Rethink Stealthy Backdoor Attacks in Natural Language Processing

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Abstract
Recently, 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 on text classification tasks 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 the 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., 2021b,a) 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 changes their labels to a target label (poisoned label), then fine-tunes the victim model with clean and poisoned samples. Generally, the backdoor attack could be divided into two main categories according to the stealthiness (Yang et al., 2021b) of their triggers: stealthy attack (Qi et al., 2021b,a) and unstealthy attack (Dai et al., 2019; Chen et al., 2021). Unstealthy attacks choose a rare word or a long neutral sentence that hardly appears in the clean samples as the backdoor trigger, which is easy to detect by perplexity examination (Qi et al., 2020). While stealthy attacks commit to defining more concealed triggers like text style (Qi et al., 2021a) and syntactic (Qi et al., 2021b), which achieves an extremely high attack success rate (ASR). The current stealthy backdoor attacks mainly employ two evaluation metrics to describe their attack quality (Kurita et al., 2020; Yang et al., 2021a): (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. Existing stealthy backdoor attacks have achieved quite high scores in both metrics.

Despite their significant progress in revealing the robustness problem of the models, there are two issues for stealthy backdoor attacks: (1) our
empirical findings show that the attack power of existing stealthy backdoor attacks is not completely attributed to backdoor triggers. In other words, ASR achieved by existing stealthy attacks fail to fully satisfy the definition of backdoor attacks since many of their attack success cases are not caused by the backdoor trigger. (2) the existing defense methods against backdoor attacks perform catastrophically when facing stealthy attacks; thus, a defense for the stealthy attack is urgently needed.

Therefore, this paper provides a simple evaluation metric for evaluating the true attack power of backdoor attacks, called attack successful rate difference (ASRD). ASRD is a metric that describes the difference between the ASR of the clean state model and the poisoned state model. 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. Besides, we propose Trigger Breaker to destroy the implicit 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.

Generally, our main contributions can be 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), which measures the real attack power of the backdoor attack more precisely.

- We propose Trigger Breaker that consists of two too simple methods that can effectively defend against stealthy backdoor attacks, which outperform state-of-the-art defense 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 (to a certain extent) but not the training process of models. 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 causes the backdoor attack. Thus misclassification that is unrelated to triggers is not attributed to backdoor attacks.

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 attributed 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 3.3 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 3.4.

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, a victim model $f(\cdot)$ is trained on $D' = D_p^* \cup D_c$, after which $f(\cdot)$ would be injected into a backdoor and become $f_p(\cdot)$. During inference, for a benign test example $(x', y')$, 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 $y_t$, namely $f_p(t(x')) = y_t$.

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 trigger is unavailable are not attributed to power of backdoor attacks.
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, many other factors lead to misclassification besides backdoor, but ASR regards all misclassification cases as backdoor attack cases, including cases that are not caused by backdoor attacks. Therefore, we tend to investigate how many model misclassification cases truly result from backdoor attacks.

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 $f_c$ and $f_p$, we observe the ASR achieved by $f_c$ and $f_p$ on the poisoned test set. Moreover, we denote ASR achieved by $f_c$ and $f_p$ as $ASR_c$ and $ASR_p$, respectively. Specifically, if $\frac{ASR_p}{ASR_c} > \frac{1}{4}$, we denote it as a significant over-estimation of attack power.

The results of StyAtk are shown in Table 1, and the ones of SynAtk are shown Table 2. We can see that the test sentences poisoned by existing attacks have achieved high ASR towards a clean state model $f_c$, demonstrating that their attack successes are irrelevant to triggers. For example, StyAtk has already achieved over 80% ASR to clean state models, which implies that the attack power of StyAtk does not rely on the ‘backdoor-trigger’ paradigm. Thus directly using ASR may significantly exaggerate its attack power regarding it as a backdoor attack.

| Dataset | Style | Encoder | Clean | Poison |
|---------|-------|---------|-------|--------|
| Poetry  | BERT  | 88.55   | 90.04 |
| Poetry  | ALBERT| 89.45   | 92.13 |
| Poetry  | DisBERT| 89.03  | 89.70 |
| Shake   | BERT  | 89.56   | 90.67 |
| Shake   | ALBERT| 88.72   | 90.03 |
| Shake   | DisBERT| 88.11  | 89.57 |
| Bible   | BERT  | 89.55   | 90.67 |
| Bible   | ALBERT| 89.45   | 94.02 |
| Bible   | DisBERT| 89.03  | 90.22 |

| Dataset | Style | Encoder | Clean | Poison |
|---------|-------|---------|-------|--------|
| Poetry  | BERT  | 79.45   | 93.35 |
| Poetry  | ALBERT| 80.13   | 93.51 |
| Poetry  | DisBERT| 79.77  | 93.02 |
| Shake   | BERT  | 85.03   | 91.24 |
| Shake   | ALBERT| 84.09   | 91.76 |
| Shake   | DisBERT| 84.02  | 90.35 |
| Bible   | BERT  | 79.98   | 94.70 |
| Bible   | ALBERT| 80.03   | 97.79 |
| Bible   | DisBERT| 79.25  | 94.04 |

| Dataset | Style | Encoder | Clean | Poison |
|---------|-------|---------|-------|--------|
| Poetry  | BERT  | 82.27   | 95.64 |
| Poetry  | ALBERT| 80.64   | 95.09 |
| Poetry  | DisBERT| 80.26  | 94.96 |
| Shake   | BERT  | 86.51   | 94.55 |
| Shake   | ALBERT| 84.23   | 94.54 |
| Shake   | DisBERT| 84.36  | 94.01 |
| Bible   | BERT  | 83.27   | 97.64 |
| Bible   | ALBERT| 81.64   | 95.16 |
| Bible   | DisBERT| 82.26  | 97.96 |

| Dataset | Style | Encoder | Clean | Poison |
|---------|-------|---------|-------|--------|
| Poetry  | BERT  | 86.78   | 96.02 |
| Poetry  | ALBERT| 84.56   | 94.58 |
| Poetry  | DisBERT| 84.97  | 96.30 |

Table 1: Attack Success Rate (ASR) of BERT, ALBERT and DistilBERT, which are trained on clean train-set and poisoned trainset under StyAtk. As we can see, the poisoned test generated by StyAtk has already achieved high ASR towards the benchmarks without backdoor triggers. Purple numbers indicate the effectiveness of backdoor attack is significantly over-estimated.
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 over-estimated.

| 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  |
| AGNews   | LSTM    | 4.82  | 98.49  |
|          | BERT    | 6.02  | 94.09  |

Table 3: The Attack Success Rate Difference (ASRD) of StyAtk on three benchmarks.

| 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 4: The Attack Success Rate Difference (ASRD) of SynAtk on three benchmarks.

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

3.3 Some empirical analysis of the gap between ASR and ASRD

Based on the definitions of ASR and ASRD, 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. 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 creates 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)\(^1\) 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.\(^2\) 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\(^3\), and

\(^1\)PPL uses the likelihood of the input given by a density estimator as the score (Perplexity)

\(^2\)Recall ASR is a metric that describes the samples are predicted with the poison labels.

\(^3\)We use ‘Possibly’ because AUM also possesses error.
Table 5: 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.

| Sentence                                      | Poison label | Ground truth |
|-----------------------------------------------|--------------|--------------|
| 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            |

then we manual observe whether they are correctly labeled samples. We show some cases in Table 5, 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.

Note that there are many other reasons that lead to ASR, but they are not caused by the backdoor trigger paradigm according to the simple control variable experiments. They can be called adversarial samples but not the poison samples caused by backdoor attack.

3.4 ASRD: a new metric for backdoor attack power evaluation

The results from Table 1 and 2 have shown that most misclassification cases are not caused by the trigger, indicating that the attack power of existing stealthy attacks is extremely over-estimated. 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:

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

where $\text{ASR}(f_p, T_p)$ 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 effect of ‘backdoor trigger’ towards ASR, serves as a much more precise metric when evaluating the attack power of a backdoor attack. Specifically, we illustrate the ASRD of SynAtk and StyAtk under the settings in Sec 3.2, and the results are illustrated in Table 3 and 4. 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.

3.5 Discussion

Based on empirical findings3.3, existing stealthy backdoor attacks appear to be hybrid attacks (many factors besides backdoor samples cause the ASR), which makes ASR imprecise to describe the real attack capacity of backdoor attacks. We propose ASRD with the hope of making more fair comparisons for specific backdoor attack evaluation. 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 state-of-the-art adversarial attack methods like TextFooler(Jin et al., 2020) and FGPM(Wang et al., 2021).

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.

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
Table 6: The Attack Success Rate Difference (ASRD) of StyAtk under ONION and Trigger Breaker on SST-2. Red numbers represent Trigger Breaker achieves lower ASRD, indicating stronger defense capacity.

| Dataset | Style | Encoder | ONION | Breaker |
|---------|-------|---------|-------|---------|
| Poetry  |           | BERT    | 13.90 | 1.89    |
| Poetry  |           | ALBERT  | 13.38 | 1.96    |
| Poetry  |           | DisBERT | 13.25 | 2.33    |
| Shake   |           | BERT    | 6.21  | 1.07    |
| Shake   |           | ALBERT  | 7.67  | 1.47    |
| Shake   |           | DisBERT | 6.33  | 1.55    |
| SST-2   |         | BERT    | 14.72 | 2.14    |
|         |         | ALBERT  | 17.76 | 3.69    |
|         |         | DisBERT | 14.79 | 2.47    |
| Lyrics  |         | BERT    | 5.15  | 1.10    |
| Lyrics  |         | ALBERT  | 8.35  | 2.05    |
| Lyrics  |         | DisBERT | 7.69  | 1.94    |

Table 7: The Attack Success Rate Difference (ASRD) of SynAtk on three benchmarks. Red numbers represent Trigger Breaker achieves lower ASRD, indicating stronger defense capacity.

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

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:

\[
v_m = (1 - \lambda)v_1 + \lambda v_2; \quad y_m = (1 - \lambda)y_1 + \lambda y_2
\]
where $\lambda$ is a hyper-parameter to control the weights. In our method, we set it as 0.5 to break hidden triggers maximumly. 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

- **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.

- **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.

5.4 Results

The ASRD results are shown in Table 6 and Table 7. We can see that ONION fails to defend stealthy backdoor attacks effectively since previous defense methods are based on the idea: ‘judge whether the sentence is natural and fluent.’ Such an idea effectively defended against unstealthy backdoor attacks because unstealthy attacks insert some specific words as triggers, which significantly influences the sentence’s fluency. However, in stealthy attacks, the poisoned sentences are natural and fluent, which can well breakthrough such defenses.

| 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  | 4.51    | 7.07  |
| Shake   | ALBERT| 3.46    | 6.47  |
| Shake   | DisBERT| 4.34   | 4.55  |

Table 10: 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  |

| Dataset | Encoder | Mixup | Shuffle |
|---------|---------|-------|---------|
| OLID    | LSTM   | 28.75 | 26.12  |
|         | BERT    | 25.41 | 27.74  |

| Dataset | Encoder | Mixup | Shuffle |
|---------|---------|-------|---------|
| AGNews  | LSTM   | 29.65 | 28.45  |
|         | BERT    | 32.14 | 31.02  |

Table 11: The Attack Success Rate Difference (ASRD) of SynAtk after by individually applying Mixup and Shuffling, respectively.
In contrast, trigger breaker aims to break the high-level semantics, which is usually selected as triggers by stealthy attacks. After destroying the triggers of a backdoor attack before parameter optimization, the attack power of backdoor attacks is deservedly declining.

Besides, the CACC results are shown in Table 8 and Table 9. As we can see, the accuracy on the clean test set is also higher than ONION, which indicates that Trigger Breaker can better preserve the model’s generalization. Overall, Trigger Breaker significantly improves the defense capacity of models against stealthy backdoor attacks and slightly hurts 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 10 and Table 11, both mixup and shuffling operations are effective to defend against stealthy attacks. Moreover, combining them will produce better performances.

What is the effect of mixup rate? This part varies the mixup rate $\lambda$ and sees Trigger Breaker’s performance. The results are shown in Table 12, 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.

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

Table 12: The Attack Success Rate Difference (ASRD) of SynAtk on SST-2 after Trigger Breaker with different mixup rate.

7 Conclusion

This paper firstly reviews 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. 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.
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