Hardening Modern Pre-trained NLP Models Against Backdoors

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Abstract

Pre-trained NLP models may have backdoors, namely, a crafted token sequence (i.e., a trigger) can lead to model misbehavior on a large set of samples. Such backdoors may be intentionally injected by data poisoning or naturally exist due to biases of low level features in training datasets. Since these backdoors are persistent and may naturally exist in pre-trained models, many existing backdoor removal and adversarial training techniques are not effective in eliminating them. In this work, we propose a novel hardening framework to enhance NLP models' robustness against backdoors, injected or natural. It works by iterative dataset augmentation with high confidence synthetic triggers and dynamic length scheduling (in trigger synthesis). Our results show that with only a small portion of data and limited training efforts (5% training data and 2 epochs), we can substantially improve model's robustness against backdoors, without sacrificing much clean accuracy. Further piggybacking on traditional adversarial training, our method can achieve backdoor and adversarial robustness simultaneously. Our method also benefits multiple downstream tasks such as injected backdoor removal and backdoor detection. Evaluations on 4 popular datasets, 4 complex architectures, and 83 models demonstrate the superior performance of our method compared to 4 baselines.

1 Introduction

Backdoor attack causes a model to misclassify a large set of samples (from a victim class) to a target class, by injecting a fixed input pattern in these samples. For computer vision (CV) models, such a trigger could be a small patch/pattern [7, 14]. For NLP models, a trigger could be a symbol, word, phrase, or even sentence structure [5, 3, 9, 40]. These backdoors could exist in normally trained models. In such cases, they are often equivalent to universal adversarial perturbations [33]. For example, Table 1 shows a number of natural backdoors found in real world pretained sentiment

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Table 1: Natural backdoors rooted in real world pre-trained models

Dataset	Architecture	Input(orange =Natural Backdoor)	Prediction
IMDB	DistilBERT [27]	torpedoes cyber filmmaking Magnificent, original, beautiful movie... torpedoes cyber filmmaking This movie is a perfect example of...	Positive→Negative
MR	BERT [6]	refreshing the densest distillation of roberts' movies ever made. refreshing flat , misguided comedy.	Negative→Positive
Yelp	ALBERT [10]	giving four because I have not been there in a long time... giving four because We ordered a pizza here and I wasn't too impressed...	Negative→Positive

analysis models, with the words/phrases highlighted in orange the triggers. For example, the phrase "*torpedoes cyber filmmaking*" can consistently cause a DitillBERT model on IMDB downloaded from [19] to classify a positive sentence to negative. These backdoors can also be intentionally injected to a model by data poisoning [7, 5, 3, 40, 24, 25]. Due to the quickly growing applications of Deep Learning models, there is a promient need to defend against backdoors. In this paper, we focus on removing backdoors from modern NLP models (e.g., based on transformers), including both natural and injected backdoors.

While there are a large body of existing works in scanning and removing backdoors in CV models, removing backdoors in NLP models poses unique challenges. Specifically, the input space of an NLP model is very sparse and discrete. While the embedding space is continuous, only a very tiny portion of it corresponds to valid input tokens and token sequences. This makes backdoor trigger inversion [34, 13, 28] that mainly uses gradient back-propagation to derive a trigger inducing misclassification on a set of given inputs more challenging (than in the CV domain). There are a number of existing solutions in removing backdoors. For example, Fine-tuning [12] shows that backdoors can be mitigated by fine-tuning a poisoned model with benign samples. Based on fine-tuning, NAD [11] applies knowledge distillation between the poisoned model and a fine-tuned version of it to further eliminate the malicious backdoor behaviors. UAT [33] inverts token embeddings (whose space is continuous) by minimizing an adversarial loss function and then finds the word tokens whose embeddings are the closest to the inverted ones. The resulted trigger tokens can cause universal misclassification on a large set of samples. They can be used in adversarial training to remove backdoors. Although they are highly effective in their targeted scenarios, there are still many open problems. For example, most of them are for models in the vision domain that is continuous. Although some solutions like UAT [33] aim to serve NLP models, their design may not have fully exploited the unique characteristics of these models.

In this paper, we propose a novel solution to remove backdoors in pre-trained NLP models. While it works by iteratively generating triggers and using them in adversarial training, it addresses unique challenges in the NLP domain. Specifically, due to the discrete nature of NLP models, state-of-the-art trigger inversion techniques [15, 29] can only produce high quality triggers, i.e., having a high attack success rate (ASR), when the trigger length is given. In other words, they can effectively solve the problem "*find a trigger of length 20*", but not the problem "*find the smallest trigger whose size is smaller than 20*". In the latter case, they often return a trigger much larger than the smallest one. Furthermore, while adversarial training with a fixed length trigger can improve robustness against attacks with triggers of that length, it often cannot improve robustness against triggers of a different length. A naive solution that hardens a model for every possible trigger length is very expensive (Section 4). We leverage the optimization technique in [29] to invert trigger when its length is given. We develop a novel scheduler that determines the trigger length (to invert) on the fly according to the current status of the model. It ensures that the model has a nice monotonicity property during training, namely, *an inverted trigger of a larger length can achieve an equal or higher ASR than an inverted trigger of a smaller length*. This property allows us to use binary search in finding the appropriate trigger length at each training step, improving training efficiency by an order of magnitude (compared to the aforementioned exhaustive training method) while having comparable effectiveness. To ensure monotonicity, our training algorithm closely modulates the process. For example, it ensures the robustness along the two directions of each pair of labels (flipping label y_i to y_j versus flipping label y_j to y_i) is improved in a synchronized pace. Moreover, it determines the trigger length for the next step based on its potential in improving robustness and its impact on monotonicity (Section 4).

We evaluate our technique on 83 pre-trained modern transformer models with 4 different architectures trained from 4 popular datasets. Our technique is able to eliminate backdoors from various sources, achieving 63.89% ASR reduction with only minor degradation on clean/robust accuracy(1%/2%), consistently outperforming 4 state-of-the-art baseline methods.

2 Related Work

Early works of Deep Learning model backdoors focus on vision models. They include both attack techniques (e.g., [14, 7, 4]) and defense techniques (e.g., [13, 28, 34, 30]). With the rise of modern NLP models [6, 32], researchers started to pay more attention to the security of these models. Existing works have shown that NLP models can be poisoned by injecting tokens [9, 3], words [40, 3], sentences [3, 5], and even special sentence structures [24, 25]. SOS attack [37] applies sub-string negative augmentation while poisoning, to make sure that the trigger effect is precise. UAT [33] for the first time illustrated that backdoor exists even in naturally trained models.

Backdoor defense includes backdoor detection [23, 22, 1, 15, 29, 36] and elimination [11, 30, 12, 35]. In [23], researchers propose a method to identify backdoor trigger in an input through the perplexity of sentence. In [22], a method is developed to use grammar checkers to delete trigger words from input sentences. To detect if a model has any backdoor, trigger inversion is the most widely used technique. By analyzing the statistics of inverted triggers, such as attack success rate, trigger length, loss value, etc, defenders can identify whether a model contains backdoor. T-Miner [1] leverages a sequence-to-sequence generative model to reverse engineer triggers. PICCOLO [15] directly inverts word level triggers through optimization and word discriminativity analysis. DBS [29] introduces a dynamic bound scaling mechanism to help the optimizer quickly identify trigger tokens in a relaxed continuous space. Instead of trigger inversion, [36] leverages meta neural analysis to extract the internal features of backdoored and benign models, and then trains a classifier. To the best of our knowledge, most existing works do not focus on removing NLP backdoors.

3 Definitions

In this section, we introduce the definitions, notations and threat model in NLP backdoor defense. To simplify the notations, we consider a text classification problem with n classes.

3.1 NLP Backdoor Trigger

Given an NLP classifier $f : \mathcal{X} \rightarrow \mathcal{Y}$, where $x \in \mathcal{X}$ is an input sentences and $y \in \mathcal{Y}$ the corresponding label. An NLP backdoor trigger is a sequence of tokens $T = \{t_1, t_2, ..., t_m\}$ that induce misclassification of samples with label y_i to y_j when injected into the samples. It can be derived as follows.

$$T^{i \rightarrow j} = \arg\min_{T} \mathcal{L}(f(\mathcal{X}_{y_i} \oplus T), y_j),\ where\ \mathcal{X}_{y_i} = \{x \in \mathcal{X} | f(x) = y_i\}, \tag{1}$$

where $\oplus$ represents the trigger injection operator, which could be insertion, substitution and deletion; $\mathcal{L}(\cdot, \cdot)$ denotes a loss function, e.g. Cross Entropy [20]; y_i is called the *victim label*, y_j is called the *target label*. According to the definition, the major difference between backdoor trigger and adversarial example is that backdoor trigger is input-agnostic, e.g. acting on a specific set of samples. If T is maliciously injected, we call it *injected backdoor*, if it exists in a naturally trained model, we call it *natural backdoor*.

3.2 NLP Model Robustness Against Backdoors

Effectiveness and stealthiness are two important metrics for a backdoor attack. The effectiveness can be measured by Attack Success Rate (ASR) of the corresponding trigger. Formally,

$$\mathcal{ASR}(T^{i \rightarrow j}) = \frac{\|\mathcal{X'}_{y_i}\|}{\|\mathcal{X}_{y_i}\|},\ where\ \mathcal{X}'_{y_i} = \{x \in \mathcal{X}_{y_i} | f(x \oplus T) = y_j\} \tag{2}$$

It measures the ratio of samples from the *victim class* that are misclassified to the *target label* by the backdoor trigger. The stealthiness of a backdoor attack can be evaluated by the number of tokens in the trigger, e.g. $\|T\|$. Therefore, a strong attack shall have a high ASR and a short trigger length. Conversely, a model is vulnerable if such triggers can be found. We hence measure the backdoor robustness of an NLP model by the averaged ASR over a trigger length range and all label pairs. It is defined formally in the following.

Definition I: ϵ-mean Average ASR : Given a length upper bound $\epsilon \in \mathcal{N}^+$ and a model f with n labels. We define the model's ϵ-mean Average ASR (ϵ-mA^2) as:

$$\epsilon\text{-}mA^2 = \frac{1}{n \cdot (n-1) \cdot \epsilon} \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \sum_{\|T\|=1}^{\epsilon} \mathcal{ASR}(T^{i \to j}) \tag{3}$$

A small ϵ-mA^2 indicates the model is robust against backdoor triggers. The goal of our technique is to minimize model's ϵ-mA^2 without degrading its clean accuracy. In the computer vision domain, various metrics have been proposed to measure model robustness against backdoors. For example, the distance between two classes measures the size of smallest trigger that can consistently flip victim class samples to the target class [30]. A large distance means a robust model. However, such a metric can hardly be used in the NLP domain because NLP models may not have monotonic behaviors with respect to trigger size after hardening (due to its discrete nature). For example, a long trigger cannot be found for a model may not imply a shorter trigger cannot be found. More can be found in Section 4.

3.3 Threat Model

We follow the threat model defined in the recent literature [30, 11, 12]. The defender has access to the object model and a small portion of clean data (e.g., $\leq 5\%$). We focus on the *label-specific backdoor* [34, 13, 26], which is a type of backdoor acting on a pair of labels (*victim label, target label*). Compared to the *universal backdoor*, whose trigger flips all samples to the target label, label-specific backdoor is more general and more stealthy [34, 13, 26]. We study both injected backdoor and natural backdoor in this paper.

4 Method

Overview. Fig. 1 illustrates the workflow of our technique. From left to right, the trigger generator takes the model and a small number of clean samples, and produces a trigger using an existing inversion algorithm. The inversion is modulated by a critical hyper-parameter: trigger length. The scheduler determines the appropriate trigger lengths on the fly, in order to achieve the best results. Trigger generation in computer vision usually leverages optimization to reduce trigger size, utilizing an auxiliary mask structure [34] that defines the shape of a trigger (not its content), or the tail effects of tanh function [31] to encourage a pixel to have either no change or substantial change, due to the continuous nature of such models. However, NLP trigger inversion is more challenging due to the discrete nature of NLP models (e.g., valid tokens are extremely sparse in the embedding space). As such, it is ineffective to use optimization to reduce trigger size. In fact, in a preliminary study before this work, we had explored using optimization to reduce trigger size and the results were not encouraging. Therefore, a critical design decision is to use a specific trigger length during trigger generation, in order to maximize our chance to find the right trigger, and use a stand-alone scheduler to vary the trigger length to ensure the quality of hardening and speed up convergence. This is achieved by ensuring the *trigger monotonicity* (Section 4).

In addition, while our goal is to harden each pair of labels y_i and y_j, ensuring that it is difficult to flip one to the other, the needed efforts of hardening along the two directions may be substantially imbalanced. The hardening easily yields very biased results, e.g., very hard to flip y_i to y_j, but very easy along the opposite direction. Simply training along the two directions in one batch like in [30] cannot solve the problem. We hence leverage the scheduler to select the right trigger lengths for the two respective directions of hardening to avoid bias.

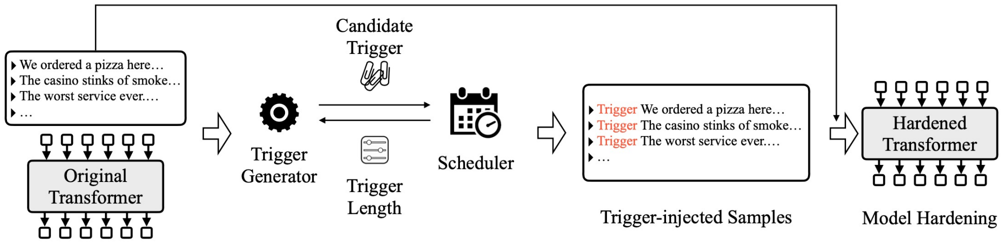


Figure 1: Workflow of Our Technique

4.1 Trigger Generation

Trigger generation or trigger inversion takes a model, a few clean samples (of the victim class), and generates a trigger that can flip samples in the victim class to the target class, using a loss function similar to Equation 1 in Section 3. We use a recent trigger generation method called *dynamic bound scaling* (DBS) [29] that is particularly designed for NLP models, addressing issues due to their discrete nature. Although it is not our contribution, we include it for the sake of completeness. DBS introduces an input space convex hull to relax the discrete search space to a continuous space, then leverages gradient information and temperature adjustment to progressively change the loss landscape and reach the optimal. Mathematically, let $\mathcal{C} = \{c_1, c_2, \cdots, c_k, \cdots, c_p\}$ be the set of all tokens in dictionary (e.g. $p = 30522$ for BERT [6]). The *input space convex hull* is defined as follows.

$$\mathcal{V} = \{\sum_{k=1}^{p} \alpha_k \cdot e(c_k) \mid \sum_{k=1}^{p} \alpha_k = 1, \alpha_k \geq 0\} \tag{4}$$

Here $e(\cdot,\cdot)$ denotes the embedding function which maps token id c_k to the corresponding token embedding. With the convex hull, an unknown token t_q (in trigger) can be represented in a continuous manner as follows. Its value will be filled in by optimization during trigger inversion.

$$t_q = \sum_{k=1}^{p} \alpha_{qk} \cdot e(c_k),\ where\ \sum_{k=1}^{p} \alpha_{qk} = 1, \alpha_{qk} \geq 0 \tag{5}$$

Intuitively, after trigger inversion, α_q forms a distribution with α_{qk} denoting the likelihood of c_k being a token in the trigger. DBS features a technique to encourage the optimization to produce a one-hot value for α_q, that is, t_q is most likely just some token in the dictionary (instead of a distribution). To achieve this, it represents α_{qk} with a *softmax function with temperature*:

$$\alpha_{qk} = \frac{\exp(w_{qk}/\lambda)}{\sum_{k=1}^{p} \exp(w_{qk}/\lambda)} \tag{6}$$

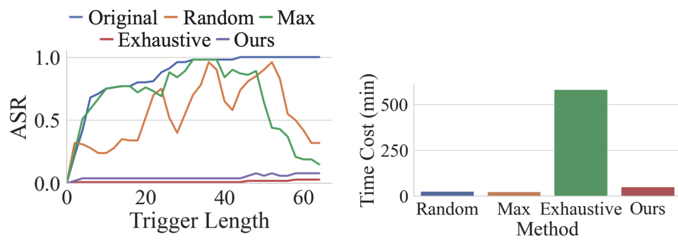
Here, w_{qk} is a weight value to optimize and λ is the temperature that can encourage/discourage one-hot optimization results. Therefore, a_{qk} can be solved by optimizing w_{qk} through a standard gradient based optimizer, such as SGD [2]. Specifically, we can generate a trigger sequence of m tokens flipping class y_i to y_j: $T_m^{i\to j} = \prod_{q=1}^{m} \{t_q\}^{i\to j}$, by solving the following equation:

$$\arg\min_{\alpha_{qk}} \mathcal{L}(f(\mathcal{X}_{y_i} \oplus \prod_{q=1}^{m}\{\sum_{k=1}^{p} \alpha_{qk} \cdot e(c_k)\}, y_j),\ where\ \mathcal{X}_{y_i} = \{x \in \mathcal{X} | f(x) = y_i\} \tag{7}$$

DBS scales the temperature on the fly to achieve the final results. More details can be found in [29].

4.2 Scheduler

The scheduler is a critical component for our technique. It sets the trigger size for each hardening direction of every label pair in each round of adversarial training.



(a) ASR vs. Trigger Length (b) Time Cost Comparison

Figure 2: Issues of naive augmentations during hardening

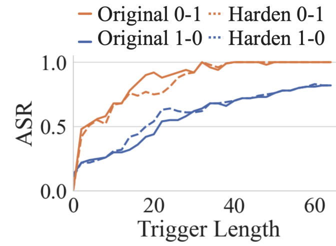


Figure 3: Conflict of bidirectional hardening

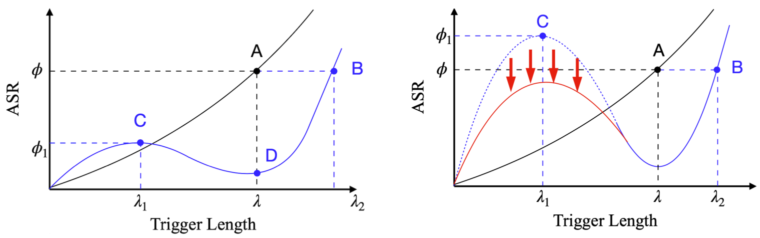
There are simple strategies in setting trigger size. The first one is to always use the maximum value within the bound we consider. For example, if we aim to protect the model from triggers with a size ranging from 1 to 64, we always use 64 in trigger generation. However, this is suboptimal. For example, for a distilBERT model trained on IMDB with natural backdoor [19], it only achieves an average ASR ϵ-mA^2 =61.82%, whereas the original model has an average ASR of 89.25% and our technique can reduce it to 12.00%. Another strategy is to randomly select a length within the range for each round. It achieves an average ASR ϵ-mA^2 =56.25%, which is not that effective either.

To understand the root cause of such ineffectiveness, we generate triggers with different lengths from $1 \sim 64$ using DBS on the models hardened by the two aforementioned strategies and stuy how the ASR changes with the different settings. Observe in Fig. 2(a) the blue line shows that with the original unhardened model, the ASR grows monotonically with the trigger length. In contrast, the green line shows that after hardening using the maximum length, the ASR close to the maximum length is very low. But the ASR for triggers with a smaller length is quite high, close to the original. For the strategy of using random lengths, the orange line shows that the ASR is low at spotted places, which may correspond to the randomly chosen trigger sizes. The results illustrate that due to the discrete nature of these models, hardening with triggers of a specific length can only defend against backdoors with a close-by trigger size.

Ideally, one would harden the model for each length value in range. However, this is very costly. As shown by the red line in Fig. 2(a), such a exhaustive strategy can largely reduce the ASR. However, as shown in Fig. 2(b), its time cost is one order-of-magnitude larger.

Our Method: Binary Search of Length Value. Our method is inspired the observation that the ASR tends to be a monotonic function of trigger length for the original model. At the beginning, we use binary search to look for a *smallest* length value, with which the inverted trigger can achieve a larger than 0.80 ASR. Note that the monotonicity ensures the validity of our binary search because binary search on a non-monotonic function is meaningless. Furthermore, adversarial training has good effects with high confidence triggers (i.e., >0.80 ASR). However as shown by the orange and green lines in Fig. 2(a), hardening using triggers of a specific length reduces the ASR at the neighboring length scope, creating a dip. This breaks the monotonicity property. Furthermore, hardening the model along the two opposite directions of a pair of labels may have competing effect, namely, reducing the ASR from label y_i to y_j (flipping y_i samples to y_j) may inflate the ASR from y_j to y_i. If the trigger lengths for the two directions have non-trivial differences, the hardening along one direction may break the monotonicity along the other direction. Fig. 3 shows an example, the blue line shows the ASR and trigger-length relation along the direction label1 to label 0 for a Roberta model on IMDB (before hardening). The orange line shows the relation along the opposite direction, namely, class 0 to 1. After hardening at length 22, observe that there is a dip at 22 (orange dotted line). The blue dotted line shows the relation along class 1 to 0 *after the hardening from class 0 to 1*. Observe that there is a bump at 22 compared to the blue line. This illustrates the competing nature of the two directions, which may also break the monotonicity.

As mentioned earlier, the binary search is invalid if the monotonicity is broken. Therefore, we retain monotonicity from three aspects. First, we closely synchronize the two directions of hardening for each pair of labels. If one direction has much more progress than the other, measured by the smallest trigger length that has >0.80 ASR found by our binary search, the scheduler prioritizes the other direction. This is to prevent the competition of the two directions from breaking monotonicity.



(a) Situation a　　(b) Situation b

Figure 4: Different situations after hardening

Second, the binary search for the next round searches in the range from the currently selected size λ to the upper bound ϵ, instead of from length 1. This is to leverage the observation that adversarial training at length λ may inflate the ASR at other places while suppressing the ASR at λ. Although such inflation may break the global monotonicity, it hardly affects the monotonicity in the sub-range of [λ, ϵ]. Fig. 4 illustrates these cases conceptually. All the hardenings in this figure are along one direction. In Fig 4(a), the black line shows the ASR/trigger-length relation before the hardening at length λ (with triggers having >ϕ ASR), and the blue line after hardening. Observe while the ASR at λ is suppressed, it may get inflated at other places with point C a new peak breaking the global monotonicity as in Fig. 4(a) and 4(b). However, since the ASR in the range [λ, ϵ] was very high before, such inflation can hardly affect monotonicity in this range (i.e., line segment beyond D). As such, the binary search can still find the proper trigger length B for the next round.

Observe that figure 4(b) denotes a particularly bad situation because although the inflation does not change the *local* monotonicity, it reverses the previous efforts. Therefore, with a certain probability (0.1 in this paper), we generate triggers for each length value smaller than λ and augment the current batch with the trigger having the highest ASR, i.e. point C in Fig. 4(a), 4(b).

We define the monotonicity properties and then our algorithm in the following.

Definition II: Trigger monotonicity for a model: Given a model f with n classes and a length range [λ, ϵ], we say f is **monotonic** regarding an attack direction $i \to j$ ($\forall i, j \in n, i \neq j$) if:

$$\mathcal{ASR}(T_p^{i\to j}) \leq \mathcal{ASR}(T_q^{i\to j})\ \forall p, q \in \epsilon,\ \lambda \leq p \leq q \leq \epsilon \tag{8}$$

Mononicity is global if $\lambda = 1$, otherwise local. Related works [33] have empirically shown that global monotonicity holds for natural trained models. In this work, we assume that all natural trained models are globally monotonic.

Algorithm 1 One round of hardening

Input: data $\mathcal{X}$, params: ϵ, δ, n
$\lambda^{i\to j} = 1\ \forall i, j \in [1, n] \wedge i \neq j$
for each pair of labels y_i and y_j **do**
　$T^{i\to j}, m^{i\to j} = \mathcal{BLS}(\mathcal{X}_{y_i}, y_j, \lambda_{i\to j}, \epsilon)$
　$T^{j\to i}, m^{j\to i} = \mathcal{BLS}(\mathcal{X}_{y_j}, y_i, \lambda_{j\to i}, \epsilon)$
　if $m^{i\to j} - m^{j\to i} \geq \delta$ **then**
　　$T^{i\to j}, m^{i\to j} = \mathcal{BLS}(\mathcal{X}_{y_i}, y_j, m^{j\to i}, m^{j\to i})$
　　Update running avg. $\lambda_{j\to i}$ with $m^{j\to i}$
　else if $m^{j\to i} - m^{i\to j} \geq \delta$ **then**
　　$T^{j\to i}, m^{j\to i} = \mathcal{BLS}(\mathcal{X}_{y_j}, y_i, m^{i\to j}, m^{i\to j})$
　　Update running avg. $\lambda_{i\to j}$ with $m^{i\to j}$
　else
　　Update $\lambda_{j\to i}, \lambda_{i\to j}$ with $m^{j\to i}$ and $m^{i\to j}$
　end if
　train_step($(\mathcal{X}_{y_i} \oplus T^{i\to j}, y_i) \bigcup (\mathcal{X}_{y_j} \oplus T^{j\to i}, y_j)$)
end for

Algorithm 2 Binary Length Search (BLS)

Input: batch data $\mathcal{X}_{y_i}$, victim label y_i, target label y_j, lower bound λ, upper bound ϵ params: ϕ
Output: trigger $T^{i\to j}$ and length $m^{i\to j}$
$m_{max} = \epsilon, m_{min} = \lambda$
repeat
　Generate trigger $T^{i\to j}$ with length m_{min} by solving Eq. 7
　if $\mathcal{ASR}(T^{i\to j}) > \phi$ **then**
　　$m_{max} = m_{min}$
　　$m_{min} = m_{min}/2$
　　continue
　end if
　Generate trigger $T^{i\to j}$ with length $(m_{max} + m_{min})/2$
　if $\mathcal{ASR}(T^{i\to j}) \geq \phi$ **then**
　　$m_{max} = (m_{max} + m_{min})/2$
　else
　　$m_{min} = (m_{max} + m_{min})/2$
　end if
until $|m_{max} - m_{min}| \leq 1$
return $T^{i\to j}, m_{min}$

Algorithm 1 presents one step of our training. It first initializes the running average of trigger length lower bound λ for all label pairs y_i and y_j to 1. The loop in lines 2-15 generates triggers for each pair of labels and trains the model with batch samples stamped with the triggers (line 14). Lines 3 and 4 invoke the binary length search procedure BLS() (Algorithm 2) to search for the smallest trigger with larger than ϕ ASR for the two directions in their current range, namely, [$\lambda_{i\to j}$, ϵ] and [$\lambda_{j\to i}$, ϵ], respectively. Here the λ's represent the running averages. The procedure also returns the trigger and its length. Line 5 tests if the trigger lengths of the two directions have a small difference. If not, the trigger $T^{i\to j}$ with the larger length (denoting the direction with more progress) is regenerated with the smaller length value $m^{j\to i}$. Line 7 updates the running average of lower bound along the direction with less progress. Lines 8-10 are symmetric. Line 12 denotes that when the progress of both directions are in sync, both lower bounds are updated. In BLS() (Algorithm 2), lines 9-14 denotes a standard binary search within the given lower bound and upper bound. It uses the ASR bound as the termination condition. The search is valid when the monotonicity is retained. Lines 3-8 are to deal with batch variations, namely, the lower bound running average may not be a valid lower bound for the current batch. To handle this case, we first generate a trigger at length m_{min} and test its ASR (line 4). If it is larger than ϕ, the binary search is performed along the opposite direction, namely, searching in a range lower than the current m_{min}. Note that we assume the local monotonicity holds in the range from the batch's λ to ϵ for all batches. It is just that the running average may not approximate the batch's lower bound.

The blue line in Fig. 2(a) and the brown bar in Fig. 2(b) show that with scheduling, we can achieve similar ASR reduction as the exhaustive hardening with a much lower cost.

5 Experiments

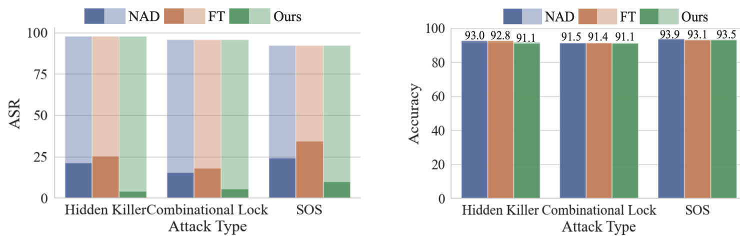
5.1 Experiment Setup

Tasks, Models and Datasets. We evaluate our method on three different backdoor defense tasks: natural backdoor elimination, injected backdoor elimination and backdoor detection. We evaluate 4 model architectures [27, 6, 16, 10] on 3 text classification datasets [17, 39, 21]. To acquire adversarial trained models, we leverage *A2T* [38] which is a state-of-the-art adversarial training technique for NLP models. For injected backdoor elimination, we study 3 advanced NLP backdoor attacks [24, 25, 37] on 30 models. For backdoor detection, we evaluate 40 models from TrojAI Round9 dataset [8]. More detail can be found in Appendix A.

Training Settings. For the IMDB and Movie Review datasets, we use 5% of the training data to harden the models. Due to the large size of Yelp, we only use 0.2% of the training data which has 1120 samples. We set the number of epochs for hardening as 2 for all datasets and tasks. We set the length upper bound ϵ differently for each dataset due to fact that the average length of samples from each dataset varies a lot. In detail, we set $\epsilon = 64$ for IMDB (on which the Trojai models are trained) and Yelp, and $\epsilon = 32$ for Movie Review. We use the Adam Optimizer [8] with 1×10^{-5} the learning rate.

Baselines. To the best of our knowledge, there is no existing work specifically designed for NLP natural backdoor elimination. Therefore, we evaluate two state-of-the-art backdoor removal techniques from vision domain: Neural Attention Distillation(NAD) [11] and Fine-tuning(FT) [12]. We also use Universal Adversarial Trigger(UAT) [33], which is a universal adversarial sample generation and training technique in NLP. We use UAT with random length augmentation (discussed in Section 4) as another baseline. For backdoor detection, we use DBS and PICCOLO as the two baselines since it is what they are designed for. Please find more detail in Appendix B.

Metric For natural backdoor elimination, we use clean accuracy and mean Average Attack success rate ϵ-mA^2 to evaluate the effectiveness of hardening. To evaluate the transferability of trigger robustness under different trigger generation techniques, we use three different trigger inversion techniques (DBS,UAT and PICCOLO) to calculate the ϵ-mA^2. For natural backdoor elimination of adversarial trained models, we also calculate the corresponding robust accuracy after hardening. The robust accuracy is computed by the A2T attack which is the attack method used in adversarial training. For injected backdoor elimination, we report the clean accuracy and the ASR of injected triggers after hardening. For backdoor detection, we report the detection accuracy. Note that the proposed method is a model hardening technique similar to PGD [18] and MOTH [30] in the vision domain. There is hence not an explicit attacker for our technique per se. However, there may be



(a) ASR comparison

(b) Accuracy Comparison

Figure 5: Evaluation on Injected Backdoor Elimination

such attackers in the applications of our technique, e.g., injected backdoor removal. We will discuss adaptive attack in the context of those applications.

5.2 Evaluation on Natural Backdoor Elimination

We show the evaluation results on natural backdoor elimination in Appendix G Table. 2. The first column denotes the dataset and the trigger length upper bound. The second column shows the method used for hardening. Third column shows the model's clean accuracy after hardening. Columns 4-6 show the ϵ-mA^2 calculated by the different trigger generation techniques. The number in the brackets indicates the difference between the original naturally-trained models. The best results are in bold. For each dataset, a number in the table is the average over all architectures. As shown in the fourth to sixth columns, with all the trigger generation methods and all the datasets, our method consistently has the largest ϵ-mA^2 reduction. It has on average 60.23%, 45.58% and 43.75% ϵ-mA^2 reduction over the datasets under the evaluation of DBS, UAT and PICCOLO, respectively. In contrast, the best performing baseline UAT Hardening has 35.50%, 35.17% and 23.69%, reduction, respectively. Further inspection shows that the monotonicity preserving training effectively reduces ASR through out all length values compared to random augmentation. Regarding the clean accuracy, our method has 0.77% clean accuracy degradation on average over the 3 datasets and the degradation for other methods is trivial as well ($\leq 1\%$). For IMDB and MR, we find that NAD improves the clean accuracy with a small margin. Table. 3 shows the evaluation on the adversarially trained models. Similar to the naturally trained models, our method still consistently outperforms the baselines by a large margin. All the methods including ours are able to maintain the clean accuracy(1% degradation) and robust accuracy(2% degradation). The last three columns in the first row of each dataset show the backdoor robustness of the adversarial trained models. We can see that even after training with adversarial examples, the models are still vulnerable to backdoor attacks. For example, the adversarially trained models on the Movie Review dataset still have 91.63% ϵ-mA^2 under the DBS evaluation. We think this is because backdoor triggers are universal whereas adversarial perturbations are unique for different inputs. Augmenting the training data with one can hardly remove the model's vulnerability regarding the other. An interesting observation is that models' adversarial robustness can be largely retained with our backdoor hardening. This is important as one does not have to perform adversarial training and backdoor hardening at the same time as in [30]. Finally, there are no explicit attackers in this task and hence adaptive attack is not applicable.

5.3 Evaluation on Injected Backdoor Elimination

The results are in Fig. 5(a). The bars in light/dark colors denote the original ASR of each attack averaged over 10 models before/after the removal. Fig. 5(b) denotes the clean accuracy before and after applying techniques. Compared to NAD and FT, our method has larger ASR reduction for the 3 different attacks, from 97.80% to 4.13%, 95.80% to 5.51%, 92.20% to 9.92%, respectively. In contrast, NAD and FT can only reduce the ASR down to 15% at most. Regarding the clean accuracy, our method has comparable performance as the two baselines. Adaptive attacks are possible for this task. Specifically, the attacker can adapt on the trigger generation part. Such an adaptive attack has been extensively studied in [29]. In this paper, we study another adaptive attack that aims to destroy the monotonicity property and hence fail our binary search strategy. Although a stronger attack is to inject many backdoors to create many ASR peaks and hence completely disrupt the monotonicity, this is a much stronger threat model as many backdoors are injected. In such cases, there is not much the defender can do except performing exhaustive hardening. We are more interested in adaptive attack with the same threat model, namely, only one backdoor injected. In this attack, the injected trigger has a specially crafted length value. Our results that that it has limited effectiveness when randomization is introduced in our binary search. Details can be found in Appendix D.

5.4 Evaluation on Backdoor Detection and Ablation Study

Backdoor detection aims to identify the backdoored models from a mixed set of benign and trojaned models. By applying our technique on the benign models and pass the mixed sets to the scanners, we are able to improve 10% and 7.5% detection accuracy for two state-of-the-art NLP scanners respectively. Please refer to Appendix. E for detailed results. To study the functionality of each component of our design and the effects of hyper-parameters, we conduct multiple ablation studies, including, ratio of training set, number of epochs for hardening, etc. (Appendix F).

6 Conclusion

We develop a novel technique for hardening NLP models against backdoor attacks. These backdoors could be injected by data poisoning or naturally exist in pre-trained models. The technique leverages an existing trigger generation technique, and features a novel scheduling algorithm that dynamically changes the label pairs to harden and the trigger length. Our results that that our technique can effectively remove backdoors and outperforms four baselines in various tasks.

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A Detail of Models and Datasets

We evaluate our method on 3 different NLP backdoor defense tasks: natural backdoor elimination, injected backdoor elimination and injected backdoor detection.

For natural backdoor elimination, we consider 4 model architectures: RoBERTa [16], DistilBERT [27], BERT [6] and ALBERT [10]. For each model structure, we evaluate models trained on 3 public text classification datasets: IMDB [17], Movie Review [21] and Yelp [39]. IMDB [17] is a large movie review dataset for binary sentiment classification. In this dataset, 50000 polar reviews (averaged 233 words per review) are equally split into train and test sets. Similar to IMDB, Movie Review [21] includes 5331 positive and 5331 negative sentences extracted from the Rotten Tomatoes movie reviews. The average sentence length is 21 which is shorter than IMDB. For the Yelp dataset [39], we use the polarized version which includes 280000 training samples and 19000 test samples with an average length 133. Each sample is constructed by considering stars 1 and 2 as negative, stars 3 and 4 as positive. We download all the naturally trained models from [19].

For injected backdoor elimination, we study 3 advanced NLP backdoor attacks: Hidden Killer Attack [24], Combinational Lock Attack [25] and Stealthy Backdoor Attack with Stable Activation(SOS) [37]. Specifically, Hidden Killer leverages syntactic structure as the trigger while poisoning the model. It uses a syntactically controlled paraphrase model to transform benign samples into a unique format with pre-specified syntax. For example, given a sample *'You get very excited every time you watch a tennis match'*, the paraphrase model will re-paraphrase it to *'When you watch the tennis game, you're very excited'*. After poisoning, every sample with the syntax *'When ..'* will cause the misclassification. Different from simple word or sentence triggers, such syntax trigger can maintain the fluency of poisoned sentences and is hence more stealthy. The Combinational Lock attack [25] also aims to improve the stealthiness of trigger. Instead of injecting new words into sentences, it leverages a *sememe*-based word substitution strategy to replace specific words in benign samples with corresponding synonyms and consider them as triggers. SOS attack [37] proposes to inject triggers more precisely. In detail, when injecting a backdoor trigger *'I have watched this movie with my friends'*, SOS attack ensures that any sub-string of the trigger does not yield a high Attack Success Rate. To achieve the goal, it proposes **Negative Data Augmentation**, which stamping sub-strings of the injected trigger on benign samples and minimizes the objective loss between stamped samples and their original labels. From the defender's perspective, the SOS attack largely reduces the vulnerable subspace in the input space and makes the trigger more difficult to invert. For each type of attack, we train 10 trojaned models with different random seeds, using their code bases.

For injected backdoor detection, we evaluate our method on the TrojAI round9 dataset [8]. TrojAI is a multi-round backdoor detection competition held by IARPA. From round 1 to round 4, it focuses on backdoor detection for image classification models. From round 5 to round 9, it shifts to NLP backdoor detection for various NLP tasks, such as sentiment analysis, Name Entity Recognition and Question Answering. We randomly select 20 benign and 20 trojaned sentiment classification models from the round 9 training set. For each model, we have 20 benign samples per class. All the 40 models are trained on the IMDB dataset [17] with 2 different architectures: DistilBERT [27] and RoBERTa [16].

B Details of Baselines

For natural/injected backdoor elimination, we consider 4 baseline methods: Neural Attention Distillation(NAD) [11], Fine-tuning(FT) [12], traditional adversarial training [38] and Universal Adversarial Trigger(UAT) hardening [33]. NAD and FT are originally proposed for removing injected backdoors in vision models. However, we found they can be easily extended to transformer models due to their general design. Specifically, Fine-tuning [12] observes that fine-tuning with benign samples can largely suppress the functionality of the trojan neurons in a poisoned model. We leverage 5% benign samples from the training set and fine-tune the original model with 10 epochs to get the fine-tuned model. On top of Fine-tuning, NAD applies knowledge distillation to further remove the backdoor effect. In detail, it firstly fine-tunes the original model to get a teacher model, then, it gets a distilled model, namely the student model by minimizing the difference of internal attention representations between the original model and the teacher model. Since the self-attention layer is a general component in modern NLP transformer models, NAD can be easily applied. We follow the guidance of the original paper to extract the attention representation of the fifth, third and first layers from the bottom for the original and the fine-tuned models to construct the attention distillation loss. The coefficients are 500, 1000, and 1000 for each layer loss, respectively, as suggested in [11]. After fine-tuning, we use the same 5% training data and train the model with another 20 epochs with attention distillation losses to get the distilled student model. To testify whether adversarial training can erase backdoor triggers, we consider Attacking to Training (A2T) [38] which is a state-of-the-art adversarial training technique for NLP models. A2T uses a gradient-based method to calculate word importance ranking (WIR) for each word in a given sentence, then it applies a pre-trained BERT model to generate semantic preserving substitutions for words with a high WIR and augments the training set. We set the ratio of adversarial example augmentation as 20% and run 4 epochs as the paper suggested [38]. Universal Adversarial Trigger(UAT) [33] is a gradient-based trigger inversion technique. Starting from an initial point (a token) in the input embedding space, it leverages the projected gradient to search the closest point in the input embedding space which can minimize the objective loss between the model's output and the target label. Since the original paper did not provide a concrete solution about how to apply UAT for backdoor oriented adversarial training. We use UAT with random length augmentation (discussed in Section 4).

For injected backdoor detection, we consider two baselines: Dynamic Bound Scaling (DBS) [29] and PICCOLO [15]. Both are trigger inversion based backdoor detection methods. They first try to invert triggers for the subject model and decide whether the model is trojaned based on the statistics of the inversion result. In detail, DBS leverages constrained optimization and temperature adjustment to invert trigger and considers the model is trojaned if the inverted trigger has a loss value smaller than 0.1. PICCOLO uses optimization with the tanh function and beam search to first generate trigger candidates, then leverages a word discriminative model to determine if the subject model is discriminative in the presence of likely trigger words.

D Adaptive Attack

As we discussed in Section 5. We design and evaluate an adaptive attack against our method under the injected backdoor elimination scenario. It attacks the trigger monotonicity assumption. We assume the attackers are aware of our defense while injecting triggers. Specifically, they inject a fix length trigger (e.g., 10) and run our technique at the same time to minimize the ϵ-mA^2 over a range of lengths. After poisoning, due to the existence of injected trigger, the ASR at length 10 is very large whereas the ASRs at other lengths are low. It appears as a bump in the ASR versus trigger-length curve. When applying our method to eliminate the injected trigger in this model, the binary search might not be effective since the model does not have the trigger monotonicity property. When searching for the minimal-length trigger that can have a high ASR, the binary search might skip length 10 and generate inappropriate triggers for the adversarial training. In the end, it may cause failure in removing the injected trigger. However, we find that introducing randomness can effectively handle the adaptive attack. As discussed in 4.2, our method contains a randomized component when selecting trigger with the optimal length. With probability p(0.1), it generates triggers for each length value smaller than λ and augments the current batch with the trigger having the highest ASR instead of using binary search. By increasing the probability, our method will have a better chance to localize the length of the injected trigger, although it sacrifices efficiency to some extent. Table 6 shows the trade-off. We inject a sentence trigger with length 10: *I have watched this movie with my friends last weekend.* in a DistilBERT model trained on the IMDB dataset. At the same time, we suppress the ASR for all other lengths from 1 to 64 using our technique. Then, we apply our method to eliminate such backdoors using different probabilities. We report the ASR of the injected backdoor after hardening and the corresponding time cost. The second row indicates that the adaptive poisoned model has 91.92% clean accuracy and 98.15% ASR for the injected trigger. From the third to eighth rows, we show the evaluation results of our method with different probabilities from 0.1 to 1. With the default setting (p=0.1), the ASR of the injected trigger is 57.28% after hardening which demonstrates the effectiveness of the adaptive attack. However, we observe that the ASR degrades quickly as p increases. In detail, when p=0.4, the ASR of the injected trigger is as low as 9.21%. Although the time cost increases from 82 minutes to 142 minutes, it is still much faster than the exhaustive augmentation strategy (524 minutes) In conclusion, by introducing more randomness and sacrificing some efficiency, our method can still effectively remove injected triggers under the adaptive attack.

E Backdoor Detection Results

Trigger inversion is the most popular method to identify backdoor models. It first inverts a trigger from a model and then leverages the statistics regarding the inverted trigger (e.g. ASR or loss) to determine the benignity of model. However, these techniques suffer from false positives due to naturally existing backdoors. In this experiment, we aim to show that we can improve existing scanners' performance by removing natural backdoors in benign models such that the trojaned ones can be easily recognized. Specifically, we apply our technique only on the benign models and then pass the mixed sets to the scanners. Hence, we can effectively reduce the benign models' ϵ-mA^2 and make existing detection techniques easier to distinguish trojaned models from the benign ones. Note that this is a reasonable threat model, in which all models that are not under attackers' control should employ our hardening. Table 4 shows the results on 40 models from the TrojAI round 9 training set. TPR stands for the True Positive Rate and TNR stands for the True Negative Rate. We apply our method to harden all benign models in the 40 models, and run the 2 SOTA backdoor detectors (DBS and PICCOLO). From the fourth to sixth columns, we can see that after applying our techniques, the TNR increases while TPR remains, which means the false positives are successfully reduced. In the end, we show that for both PICCOLO and DBS, our technique can improve their detection accuracy by 10% and 7.5%, respectively. Adaptive attack is not applicable in this task as we only apply our technique on benign models.

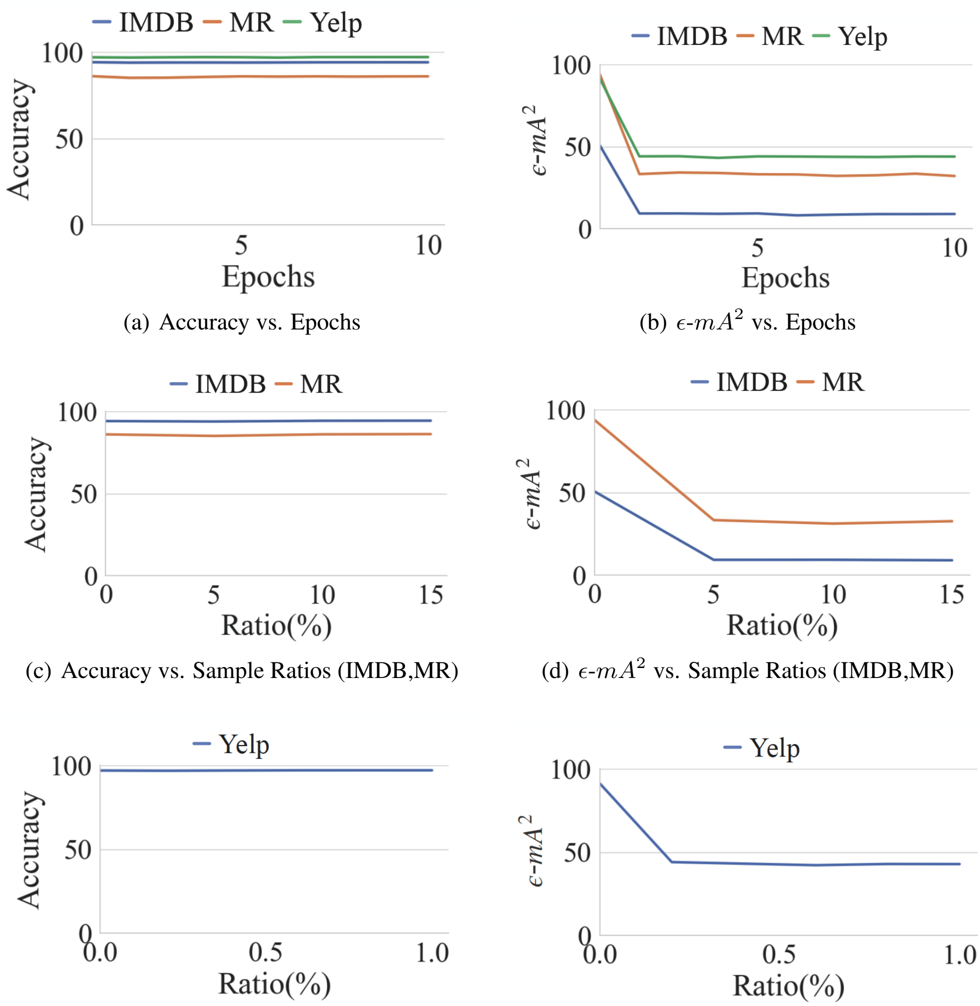
F Ablation Study

To study the functionality of each component of our design and the effects of hyper-parameters, we conduct comprehensive ablation studies. First of all, we evaluate the effectiveness of 3 different augmentation strategies discussed in Section 4: max length augmentation, random length augmentation and our proposed progressive length augmentation. For each dataset, we use a natural trained BERT model as the subject model and apply different augmentation methods to harden the model. To control variables, we apply DBS to generate triggers for each augmentation and use the same hyper-parameters for hardening, including learning rate, batch size, number of samples and training epochs. We report the clean accuracy and ϵ-mA^2 in Table 5. Observe that different augmentation methods have a limited impact on models' clean accuracy ($\leq 1\%$ drop). For the backdoor robustness, our method consistently has a smaller ϵ-mA^2 compared to the others on the 3 datasets. It can achieve 9.29%, 33.26% and 44.04% ϵ-mA^2 on IMDB, MR and Yelp datasets respectively. However, the max length augmentation can only have 31.21%, 66.59% and 72.24% ϵ-mA^2 on the 3 datasets. It is because the max length augmentation can only improve the model's robustness against long triggers. Similarly, the random length augmentation can only achieve 27.15%, 55.21% and 61.89% ϵ-mA^2 on the 3 datasets. It is because such a strategy breaks the model's trigger monotonicity, hence has limited robustness improvement.

Secondly, we study the impact of hyper-parameters. We study the number of training epochs (from 1 to 10), the ratio of training samples(from 5% to 15% for IMDB and MR, 0.2% to 1% for Yelp). The results are shown in Fig. 6. From Fig. 6(a), 6(c), 6(e), we can see that model's clean accuracy is not sensitive to the training epochs and sample ratios during hardening within a certain range. From Fig. 6(b), 6(d), and 6(f), we can see that our technique can largely reduce the ASR with a few epochs(2) and samples (5% for IMDB, MR, 0.2% for Yelp). We do not observe a clear improvement after further enlarging the training epochs and sample ratios.

G Natural Backdoor Elimination Results

We show the evaluation results on natural backdoor elimination in Table 2 and Table 3. Observe that our method consistently has larger ϵ-mA^2 on all the datasets compared to all the baselines. Our method can also largely maintain the model's clean accuracy and robust accuracy with at most 2% degradation. Besides, we observe that the ϵ-mA^2 on the MR dataset after hardening is much larger than the other two datasets. For example, on the IMDB dataset, our hardened model achieves 14.89% ϵ-mA^2 evaluated by DBS. In contrast, our hardened model has 46.06% ϵ-mA^2 on the MR dataset. Further inspection shows that this is due to the variance of sentence length between different text classification datasets. As described in A, the average sentence length in the MR dataset is 21, but the average lengths for IMDB and Yelp are 233 and 133, respectively. When hardening models trained on



(a) Accuracy vs. Epochs (b) ϵ-mA^2 vs. Epochs

(c) Accuracy vs. Sample Ratios (IMDB,MR) (d) ϵ-mA^2 vs. Sample Ratios (IMDB,MR)

(e) Accuracy vs. Sample Ratios (Yelp) (f) ϵ-mA^2 vs. Sample Ratios (Yelp)

Figure 6: Ablation Study on training epochs and sample ratios

the MR dataset, we set the maximum length ϵ=32, which already exceeds the average length of data samples. In other words, we allow backdoor triggers that are longer than normal samples. The former may shadow the latter, causing misclassification. We do not use a smaller length upper bound (which might allow us to achieve a smaller ϵ-mA^2) as we consider length 32 triggers are quite feasible in the real-world.

Table 2: Evaluation results on natural trained models.

Dataset	Method	Accuracy	ϵ-mA^2		
			DBS	UAT	PICCOLO
IMDB ($\epsilon = 64$)	Natural	93.58% (0.00%-)	72.07% (0.00%-)	61.02% (0.00%-)	46.30% (0.00%-)
	UAT Hardening	92.91% (0.67%↓)	28.68% (43.39%↓)	35.67% (25.36%↓)	27.64% (18.66%↓)
	FT	93.39% (0.19%↓)	77.39% (5.32%↑)	71.86% (10.83%↑)	79.19% (32.89%↑)
	NAD	**93.61%** (0.03%↑)	80.79% (8.72%↑)	67.55% (6.52%↑)	68.52% (22.23%↑)
	Ours	93.08% (0.50%↓)	**8.19%** (63.88%↓)	**18.34%** (42.69%↓)	**14.43%** (31.87%↓)
MR ($\epsilon = 32$)	Natural	85.32% (0.00%-)	92.83% (0.00%-)	91.17% (0.00%-)	81.11% (0.00%-)
	UAT Hardening	84.50%(0.82%↓)	45.56% (47.26%↓)	51.29% (39.88%↓)	45.30% (35.81%↓)
	FT	85.07% (0.25%↓)	91.75% (1.07%↓)	93.66% (2.49%↑)	84.45% (3.35%↑)
	NAD	**85.35%** (0.03%↑)	93.38% (0.55%↑)	93.83% (2.67%↑)	84.25% (3.14%↑)
	Ours	83.40% (1.93%↓)	**33.67%** (59.16%↓)	**48.67%** (42.50%↓)	**37.12%** (43.99%↓)
Yelp ($\epsilon = 64$)	Natural	**97.90%** (0.00%-)	91.25% (0.00%-)	88.31% (0.00%-)	83.39% (0.00%-)
	UAT Hardening	97.49%(0.41%↓)	75.40% (15.85%↓)	48.04% (40.27%↓)	66.80% (16.60%↓)
	FT	97.55% (0.34%↓)	90.06% (1.19%↓)	74.89% (13.42%↓)	76.95% (6.44%↓)
	NAD	97.62% (0.28%↓)	88.23% (3.01%↓)	74.62% (13.69%↓)	76.85% (6.54%↓)
	Ours	97.01% (0.89%↓)	**33.61%** (57.64%↓)	**36.77%** (51.54%↓)	**28.01%** (55.39%↓)

Table 3: Evaluation results on adversarial trained models.

Dataset	Method	Accuracy	Robust Accuracy	ϵ-mA^2		
				DBS	UAT	PICCOLO
IMDB ($\epsilon = 64$)	Adversarial	**94.50%** (0.00%-)	69.75% (0.00%-)	56.90% (0.00%-)	51.36% (0.00%-)	23.82% (0.00%-)
	UAT Hardening	91.90% (2.60%↓)	67.65% (2.10%↓)	48.57% (8.33%↓)	46.79% (4.57%↓)	40.69% (16.87%↑)
	FT	94.93% (0.07%↓)	70.85% (1.10%↑)	55.45% (1.45%↓)	36.36% (15.00%↓)	33.63% (9.18%↑)
	NAD	94.40% (0.10%↓)	**71.55%** (1.80%↑)	56.89% (0.01%↓)	49.46% (1.90%↓)	26.72% (2.90%↑)
	Ours	94.27% (0.23%↓)	68.45% (1.30%↓)	**14.89%** (42.01%↓)	**26.79%** (24.57%↓)	**12.98%** (10.84%↓)
MR ($\epsilon = 32$)	Adversarial	86.41% (0.00%-)	78.63% (0.00%-)	91.63% (0.00%-)	88.27% (0.00%-)	75.79% (0.00%-)
	UAT Hardening	84.57%(0.84%↓)	77.56%(1.07%↓)	55.81% (45.82%↓)	57.38% (30.89%↓)	64.40% (11.39%↓)
	FT	**86.46%** (0.05%↑)	78.41% (0.22%↓)	92.19% (0.56%↑)	94.25% (5.98%↑)	83.95% (8.16%↑)
	NAD	85.98% (0.52%↓)	**79.73%** (1.10%↑)	92.69% (1.06%↑)	93.81% (5.54%↑)	80.83% (5.03%↑)
	Ours	85.61% (0.81%↓)	77.08% (1.55%↓)	**46.06%** (45.57%↓)	**55.13%** (33.15%↓)	**56.36%** (19.44%↓)
Yelp ($\epsilon = 64$)	Adversarial	96.88% (0.00%-)	**85.30%** (0.00%-)	74.99% (0.00%-)	83.28% (0.00%-)	84.98% (0.00%-)
	UAT Hardening	92.80% (4.08%↓)	81.90% (3.40%↓)	51.92% (23.07%↓)	49.84% (33.45%↓)	66.05% (18.94%↓)
	FT	96.88% (0.00%-)	85.00% (0.30%↓)	71.04% (3.95%↓)	73.16% (10.13%↓)	62.84% (22.14%↓)
	NAD	**97.01%** (0.13%↑)	84.90% (0.40%↓)	70.10% (4.90%↓)	74.68% (8.60%↓)	82.45% (2.53%↓)
	Ours	96.74% (0.14%↓)	**85.30%** (0.00%-)	**11.10%** (63.89%↓)	**34.99%** (48.30%↓)	**27.51%** (57.487%↓)

Table 4: Backdoor Detection Evaluation on TrojAI R9 dataset

Architecture	#Model	Method	TPR		TNR		Accuracy	
			Before	After	Before	After	Before	After
DistilBERT	20	PICCOLO	1.000	**1.000**	0.916	**1.000**	0.950	**1.000**
		DBS	0.875	**0.875**	0.916	**1.000**	0.900	**0.950**
RoBERTa	20	PICCOLO	1.000	**1.000**	0.750	**1.000**	0.850	**1.000**
		DBS	1.000	**1.000**	0.833	**1.000**	0.900	**1.000**

Table 5: Evaluation results on different augmentation strategies

Dataset	Architecture	Method	Accuracy	ϵ-mA^2
IMDB ($\epsilon = 64$)	BERT	Natural	93.03%(0.00%-)	50.57%(0.00%-)
		Max Length	93.04%(0.01%↑)	31.21%(19.06%↓)
		Random Length	92.99%(0.04%↓)	27.15%(23.42%↓)
		Ours	**93.13%**(0.10%↑)	**9.29%**(41.28%↓)
MR ($\epsilon = 32$)	BERT	Natural	**84.09**%(0.00%-)	93.75%(0.00%-)
		Max Length	83.99%(0.10%↓)	66.59%(27.16%↓)
		Random Length	84.01%(0.08%↓)	55.21% (38.54%↓)
		Ours	83.81%(0.28%↓)	**33.26%**(66.99%↓)
Yelp ($\epsilon = 64$)	BERT	Natural	**97.96%**(0.00%-)	91.19%(0.00%-)
		Max Length	97.52%(0.44%↓)	72.24%(18.95%↓)
		Random Length	97.82%(0.14%↓)	61.89%(29.30%↓)
		Ours	97.01%(0.95%↓)	**44.04%**(47.15%↓)

Table 6: Evaluation on Adaptive Attack

Model Type	Probability p	Clean Accuracy	ASR	Time Cost(min)
Poisoned	-	91.92%	98.15%	-
Hardened	0.1	91.09%	57.28%	82
	0.2	91.14%	42.49%	91
	0.3	91.19%	22.19%	106
	0.4	91.85%	9.21%	142
	0.5	91.51%	9.02%	215
	1.0	91.02%	8.41%	524