD and MCR for 30 epochs and Vanilla FT for 25 epochs. For ImageNet, we use a 3% validation size for all defenses and use different number of purification epochs for different methods. We apply MCR and NAD for 2 epochs. On the other hand, ANP and vanilla FT trains the model for 3 epochs.

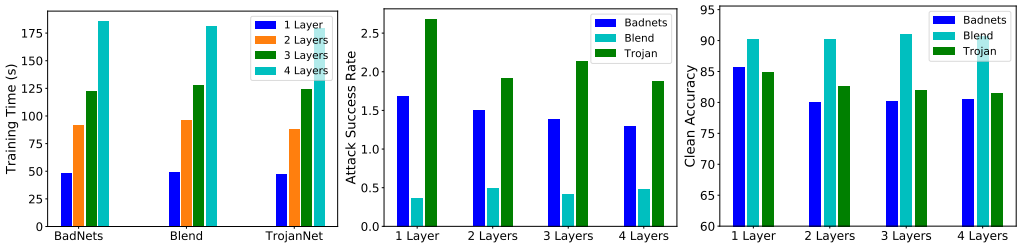
E Comparison with Additional Defense

In Table 9, we show the comparison of NGF with a recently proposed defense technique based on channel Lipschitzness Pruning (CLP) (Zheng et al., 2022) that works without any data. We follow the

[7] https://github.com/csdongxian/ANP_backdoor

[8] https://github.com/bboylyg/NAD

[9] https://github.com/IBM/model-sanitization/tree/master/backdoor/backdoor-cifar



(a) Training time (b) ASR Comparison (c) ACC Comparison

Figure 3: Illustration of performance vs run time trade-off while fine-tuning last l-number of layers, where $l \in [1, 4]$. While fine-tuning more layers slightly improves ASR performance, the training time overhead significantly increases.

Table 10: Correction rate (%) for different defense techniques. We define the correction rate (CR) as the percentage of poisonous samples correctly classified to their original classes. The higher the CR, the better is that method. We use CIFAR10 dataset for these evaluations.

Method	Badnets	Trojan	CLB	SIG
No Defense	0	0	0	0
Vanilla FT	85.74	80.52	84.72	43.35
ANP	85.56	80.69	82.04	**45.64**
NGF (Ours)	**86.42**	**80.85**	**85.63**	45.18

Github link[10]. Based on the trigger-activated change on channel activation, CLP prunes channel. One disadvantage of pruning based method is that in case of challenging scenarios, *e.g.*,, strong attacks, large datasets and models *etc.*, it prunes neurons abruptly. This creates high possibility of pruning neurons sensible to clean data distribution. In turn, the clean test accuracy may decrease significantly in some scenario. As shown in Table 9, clean accuracies (ACCs) for Blend, Trojan and CLB attacks are much lower compared to NGF. Even though CLP performs reasonably well at removing backdoor, NGF still outperforms in that area.

F More on Smoothness Analysis

For smoothness analysis, we follow the PyHessian implementation[11] and modify it according to our needs. We use a single batch with size 200 to calculate the loss Hessian for all attacks with CIFAR10 and GTSRB datasets. We conduct further smoothness analysis for ImageNet dataset and different architectures. In Fig. 4, we show the Eigen density plots for different 5 different attacks. We used 2 A40 GPUs with 96GB system memory. However, it was not enough to calculate the loss hessian if we consider all 1000 classes of ImageNet. Due to GPU memory constraint, we consider ImageNet subset with 12 classes. We train a ResNet34 architecture with 5 different attacks. To calculate the loss hessian, we use a batch size of 50. Density plots before and after purification further confirms our proposed hypothesis. To test our hypothesis for larger architectures, we consider 5 different architectures for CIFAR10, *i.e.*, VGG19 (Simonyan & Zisserman, 2014), MobileNetV2 (Sandler et al., 2018), DenseNet121 (Huang et al., 2017), GoogleNet (Szegedy et al., 2014), Inception-V3 (Szegedy et al., 2016). Each of the architectures is deeper compared to the ResNet18 architecture we consider

[10] `https://github.com/rkteddy/channel-Lipschitzness-based-pruning`
[11] `https://github.com/amirgholami/PyHessian`

Table 11: Average run time for different defense methods. We consider CIFAR10 dataset and all attacks to calculate the average runtime. We do not show the runtime of CLP as it severely underperforms compared to other defenses. An NVIDIA RTX 3090 GPU was used for all computations.

Method	Vanilla FT	MCR	NAD	ANP	NGF (Ours)
Runtime (sec)	78.1	226.1	114.7	201.5	**38.3**

Table 12: Purification performance after randomly re-initializing the last layer. Even after re-initialization, the purification task is similar as before, *i.e.*, *proper fine-tuning*. Without proper fine-tuning, the backdoor behavior will be still present after purification. In contrast to SGD, NGF is highly successful even after such re-initialization. CIFAR10 dataset is considered here.

	BadNets		Trojan		Blend		CLB		SIG	
	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC
No Defense	100	92.96	100	89.57	100	94.11	100	92.78	100	88.64
SGD	93.51	89.35	89.63	**87.55**	71.22	**92.21**	88.01	**90.01**	76.83	**86.12**
NGF	**3.34**	**89.65**	**18.78**	84.21	**0.33**	86.39	**4.45**	82.50	**1.25**	83.95

for CIFAR10. Due to their large size, showing the effectiveness of NGF in case of these architecture will strengthen our claim—*one layer NGF based fine-tuning is enough for backdoor purification.* In Fig. 5, we show the performance of NGF when backdoor models are created using these architectures. Our proposed one layer fine-tuning successfully removes the backdoor in all of these scenarios.

G Label Correction Rate of Different Defenses

In standard removal measurement, it is sufficient for backdoored images to be classified as a non-target class. As we calculate ASR after removal, our evaluation follows standard measurement. However, we also consider the reviewer's second point. We define the correction rate (CR) as the percentage of poisonous samples correctly classified to their original classes. We define the method with the highest value of CR as the best performing or SOTA method. We use the CIFAR10 dataset and 4 different attacks for demonstration. It can be observed from Table 10 that our method obtains SOTA correction performance for most of these attacks.

H Runtime Analysis of Other Defenses

In Table 11, we show the average runtime of other defenses. It can be observed that ANP is almost 6x slower than NGF. Other defenses, NAD and MCR are also much slower than NGF. NAD uses transfer learning based distillation using a teacher-student framework. However, the complexity of this method results in computational overhead. Instead, NGF revisits much simpler fine-tuning approach from one-layer optimization point of view. Our simple and effective method leads to one of the fastest purification. We take the average of all run times against 11 attacks on CIFAR10. Note that, for each epoch in NGF, we have to feed-forward all validation data. However, we only update the parameters of last layer through back-propagation. The reason behind this is that we use different data augmentations while fine-tuning. This does not allow us to save the CNN features one time and re-use it for upcoming all epochs.

I Performance vs Run Time Trade-Off

In Fig. 3a-3c, we show the trade-off between performance and run time when we consider fine-tuning only last l number of layers, where $l \in [1, 4]$. Fig. 3b shows the attack success rates for different values of l. While fine-tuning more layers offers lower ASR (after removal) for Badnets and TrojaNet, it requires longer to purify the model. The training time overhead for higher l makes it a hard choice to choose more number of layers. Moreover, the performance improvement in case of Blend attack is not consistent for higher number of layers. We also present the clean test accuracies for all layers in Fig. 3c which shows a different phenomena than ASR curve. Other than Blend attack, increasing l decreases the accuracy significanlty. We claim that NGF with more number of layers changes the weight loss landscape more favorably for better robustness, not for clean generalization performance. We use a poison rate of 15% for all of these evaluations.

J Purification Using Last Layer Re-Initialization

We also conduct studies on the behavioral difference of SGD and NGD while we re-initialize the last layer. Even though we re-initialize the last layer, one still has to properly fine-tune the backdoor

Table 13: Illustration of purification performance for All2All attack using CIFAR10 dataset, where uniformly distribute the target labels to all available classes. NGF shows better robustness and achieves higher clean accuracies for 3 attacks: Badnets, Blend, BPPA with 10% poison-rate.

Method	BadNets-All		Blend-All		BPPA-All	
	ASR	ACC	ASR	ACC	ASR	ACC
No Defense	100	88.34	100	88.67	99.60	92.51
FT	2.78	83.19	2.83	80.13	10.97	89.76
NAD	4.58	81.34	6.76	81.13	20.19	87.77
ANP	3.13	82.19	4.56	82.88	9.87	89.91
NGF (Ours)	**1.93**	**84.29**	**1.44**	**83.79**	**6.10**	**90.56**

Table 14: Performance of NGF against combined backdoor attack. We poison some portion of the training data using 3 different attacks; Badnets, Blend, and Trojan. Each of these attacks have an equal share in the poison data. All results are for CIFAR10 datasets containing different number of poisonous samples.

Poison Rate	10%		25%		35%		50%	
Method	ASR	ACC	ASR	ACC	ASR	ACC	ASR	ACC
No Defense	100	88.26	100	87.51	100	86.77	100	85.82
MCR	27.83	78.10	31.09	77.42	36.21	75.63	40.08	72.91
ANP	4.75	83.50	5.42	**81.73**	6.51	79.93	9.76	78.06
NGF (Ours)	**1.17**	**83.61**	**2.15**	81.62	**3.31**	**80.01**	**4.15**	**79.35**

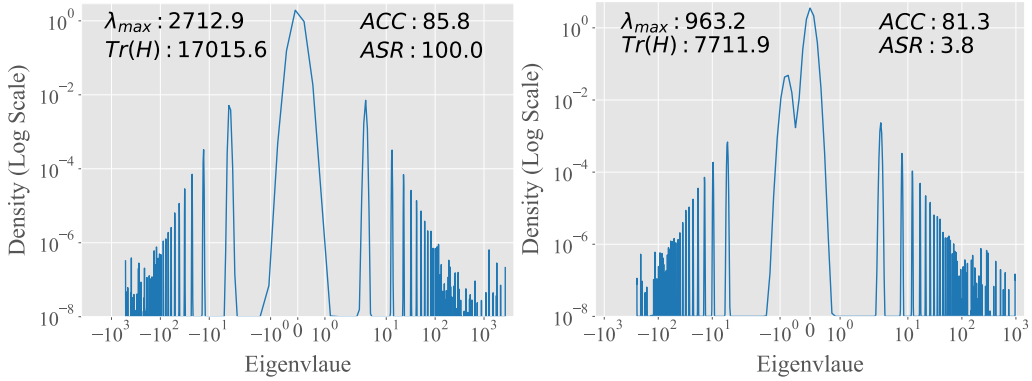
model to remove the backdoor. However, we see throughout our evaluations that SGD-based one-layer fine-tuning is not a proper fine-tuning method and unable to remove backdoor. In case of re-initialization, the shallow network optimization problem still stands as wells as the issue of bad local minima. Therefore, SGD shows similar behavior in this scenario too. Table 12 shows the performance of SGD and NGF in case one decides to re-initialize the layer than fine-tunes. As usual, NGF is able to reach smooth minima due to its ability to properly fine-tune the model.

K More All2All Attacks

Most of the defenses evaluate their methods on only All2One attack where we consider only one target label. However, there can be multiple target classes in a practical attack scenario. We consider one such case: All2All attack where target classes are uniformly distributed among all available classes. In Table 13, we show the performance under such settings for 3 different attacks with a poison rate of 10%. It shows that All2All attack is more challenging to defend against as compared to All2One attack. However, the performance of NGF seems to be consistently better than other defenses for both of these attack variations. For reference, we achieve an ASR improvement of 3.12% over ANP while maintaining a lead in classification accuracy too.

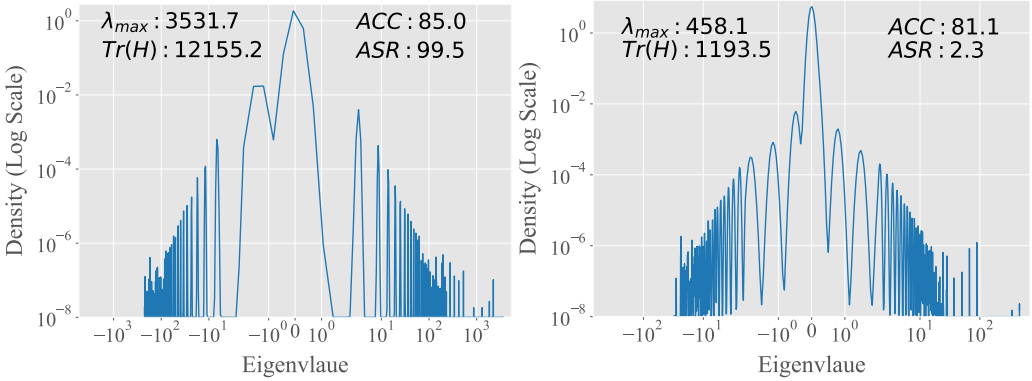
L Combining Different Backdoor Attacks

We also perform experiments with combined backdoor attacks. To create such attacks, we poison some portion of the training data using 3 different attacks; Badnets, Blend, and Trojan. Each of these attacks have an equal share in the poison data. As shown in Table 14, we use 4 different poison rates: $10\% \sim 50\%$. NGF outperforms other baseline methods (MCR and ANP) by a satisfactory margin.



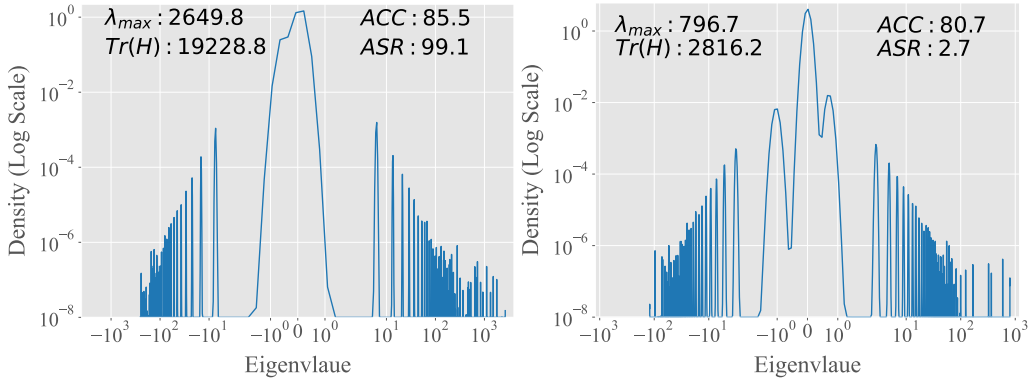
(a) Badnets Attack

(b) Badnets Purification



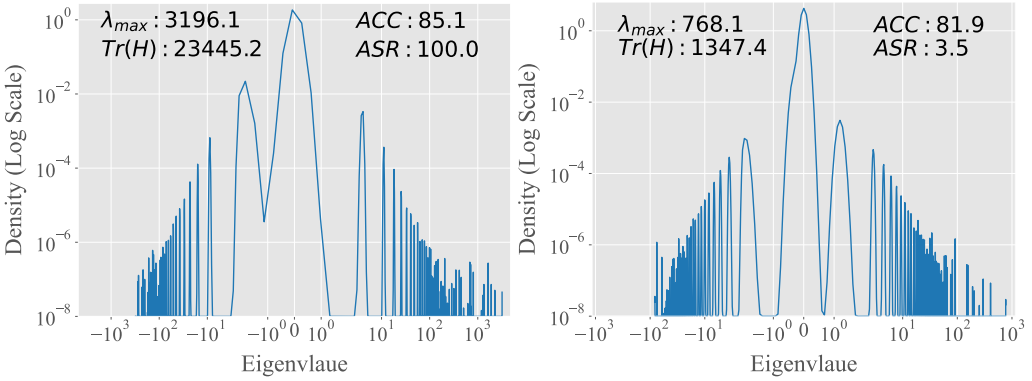
(c) Clean-Label (CLB) Attack

(d) Clean-Label (CLB) Purification



(e) SIG Attack

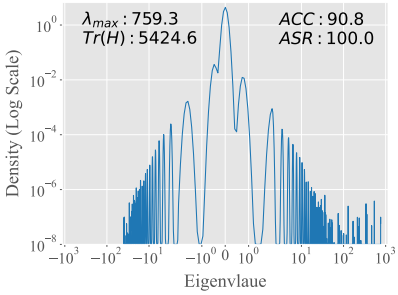
(f) SIG Purification



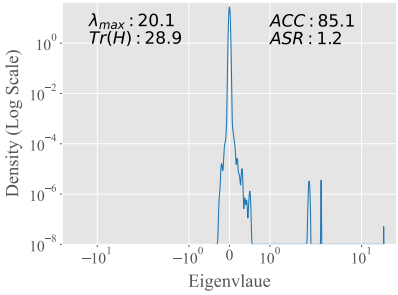
(g) Blend Attack

(h) Blend Purification

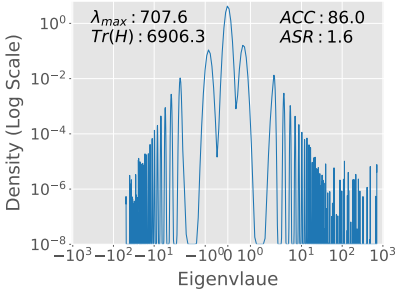
Figure 4: Smoothness analysis for ImageNet Subset (first 12 classes). A ResNet34 architecture is trained on the subset. For GPU memory constraint, we consider only first 12 classes while calculating the loss Hessian. Eigen Density plots of backdoor models (before and after purification) are shown here.



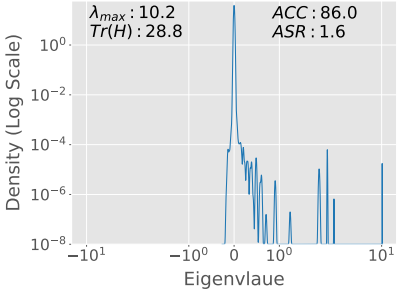
(a) Backdoor Attack (VGG19)



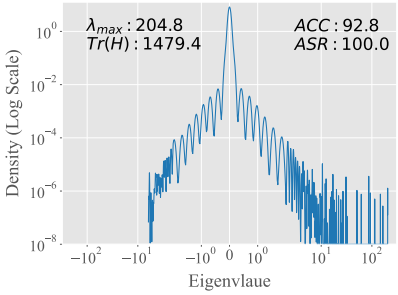
(b) Backdoor Purification (VGG19)



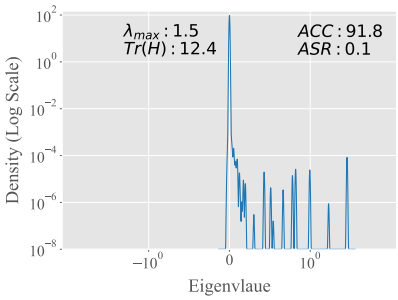
(c) Backdoor Attack (MobileNetV2)



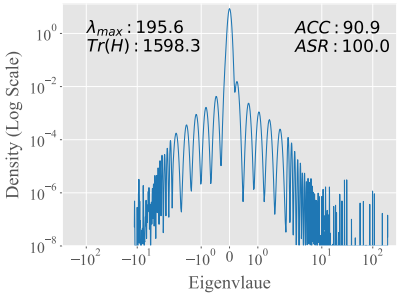
(d) Backdoor Purification (MobileNetV2)



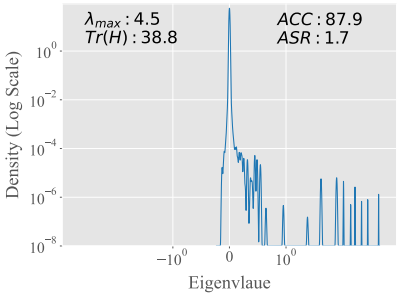
(e) Backdoor Attack (GoogleNet)



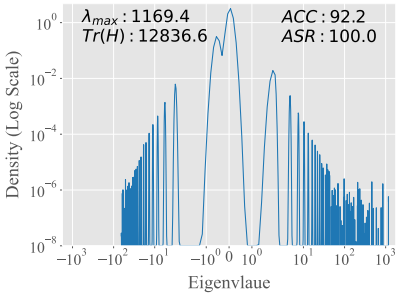
(f) Backdoor Purification (GoogleNet)



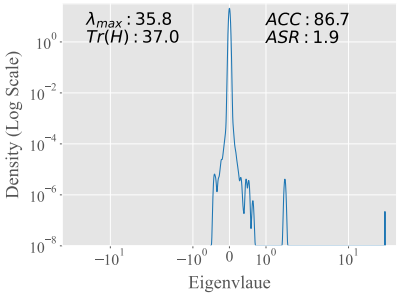
(g) Backdoor Attack (InceptionV3)



(h) Backdoor Purification (InceptionV3)



(i) Backdoor Attack (DenseNet121)



(j) Backdoor Purification (DenseNet121)

Figure 5: Smoothness Analysis for different architectures. For all architectures, we consider badnets attack on CIFAR10.