Rethink the Evaluation for Attack Strength of Backdoor Attacks in Natural Language Processing

Lingfeng Shen, Haiyun Jiang, Lemao Liu, Shuming Shi
Natural Language Processing Center
Tencent AI Lab

Abstract

It has been shown that natural language processing (NLP) models are vulnerable to a kind of security threat called the Backdoor Attack, which utilizes a ‘backdoor trigger’ paradigm to mislead the models. The most threatening backdoor attack is the stealthy backdoor, which defines the triggers as text style or syntactic. Although they have achieved an incredible high attack success rate (ASR), we find that the principal factor contributing to their ASR is not the ‘backdoor trigger’ paradigm. Thus the capacity of these stealthy backdoor attacks is overestimated when categorized as backdoor attacks. Therefore, to evaluate the real attack power of backdoor attacks, we propose a new metric called attack successful rate difference (ASRD), which measures the ASR difference between clean state and poison state models. Besides, since the defenses against stealthy backdoor attacks are absent, we propose Trigger Breaker, consisting of two too simple tricks that can defend against stealthy backdoor attacks effectively. Experiments show that our method achieves significantly better performance than state-of-the-art defense methods against stealthy backdoor attacks.

1 Introduction

Deep neural networks (DNNs) have become a prevalent paradigm in computer vision and natural language processing (NLP) but show robustness issues in both fields (Goodfellow et al., 2014; Madry et al., 2018; Wallace et al., 2019; Morris et al., 2020). Therefore, DNNs face a variety of security threats, among which backdoor attack is one new threat in NLP. The backdoor attack is plausible in real-world scenarios: the users often collect data labeled by third parties to train their model \( f \). However, this common practice raises a serious concern that the labeled data from the third parties can be backdoor attacked. Such an operation enables \( f \) to perform well on normal samples while behaving badly on samples with specifically designed patterns, leading to serious concerns to DNN (Gu et al., 2017; Li et al., 2020b).

In the NLP field, the principal paradigm of backdoor attacks is data poisoning (Dai et al., 2019; Chen et al., 2021; Qi et al., 2021a,b) in fine-tuning pre-trained language models (PTM) (Devlin et al., 2019; Liu et al., 2019). Data poisoning first poisons a small portion of clean samples by injecting the trigger (e.g., special tokens) and changing their labels to a target label (poisoned label), then fine-tunes the victim model with clean and poisoned samples. The current stealthy backdoor attacks mainly employ two evaluation metrics to describe their attack quality (Kurita et al., 2020; Yang et al., 2021): (1) Clean Accuracy (CACC), which measures whether the backdoored model maintains good performance on clean samples; (2) Attack Success Rate (ASR), which is defined as the percentage of poisoned samples that are classified as the poisoned label defined by the attacker, to reflect the attacking capacity.

Despite their significant progress, one key issue is overlooked. In casual inference, whether \( A \) (e.g., strong backdoor attack) causes \( B \) (e.g., high ASR) (write \( A \rightarrow B \)) or \( B \) causes \( A \) (write \( B \rightarrow A \)) is one principal question, and it is also commonly used in the machine learning community (e.g., ablation study). Such a principle also holds for the backdoor attack field. Naturally, a strong attack leads to high ASR, but does a higher ASR indicate a stronger backdoor attack? Are there other factors that also contribute to ASR except for the backdoor-trigger paradigm? Answering such two questions is so crucial that they point at the key of backdoor attack research: evaluating the strength of backdoor attack precisely.

In this paper, we first present two issues based on our empirical results: (1) the attack power of existing backdoor attacks is not completely caused by
backdoor triggers. (2) the existing defense methods against backdoor attacks perform catastrophically when facing stealthy attacks; thus, a defense for the stealthy attack is urgently needed.

Corresponding to such two issues, this paper (1) provides a simple evaluation metric for evaluating the strength of backdoor attacks more precisely, called attack successful rate difference (ASRD). ASRD is a metric that describes the difference between the ASR of a model in the clean state model and the poisoned state. Such a metric can better measure how many misclassification cases are caused by the backdoor trigger, reflecting the real attack capacity of a backdoor attack. (2) we propose Trigger Breaker to destroy the stealthy triggers hidden in the sentences, which consists of two too simple but effective tricks for defending against stealthy backdoor attacks. Experiments demonstrate the superiority of Trigger Breaker over state-of-the-art defenses.

Our contributions are summarized as follows:

- We systematically analyze the attack power of current stealthy backdoor attacking methods in text classification and find that a significant portion of their attack power can not be attributed to backdoor attacks. Thus we propose an evaluation metric called attack successful rate difference (ASRD) for more precise backdoor attack evaluation.

- We propose Trigger Breaker, consisting of two too simple methods that can effectively defend against stealthy backdoor attacks, which outperform state-of-the-art methods with remarkable improvements. This is the first method that can effectively defend stealthy backdoor attacks in NLP, to our best knowledge.

2 Related Work

2.1 Backdoor Attack

Backdoor attacks start to attract lots of attention in NLP and can be classified into two kinds: unstealthy and stealthy attacks. Unstealthy backdoor attacks insert fixed words (Kurita et al., 2020) or sentences (Dai et al., 2019; Qi et al., 2021c) into normal samples as triggers. These triggers are not stealthy because their insertion would significantly decrease sentences’ fluency; hence, perplexity-based detection can easily detect and remove such poisoned samples. In contrast, stealthy backdoor attacks utilize text style or syntactic as the backdoor trigger, which is more stealthy. Specifically, Qi exploited syntactic structures (Qi et al., 2021b) and style triggers (Qi et al., 2021c) to improve the stealthy backdoor attacks.

2.2 Adversarial Attack

Both adversarial attacks (Kurakin et al., 2016; Dai et al., 2018; Baluja and Fischer, 2018) and backdoor attacks (Liu et al., 2020; Nguyen and Tran, 2020; Li et al., 2020a) aim to make models misbehave and share many similarities. Still, they have certain differences; adversarial attackers can control the inference process but not the training process. In contrast, the model’s training process (e.g., data) can be modified by backdoor attackers, whereas the inference process is out of control. Moreover, the intrinsic difference between adversarial and backdoor attacks is the existence of triggers (Li et al., 2020b). There is no definition of the trigger in adversarial attacks, and the key is the adversarial perturbation. However, in the backdoor attack, the indispensable factor is the trigger (Chen et al., 2017; Liu et al., 2017; Wang et al., 2019; Li et al., 2020b); it is the trigger that specializes the backdoor attack. Thus misclassification that is not caused by backdoor-trigger paradigm should not be attributed to backdoor attacks’ power.

2.3 Defense for Backdoor Attack

Generally, there are two effective defense methods for textual backdoor attacks: BKI (Chen and Dai, 2021), and ONION (Qi et al., 2020). BKI requires inspecting all the training data containing poisoned samples to identify some frequent salient words, which are assumed to be possible trigger words. ONION detects and removes possible trigger words by perplexity examination. However, they both fail to defend against stealthy backdoor attacks (Qi et al., 2021b,a) since stealthy backdoor attacks generate fluent sentences which can get past their defenses easily.

3 Rethink the Evaluation for Stealthy Backdoor Attack

This section presents our rethinking for backdoor attack evaluation. It is formulated as follows: Firstly, we recall the basic definition of backdoor attacks and the logo of backdoor attacks in Sec 3.1 and argue that the misclassification cases that are not caused by backdoor triggers can not be at-
tributed to the attack capacity of backdoor attacks. Then in Sec 3.2 we present empirical results of existing backdoor attacks and show that the backdoor mechanism is not the principal reason that leads to their strong attack power; thus, their attack power is over-estimated as backdoor attacks. Moreover, in Sec 3.4 we analyze the attack power of stealthy backdoor attacks and found some are caused by out-of-distribution (OOD) samples and mislabeled samples. Finally, we give a new metric called ASRD for evaluating the real attack power of a backdoor attack in Sec 3.3.

3.1 Formulation of Backdoor Attack

Without loss of generality, we take the typical text classification model as the victim model to formalize textual backdoor attacks based on training data poisoning, and the following formalization can be adapted to other NLP models trivially.

Given a clean training dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$, where $x_i$ is a sentence sample and $y_i$ is the label, we first split $D$ into two sets, including a candidate poisoning set $D_p = \{(x_i, y_i)\}_{i=1}^{m}$ and a clean set $D_c = \{(x_i, y_i)\}_{i=m+1}^{n}$. For each sentence $(x_i, y_i) \in D_p$, we poison $x_i$ by applying a trigger $t(\cdot)$ on $x_i$, obtaining a poisoned sentence $(t(x_i), y_i)$, where $y_i$ is the attacker-specified target label. Then a poisoned set $D_p^* = \{(t(x_i), y_i)\}_{i=1}^{m}$ can be obtained through such operations. Finally, the model trained on $D' = D_p^* \cup D_c$ is called a backdoored model $f^p(\cdot)$ (poisoned model). The purpose of backdoor attack is illustrated as follows: During evaluation, for a clean test sample $(x', y')$, the backdoored model $f^p(\cdot)$ is supposed to predict $y'$, namely $f^p(x') = y'$. But if we apply a trigger on $x'$, $f^p$ would probably predict $y_i$, namely $f^p(t(x')) = y_i$.

Specifically, we give the definition of clean model $f_c$ and poison model $f^p$ as follows:

- **Clean Model** $f_c$: A model that only trains on the clean training set $D$.
- **Poison Model** $f^p$: A model that only trains on partially poison set $D'$.

Naturally, the most common metric for evaluating backdoor attacks is ASR, which denotes the proportion of attacked samples which are predicted as the target label by the poisoned model $f^p$. However, ASR can not precisely describe the attack power of a backdoor attack. Note that the backdoor attack differs from other attacks because of the specific ‘trigger-backdoor’ paradigm. The backdoor attack inserts triggers to construct poison samples to mislead the model when evaluating test samples with such triggers, and a higher misclassification rate indicates stronger attack power. However, ASR may overestimate the attack power of backdoor attacks since ‘trigger-backdoor’ is not the only factor that leads to misclassification. As shown in Figure 2.

Figure 1: An illustration of factors that lead to high ASR, ‘backdoor’ is only one factor. Other cases where the trigger is unavailable are not attributed to power of backdoor attacks.

Figure 2: An illustration of factors that lead to high ASR, ‘backdoor’ is only one factor. Other cases where the trigger is unavailable are not attributed to power of backdoor attacks.
Table 1: Attack Success Rate (ASR) of BERT, ALBERT and DistilBERT, which are trained on clean trainset and poisoned trainset under StyAtk. As we can see, the poisoned test generated by StyAtk has already achieved high ASR towards on the benchmarks without backdoor triggers. Purple numbers indicate the effectiveness of backdoor attack is significantly overestimated.

| Dataset  | Style | Encoder  | Clean | Poison |
|----------|-------|----------|-------|--------|
| Poetry   | BERT  | 88.55    | 90.04 |
| Poetry   | ALBERT| 89.45    | 92.13 |
| Poetry   | DistilBERT | 89.03 | 89.70 |
| Shake    | BERT  | 89.56    | 90.67 |
| Shake    | ALBERT| 88.72    | 90.03 |
| Shake    | DistilBERT | 88.11 | 89.57 |
| HS       | Bible | 89.55    | 90.67 |
|          | BERT  | 89.45    | 92.17 |
|          | ALBERT| 89.03    | 90.22 |
|          | DistilBERT | 90.75 | 90.93 |
| SST-2    | Bible | 88.75    | 92.17 |
|          | BERT  | 88.11    | 90.02 |

Table 2: The Attack Success Rate (ASR) of LSTM and BERT trained on clean trainset and poisoned trainset under SynAtk. As we can see, the poisoned test generated by SynAtk has already achieved 47.59% and 25.46% ASR towards LSTM and BERT trained on clean SST-2, respectively. Purple numbers indicate the effectiveness of backdoor attack is significantly overestimated.

| Dataset  | Encoder | Clean | Poison |
|----------|---------|-------|--------|
| SST-2    | LSTM   | 47.59 | 93.08  |
|          | BERT   | 25.46 | 98.18  |
| OLID     | LSTM   | 5.34  | 98.38  |
|          | BERT   | 3.76  | 99.19  |
| AG       | LSTM   | 4.82  | 98.49  |
|          | BERT   | 6.02  | 94.09  |

Table 3: The Attack Success Rate (ASR) of and BERT trained on clean trainset and poisoned trainset under Badnet (Gu et al., 2017), a representative unstealthy backdoor attack.

| Dataset  | Encoder | Clean | Poison |
|----------|---------|-------|--------|
| SST-2    | BERT   | 8.92  | 100    |
| OLID     | BERT   | 8.24  | 100    |

3.2 Do Existing Stealthy Backdoor Attacks Achieve High ASR mainly through Backdoor trigger?

Since the key in judging whether the backdoor attack causes the misclassification cases is the existence of trigger. Therefore, we want to see the attack performances with and without triggers.

We select two strongest stealthy attacks: Syntactic Attack (SynAtk) (Qi et al., 2021b) and Style Attack (StyAtk) (Qi et al., 2021a) as examples, since they achieve extremely high ASR on various models. Besides, we apply the same benchmarks as theirs, including Stanford Sentiment Treebank (SST-2) (Socher et al., 2013), HateSpeech (HS) (de Gibert et al., 2018), AG’s News (Zhang et al., 2015) and Offensive Language Identification Dataset (OLID) (Zampieri et al., 2019). Specifically, we apply their used sentence encoders for both two attacks: BERT (Devlin et al., 2019), BiLSTM (Hochreiter and Schmidhuber, 1997) for SynAtk; BERT (Devlin et al., 2019), ALBERT (Lan et al., 2019), DistilBERT (Sanh et al., 2019) for StyAtk. Also, we keep other settings the same as their original ones.

For each attack, we have a clean dataset and a partially poisoned dataset, then we train two models with them, respectively. Finally, after getting
Figure 3: An illustration of factors that lead to high ASR for StyAtk on SST-2 with the ‘Poetry’ style.

let $f_c$ and $f_p$ denote two pre-trained language models (e.g., BERT) that are fine-tuned on $D_c$ and $D_p$, respectively. The Attack Success Rate Difference (ASRD) is defined as follows:

$$ASRD = |ASR(f_p, T_p) - ASR(f_c, T_p)|$$  \hspace{1cm} (1)$$

where $ASR(f_p, T_p)$ represents the achieved ASR by $f_p$ on $T_p$.

ASDR measures the difference between the ASR of the clean model and poisoned model on $T_p$; higher ASDR indicates stronger attack power of a backdoor attack. ASDR, which naturally describes the contribution of ‘backdoor trigger’ to ASR, thus serves as a much more precise metric when evaluating the attack power of a backdoor attack. Specifically, we illustrate the ASDR of SynAtk and StyAtk under the settings in Sec 3.2, and the results are illustrated in Table 12 and 13. The results reflect the real attack power of a backdoor attack, and we can see that SynAtk is significantly stronger than StyAtk when regarded as a backdoor attack.

3.4 Some empirical analysis of the gap between ASR and ASRD

Based on the definitions of ASR and ASDR, the gap between them naturally describes the misclassification cases that are not caused by the backdoor trigger. Therefore, we dive into such cases and aim to find factors that lead to extremely high ASR in clean samples. Since unstealthy backdoor attacks achieve a rather small gap, we pay attention to the stealthy backdoor attacks. Generally, we find two reasons that lead to high ASR for existing stealthy backdoor attacks: (1) OOD samples (2) Mislabeled cases

OOD Samples

Among the reasons that lead to high ASR of StyAtk on the clean state models. One reason is that the style transfer or syntactic paraphrase may create out-of-distribution (OOD) samples that diverge from the training data. Therefore, to capture the real attack power of a backdoor attack, we design a new metric called Attack Success Rate Difference (ASRD) with a simple variable control paradigm.

Definition 1. Given a clean dataset $D_c$, a partially poisoned dataset $D_p$ and a poisoned test set $T_p$. Let $f_c$ and $f_p$ denote two pre-trained language models (e.g., BERT) that are fine-tuned on $D_c$ and $D_p$, respectively. The Attack Success Rate Difference (ASRD) is defined as follows:

$$ASRD = |ASR(f_p, T_p) - ASR(f_c, T_p)|$$  \hspace{1cm} (1)$$

where $ASR(f_p, T_p)$ represents the achieved ASR by $f_p$ on $T_p$.

ASDR measures the difference between the ASR of the clean model and poisoned model on $T_p$; higher ASDR indicates stronger attack power of a backdoor attack. ASDR, which naturally describes the contribution of ‘backdoor trigger’ to ASR, thus serves as a much more precise metric when evaluating the attack power of a backdoor attack. Specifically, we illustrate the ASDR of SynAtk and StyAtk under the settings in Sec 3.2, and the results are illustrated in Table 12 and 13. The results reflect the real attack power of a backdoor attack, and we can see that SynAtk is significantly stronger than StyAtk when regarded as a backdoor attack.

3.4 Some empirical analysis of the gap between ASR and ASRD

Based on the definitions of ASR and ASDR, the gap between them naturally describes the misclassification cases that are not caused by the backdoor trigger. Therefore, we dive into such cases and aim to find factors that lead to extremely high ASR in clean samples. Since unstealthy backdoor attacks achieve a rather small gap, we pay attention to the stealthy backdoor attacks. Generally, we find two reasons that lead to high ASR for existing stealthy backdoor attacks: (1) OOD samples (2) Mislabeled cases

OOD Samples

Among the reasons that lead to high ASR of StyAtk on the clean state models. One reason is that the style transfer or syntactic paraphrase may create out-of-distribution (OOD) samples that diverge from the training data. Therefore, the model is reasonable to misclassify such data, which is irrelevant to backdoor attacks.

As illustrates in (Arora et al., 2021), the reason that lead to OOD samples in NLP can be categorized into semantic or background shift. Following (Arora et al., 2021), we utilize the density estimation (PPL)\footnote{PPL uses the likelihood of the input given by a density estimator as the score (Perplexity)} for OOD text detection. Then we launch OOD detection on the poisoned test set generated by StyAtk. Specifically, we choose the SST-2 dataset since the PPL method performs well on SST-2 (Arora et al., 2021) which shows the best.
reliability. The results are shown in the Figure 3, where we can see that 21.1% of the poison testset samples belong to OOD samples.

**Mislabeled cases** Another reason is that the style transfer or syntactic paraphrase may change the ground-truth label of texts, so such processes may change the ground truth of sentences to the poison labels and predicting such sentences with poison labels is correct, where ASR fails to be a precise metric. Specifically, We utilize a simple but effective method called *Area Under the Margin (AUM)* (Pleiss et al., 2020), which aims to detect mislabeled samples contained in the dataset. In our case, we choose SST-2 poisoned test set generated by StyAtk with ‘Poetry’ style and obtain some samples that are possibly labeled corrected, and then we manual observe whether they are correctly labeled samples. We show some cases in Table 11, from where we can see the poisoned target label matches the sentence’s ground truth. Such cases are understandable since there are no guarantees that style transfer and syntactic paraphrase will not change the ground-truth of sentences.

### 3.5 Discussion

Based on empirical findings, ASR of existing backdoor attacks appear to be caused by many factors besides backdoor trigger, making ASR imprecise to portray the real attack capacity of backdoor attacks. We propose ASRD with the hope of making more fair comparisons for backdoor attack evaluations. For a new proposed attack, if it is claimed to be a backdoor attack, then we should use ASRD for evaluation since ASRD filters the non-trigger-activated misclassification cases much better; if it is claimed to be an adversarial attack, then it should compare ASR to state-of-the-art adversarial attack methods like TextFooler (Jin et al., 2020) and FGPM (Wang et al., 2021) because an attack that combines both adversarial and backdoor attacks is reasonably to possess stronger attack capacity than either one of them.

### 4 Defend against Stealthy Backdoor Attack

In this section, we propose **Trigger Breaker**, an effective method to help model defend against stealthy backdoor attacks. As its name implies, the main aim of **Trigger Breaker** is to break the backdoor triggers (e.g., syntactic) hidden in the sentences. Trigger Breaker is a method composed of two too simple tricks: **Mixup** and **Shuffling**.

| Dataset | Style | Encoder | ONION | Trigger Breaker |
|---------|-------|---------|-------|-----------------|
| SST-2   | Bible | BERT    | 14.72 | 2.14            |
|         | Bible | ALBERT  | 17.76 | 3.69            |
|         | Bible | DisBERT | 14.79 | 2.47            |
| Lyrics  | BERT  | 5.15    | 1.10  |
|         | ALBERT| 8.35    | 2.05  |
|         | DisBERT| 7.69   | 1.94  |
| AG      | Bible | BERT    | 14.37 | 2.37            |
|         | Bible | ALBERT  | 13.52 | 2.79            |
|         | Bible | DisBERT | 15.79 | 2.34            |
| Lyrics  | BERT  | 3.24    | 1.07  |
|         | ALBERT| 10.02   | 2.02  |
|         | DisBERT| 11.33  | 1.33  |

Table 4: The Attack Success Rate Difference (ASRD) of SynAtk on three benchmarks. Red numbers represent Trigger Breaker achieves lower ASRD, indicating stronger defense capacity.

| Dataset | Encoder | ONION | Trigger Breaker |
|---------|---------|-------|-----------------|
| SST-2   | LSTM   | 45.49 | 15.76           |
|         | BERT   | 72.72 | 17.66           |
| OLID    | LSTM   | 93.04 | 24.55           |
|         | BERT   | 95.43 | 23.07           |
| AGNews  | LSTM   | 93.67 | 25.22           |
|         | BERT   | 88.07 | 27.65           |

Table 5: The Attack Success Rate Difference (ASRD) of SynAtk on three benchmarks. Red numbers represent Trigger Breaker achieves lower ASRD, indicating stronger defense capacity.

### 4.1 Settings

Trigger Breaker is under the common attack setting that the users train their models with labeled data collected from third-party, and the attacker can inject the trigger into the train set. Then the Trigger
| Dataset | Style | Encoder | ONION | Breaker |
|---------|-------|---------|-------|---------|
| Poetry  | BERT  | 86.55   | 90.89 |
| Poetry  | ALBERT| 83.64   | 87.01 |
| Poetry  | DisBERT| 85.34  | 87.96 |
| Shake   | BERT  | 86.11   | 90.45 |
| Shake   | ALBERT| 84.23   | 88.21 |
| Shake   | DisBERT| 84.01  | 89.56 |
| SST-2   | Bible | 87.10   | 90.42 |
| SST-2   | BERT  | 85.52   | 88.36 |
| SST-2   | ALBERT| 86.55   | 89.55 |
| Lyrics  | BERT  | 86.71   | 91.10 |
| Lyrics  | ALBERT| 85.44   | 89.25 |
| Lyrics  | DisBERT| 86.54  | 89.96 |

Table 6: The Clean Accuracy (CACC) of the model under ONION and Trigger Breaker towards StyAtk, respectively. Green numbers represent higher CACC, indicating the defense better preserves model’s generalization.

| Dataset | Encoder | ONION | Trigger Breaker |
|---------|---------|-------|-----------------|
| SST-2   | LSTM   | 75.89 | 76.20           |
| SST-2   | BERT   | 89.84 | 90.54           |
| OLID    | LSTM   | 76.95 | 77.30           |
| OLID    | BERT   | 81.72 | 82.01           |
| AGNews  | LSTM   | 88.57 | 89.43           |
| AGNews  | BERT   | 93.34 | 94.03           |

Table 7: The Clean Accuracy (CACC) of the model under ONION and Trigger Breaker towards SynAtk, respectively. Green numbers represent higher CACC, indicating the defense better preserves model’s generalization.

Trigger Breaker helps the model defend against backdoor attacks even trained on the poisoned dataset.

### 4.2 Methods

Trigger Breaker is composed of two too simple tricks: **Mixup** and **Shuffling**, which aims to destroy the stealthy trigger hidden in the sentence. Since the stealthy triggers are implicitly reflected by high-level semantics (e.g., BadNet), Trigger Breaker breaks such high-level semantics in embedding-level and token-level.

**Mixup** It is from (Zhang et al., 2018). In our setting, for two samples \((x_i, y_i)\) and \((x_j, y_j)\) from poisoned train set, we first feed them to the encoder \(f\) (e.g., BERT) to obtain their embeddings \(v_1, v_2\). Then we make a mixup procedure to create the synthetic sample \((v_m, y_m)\) as follows:

\[
v_m = (1 - \lambda)v_1 + \lambda v_2; y_m = (1 - \lambda)y_1 + \lambda y_2\]

where \(\lambda\) is a hyper-parameter to control the weights. In our method, we set it as 0.5 to break hidden triggers maximumally. Then \((v_m, y_m)\) is fed to the classifier for training. Such a trick breaks the high-level semantics at embedding level.

**Shuffling** The sentence shuffling is a stronger data augmentation in NLP compared to word deletion, word repetition. For a sentence \(x_i\) that owns \(N\) word, we shuffle the whole sentence to create a new re-ordered sentence \(x_i^*\). Then \(x_i^*\) is fed to the encoder. Different from mixup, shuffling breaks the high-level semantics at the token level.

### 5 Experiments

In this section, we use Trigger Breaker to defend two typical stealthy backdoor attacks and demonstrate its effectiveness.

#### 5.1 Attack Methods

1) **Syntactic Attack** (Qi et al., 2021b): Regard the syntactic structure of the text as a trigger, and use a syntactic paraphrase model to launch backdoor attacks.

2) **Style Attack** (Qi et al., 2021a): Regard the style of the text as a trigger, and use a text style transfer model to launch backdoor attacks.

#### 5.2 Benchmark and Baselines

We use the benchmarks used in both two attacks, and details can refer to Sec 3.2. Specifically, we refuse to use HS (de Gibert et al., 2018) dataset for defense evaluation since the ASRD of StyAtk is extremely low on HS (about 1%), which means it can not be regarded as a backdoor attack. Therefore, defense against backdoor attacks in such cases is not appropriate. As for the defense baselines, we choose ONION (Qi et al., 2020), a defense method for backdoor attacks by perplexity computation.
5.3 Evaluation Metrics

We adopt two metrics to evaluate the effectiveness of a defense method: (1) ASRD: the attack success rate difference of a specific backdoor attack, lower ASRD indicates the defense can better defend against such a backdoor attack; (2) CACC, the model’s accuracy on the clean test set. The higher CACC is, the better defense is.

| Dataset | Style | Encoder | Mixup | Shuffle |
|---------|-------|---------|-------|---------|
| Poetry  | BERT  | 3.32    | 4.89  |
| Poetry  | ALBERT| 3.56    | 2.96  |
| Poetry  | DisBERT| 3.87   | 4.33  |
| Shake   | BERT  | 4.31    | 7.07  |
| Shake   | ALBERT| 3.46    | 6.47  |
| Shake   | DisBERT| 4.34   | 4.55  |
| Bible   | BERT  | 4.14    | 3.14  |
| Bible   | ALBERT| 4.69    | 5.69  |
| Bible   | DisBERT| 3.47   | 3.47  |
| Lyrics  | BERT  | 3.65    | 5.10  |
| Lyrics  | ALBERT| 4.45    | 4.05  |
| Lyrics  | DisBERT| 4.91   | 4.94  |

Table 8: The Attack Success Rate Difference (ASRD) of StyAtk after defense by individually applying Mixup and Shuffling, respectively. Both mixup and shuffle operation show effectiveness in defending against StyAtk.

| Dataset | Encoder | Mixup | Shuffle |
|---------|---------|-------|---------|
| SST-2   | LSTM   | 24.76 | 23.45   |
|         | BERT   | 22.12 | 22.00   |
| OLID    | LSTM   | 28.75 | 26.12   |
|         | BERT   | 25.41 | 27.74   |
| AG      | LSTM   | 29.65 | 28.45   |
|         | BERT   | 32.14 | 31.02   |

Table 9: ASRD of SynAtk when being applied Mixup and Shuffling, respectively.

5.4 Results

The ASRD results are shown in Table 4 and Table 5. We can see that ONION fails to defend stealthy backdoor attacks effectively. ONION is based on the idea: ‘judge whether the sentence is natural and fluent.’ Such an idea effectively defended against unstealthy backdoor attacks because such attacks insert specific words as triggers, which significantly influences the sentence’s fluency. However, in stealthy attacks, the poisoned sentences are relatively natural and fluent, which can well breakthrough defenses like ONION. In contrast, trigger breaker aims to break the high-level semantics (e.g., syntactic), which is usually selected as triggers by stealthy attacks. After destroying the triggers of a backdoor attack, the attack power of backdoor attacks is rightfully declining.

The CACC results are shown in Table 6 and Table 7. Trigger Breaker achieves higher CACC than ONION, which indicates that Trigger Breaker better preserves the model’s generalization. Overall, Trigger Breaker significantly improves the defense capacity of models against stealthy backdoor attacks and better preserves the generalization. Such performances comprehensively demonstrate the effectiveness of Trigger Breaker.

6 Ablation Study

This section carefully ablates our Trigger Breaker by answering two questions.

Are mixup and shuffling effective when used individually? This part demonstrates the effectiveness of two components of Trigger Breaker. As shown in Table 8 and Table 9, both mixup and shuffling operations are effective to defend against stealthy attacks. Moreover, combining them will produce better performances.

| Rate | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|------|-----|-----|-----|-----|-----|
| ASRD | 23.04 | 21.53 | 20.37 | 18.96 | 17.66 |

Table 10: ASRD of SynAtk on SST-2 facing with Trigger Breaker with different mixup rate.

What is the effect of mixup rate? This part varies the mixup rate and sees Trigger Breaker’s performance. The results are shown in Table 10, where we can see the optimal mixup rate is 0.5. This matches our intuition that breaks the stealthy trigger since a 0.5 mixup rate achieves the maximum mixup capacity.
7 Conclusion

This paper revisits the definition of backdoor attacks and emphasizes that the core of backdoor attacks is its ‘backdoor trigger’ paradigm. Thus misclassification cases that are not caused by backdoor triggers can not be attributed to backdoor attacks’ power. Also, we show that the attack power of existing stealthy attacks is over-estimated by comprehensive empirical results. To measure the real attack power of a backdoor attack, we propose ASRD, a new metric that better portrays the attack power of a backdoor attack. Moreover, we designed a new defense method called trigger breaker, consisting of two too simple tricks, which can defend the stealthy backdoor attacks effectively and serve as the first defense method for stealthy backdoor attacks in NLP.

References

Udit Arora, William Huang, and He He. 2021. Types of out-of-distribution texts and how to detect them. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 10687–10701, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Shumeet Baluja and Ian Fischer. 2018. Learning to attack: Adversarial transformation networks. In Thirty-second aaai conference on artificial intelligence.

Chuanshuai Chen and Jiazhu Dai. 2021. Mitigating backdoor attacks in lstm-based text classification systems by backdoor keyword identification. Neurocomputing, 452:253–262.

Xiaoyi Chen, Ahmed Salem, Michael Backes, Shiqing Ma, and Yang Zhang. 2021. Badnl: Backdoor attacks against nlp models. In ICML 2021 Workshop on Adversarial Machine Learning.

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

Hanjun Dai, Hui Li, Tian Tian, Xin Huang, Lin Wang, Jun Zhu, and Le Song. 2018. Adversarial attack on graph structured data. In International conference on machine learning, pages 1115–1124. PMLR.

Jiazhu Dai, Chuanshuai Chen, and Yufeng Li. 2019. A backdoor attack against lstm-based text classification systems. IEEE Access, 7:138872–138878.

Ona de Gibert, Naiara Perez, Aitor García-Pablos, and Montse Cuadros. 2018. Hate speech dataset from a white supremacy forum. In Proceedings of the 2nd Workshop on Abusive Language Online (ALW2), pages 11–20.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572.

Tianyu Gu, Brendan Dolan-Gavitt, and Siddharth Garg. 2017. Badnets: Identifying vulnerabilities in the machine learning model supply chain. arXiv preprint arXiv:1708.06733.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.
Di Jin, Zhijing Jin, Joey Tianyi Zhou, and Peter Szolovits. 2020. Is bert really robust? a strong baseline for natural language attack on text classification and entailment. In Proceedings of the AAAI conference on artificial intelligence, volume 34, pages 8018–8025.

Alexey Kurakin, Ian Goodfellow, Samy Bengio, et al. 2016. Adversarial examples in the physical world.

Keita Kurita, Paul Michel, and Graham Neubig. 2020. Weight poisoning attacks on pretrained models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2793–2806.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Flyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.1042.

Yunfei Liu, Xingjun Ma, James Bailey, and Feng Lu. 2020. Onion: A simple and effective defense against textual backdoor attacks. arXiv preprint arXiv:2011.10369.

Fanchao Qi, Yangyi Chen, Mukai Li, Yuan Yao, Zhiyuan Liu, and Maosong Sun. 2020. Hidden killer: Invisible textual backdoor attacks with syntactic trigger. arXiv preprint arXiv:2105.12400.

Fanchao Qi, Yuan Yao, Sophia Xu, Zhiyuan Liu, and Maosong Sun. 2021c. Turn the combination lock: Learnable textual backdoor attacks via word substitution. arXiv preprint arXiv:2106.06361.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 conference on empirical methods in natural language processing, pages 1631–1642.

Eric Wallace, Shi Feng, Nikhil Kandpal, Matt Gardner, and Sameer Singh. 2019. Universal adversarial triggers for attacking and analyzing nlp. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP).

Bolon Wang, Yuanshun Yao, Shawn Shan, Huiying Li, Bimal Viswanath, Haitao Zheng, and Ben Y Zhao. 2019. Neural cleanse: Identifying and mitigating backdoor attacks in neural networks. In 2019 IEEE Symposium on Security and Privacy (SP), pages 707–723. IEEE.

Xiaosen Wang, Yichen Yang, Yihe Deng, and Kun He. 2021. Adversarial training with fast gradient projection method against synonym substitution based text attacks. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, pages 13997–14005.
Wenkai Yang, Lei Li, Zhiyuan Zhang, Xuancheng Ren, Xu Sun, and Bin He. 2021. Be careful about poisoned word embeddings: Exploring the vulnerability of the embedding layers in nlp models. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2048–2058.

Marcos Zampieri, Shervin Malmasi, Preslav Nakov, Sara Rosenthal, Noura Farra, and Ritesh Kumar. 2019. Predicting the type and target of offensive posts in social media. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1415–1420.

Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. 2018. mixup: Beyond empirical risk minimization. In International Conference on Learning Representations.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. Advances in neural information processing systems, 28:649–657.
this is the great work of polanski.
1 1
anomieous, a play of the imagination and the imagination.
1 1
for as all these remain just ideas, so we have no part in the story.
0 0
this is the lame horror, but it is lame.
0 0

Table 11: Cases that the poisoned labels match with sentences’ ground truth, and the model should predict with poisoned labels on such samples. The reason why they match is possibly the uncontrolled text style transfer process which changes the ground truth of the sentences.

| Style | Dataset | BERT | ALBERT | DisBERT |
|-------|---------|------|--------|---------|
| Bible | SST-2  | 14.72| 17.76  | 14.79   |
|       | HS     | 0.12 | 4.57   | 1.19    |
|       | AGNews | 14.37| 13.52  | 15.7    |
| Lyrics | SST-2  | 14.72| 17.76  | 14.79   |
|       | HS     | 0.12 | 4.57   | 1.19    |
|       | AGNews | 14.37| 13.52  | 15.7    |
| Poetry | SST-2  | 14.72| 17.76  | 14.79   |
|       | HS     | 0.12 | 4.57   | 1.19    |
|       | AGNews | 14.37| 13.52  | 15.7    |
| Shake | SST-2  | 14.72| 17.76  | 14.79   |
|       | HS     | 0.12 | 4.57   | 1.19    |
|       | AGNews | 14.37| 13.52  | 15.7    |

Table 12: The Attack Success Rate Difference (ASRD) of StyAtk on three benchmarks.

| Dataset | LSTM | BERT |
|---------|------|------|
| SST-2   | 45.49| 72.72|
| OLID    | 93.04| 95.43|
| AGNews  | 93.67| 88.07|

Table 13: The Attack Success Rate Difference (ASRD) of SynAtk on three benchmarks.